UNIVERSITY OF SOUTHAMPTON

FACULTY OF ENGINEERING AND THE ENVIRONMENT

Centre for Environmental Science

Enhancing Urban Road Traffic Carbon Dioxide Emissions Models

by

Matt Grote

Thesis for the degree of Doctor of Engineering

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ABSTRACT

FACULTY OF ENGINEERING AND THE ENVIRONMENT

Transport and the Environment

Thesis for the degree of Doctor of Engineering

ENHANCING URBAN ROAD TRAFFIC CARBON DIOXIDE EMISSIONS MODELS

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The aim of this project was to provide a more accurate representation of road traffic carbon dioxide (CO_2) emissions in urban areas, whilst remaining within limited Local Government Authority (LGA) resources. Tailpipe emissions from vehicles on urban roads have damaging impacts, with the problem exacerbated by the common occurrence of congestion. The scope of the project was CO_2 because it is by far the largest constituent (99%) of road traffic greenhouse gas emissions. LGAs are typically responsible for facilitating mitigation of these emissions and must engage in emissions modelling to quantify the impact of transport interventions. A review of relevant literature identified a research gap, which constituted an investigation into whether a Traffic Variable Emissions Model (EM) (i.e. based on input data aggregated at traffic level rather than disaggregated at vehicle level) represented optimal complexity for LGAs, improving on the ability of well-established Average Speed EMs to capture the influence on emissions of congestion, whilst remaining within resource constraints. British LGAs (n=34) were surveyed to discover general attitudes to emissions modelling. Results showed that resource scarcity is important, with particular importance attached to EM reusability and convenient input data sources. Data sources rated highly for convenience were Urban Traffic Control (UTC) systems and Road Traffic Models (RTMs).

A new Traffic Variable EM was developed termed the Practical EM for Local Authorities (PEMLA). Using Southampton as a testbed, 514 real-world GPS driving patterns (1Hz speed-time profiles) were collected from 49 drivers of different vehicle types and used as inputs to a detailed, instantaneous EM to calculate accurate vehicle CO_2 emissions (assumed to represent 'real-world' emissions). Concurrent data were collected from Inductive Loop Detectors (ILDs installed as part of UTC systems) crossed by vehicles during their journeys and used to calculate values for selected traffic variables. Relationships between traffic variables (predictor variables) and accurate emissions (outcome variable) were examined using statistical analysis. Results showed that PEMLA outperformed the well-established, next-best alternative EM available to LGAs (an Average Speed

EM), with mean predictions of PEMLA found to be 2% greater than observed values, whilst mean predictions of the alternative EM were 12% less.

PEMLA's contribution is two-fold. Firstly, it is closer to optimal complexity than the well-established Average Speed EM alternative. This was for two reasons: (1) PEMLA was more accurate through using as inputs other traffic variable congestion indicators (in addition to traffic average speed), which improved its ability to capture the influence of congestion on emissions; and (2) PEMLA consumes similar (or potentially lower) resources to operate because inputs are generated from ILD data, which are a by-product of UTC systems or can be readily simulated in RTMs. Secondly, it possesses attributes that addressed the identified limitations of other Traffic Variable EM alternatives. These two contributions make PEMLA a suitable option to be recommended for LGA use.

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Appendix B

Grote M, Williams I, Preston J and Kemp S (2016) 'Local government authority attitudes to road traffic CO_2 emissions modelling: a British case study', *Transportation Planning and Technology*, 1-19.

Appendix C

Local Government Authority Road Traffic Emissions Questionnaire – Paper version of the questionnaire survey distributed in the online iSurvey format.

Appendix D

Grote M, Williams I, Preston J and Kemp S. A practical method for predicting road traffic carbon dioxide emissions. Transportation Research Board (TRB) 96th Annual Meeting, 8-12 January 2017, Washington D.C., USA. Transportation Research Board.

Appendix E

Southampton SCOOT UTC system ILD wiring diagrams.

DECLARATION OF AUTHORSHIP

I, Matt Grote

declare that this thesis and the work presented in it are my own and has been generated by me as the result of my own original research.

Enhancing Urban Road Traffic Carbon Dioxide Emissions Models.

I confirm that:

1. This work was done wholly or mainly while in candidature for a research degree at this University;
2. Where any part of this thesis has previously been submitted for a degree or any other qualification at this University or any other institution, this has been clearly stated;
3. Where I have consulted the published work of others, this is always clearly attributed;
4. Where I have quoted from the work of others, the source is always given. With the exception of such quotations, this thesis is entirely my own work;
5. I have acknowledged all main sources of help;
6. Where the thesis is based on work done by myself jointly with others, I have made clear exactly what was done by others and what I have contributed myself;
7. Parts of this work have been published as:

   Grote M, Williams I and Preston J (2014) 'Direct carbon dioxide emissions from civil aircraft', *Atmospheric Environment*, 95, 214-224.

   Grote M, Williams I, Preston J and Kemp S (2016) 'Including congestion effects in urban road traffic CO_2 emissions modelling: Do Local Government Authorities have the right options?', *Transportation Research Part D: Transport and Environment*, 43, 95-106.

Grote M, Williams I, Preston J and Kemp S (2016) 'Local government authority attitudes to road traffic CO_2 emissions modelling: a British case study', *Transportation Planning and Technology*, 1-19.

Signed:

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DEFINITIONS AND ABBREVIATIONS

ACEA	European Automobile Manufacturers Association
Adj. R^2	Adjusted R^2 – an estimate of what R^2 would be if a model was based on analysis of the entire population rather than only a sample from the population
ADMS	Atmospheric Dispersion Modelling System – software application produced by Cambridge Environmental Research Consultants
AIMSUN (RTM)	Advanced Interactive Microscopic Simulator for Urban and Non-Urban Networks – produced by Transport Simulation Systems
AIRE (EM)	Analysis of Instantaneous Road Emissions – produced by SIAS Limited and Transport for Scotland
AMITRAN	Assessment Methodology for ICT in Transport – European Commission 7th Framework project
ANPR	Automatic Number Plate Recognition
AQ emissions	Air Quality emissions
ARCADY (RTM)	Assessment of Roundabout Capacity and Delay – produced by TRL
ARTEMIS	Assessment and Reliability of Transport Emission Models and Inventory Systems – European Commission 5th Framework project
ASTRID	Automatic SCOOT Traffic Information Database
ATC	Automatic Traffic Count
ATC-Pneumatic	Automatic Traffic Count by pneumatic tube
ATC-SDR	Automatic Traffic Count by Speed Detection Radar
AURN	Automatic Urban and Rural Network
AVI	Automatic Vehicle Identification
BEV	Battery Electric Vehicle
CA	Combined Authority
CAN	Controller Area Network
CARBOTRAF	European Commission 7th Framework project
CE-CERT	College of Engineering – Center for Environmental Research and Technology at the University of California
CH_4	Methane
CMEM (EM)	Comprehensive Modal Emissions Model – produced by CE-CERT
CNG	Compressed Natural Gas
CO	Carbon monoxide

CO_2	Carbon dioxide
CO_2e	CO_2-equivalent – the amount of CO_2 emitted that would cause the same time-integrated radiative forcing, over a given time-horizon, as an emitted amount of another GHG
COBA	Cost Benefit Analysis – software application for road improvement appraisal produced by TRL and sponsored by Highways England
CONTRAM (RTM)	Continuous Traffic Assignment Model – produced by Mott MacDonald and TRL, but no longer available to new users
COPERT (EM)	Computer Programme to calculate Emissions from Road Transport – coordinated by the EEA
CRUISE (EM)	Produced by AVL LIST GmbH
CSEE	Cold-Start Excess Emissions
CUBE Avenue (RTM)	Produced by Citilabs
CUBE Dynamism (RTM)	Produced by Citilabs
CUBE Voyager (RTM)	Produced by Citilabs
DCLG	UK national government's Department for Communities and Local Government
DCM (EM)	Delay Correction Model – produced by Song *et al.* (2015)
DECADE	European Commission 5th Framework project
DECC	UK national government's Department of Energy & Climate Change (abolished in July 2016)
DEEM (EM)	Direct Energy-use and Emissions Model – sub-model of UKTCM
DEFRA	UK national government's Department for Environment Food & Rural Affairs
DELTA (RTM)	Land-use/transport interaction analysis – produced by David Simmonds Consultancy
DEFRA GHG EFs (EM)	Greenhouse Gas Conversion Factor Repository – produced by DEFRA
DfT	UK national government's Department for Transport
DMRB	Design Manual for Roads and Bridges – DfT guidance on the design, assessment and operation of trunk roads and motorways, including methods for calculating road traffic emissions
DRACULA (RTM)	Dynamic Route Assignment Combining User Learning and Microsimulation – produced by the University of Leeds

DRIVE	Dedicated Road Infrastructure for Vehicle safety in Europe – European Commission 2nd Framework project
Driving cycle	Standardised driving pattern over which a vehicle's emissions are measured during a laboratory emissions test
Driving pattern	Fine grained time series (e.g. 1Hz) of speed points for an individual vehicle, also known as a speed-time profile
DSS	Decision Support System – sub-system of CARBOTRAF
DUKES	Digest of UK Energy Statistics
EC	European Commission
EEA	European Environment Agency
EF	Emission Factor (e.g. gCO_2/VKM)
EIA	Environmental Impact Assessment
EM	Emissions Model
EMFAC (EM)	EMission FACtors – produced by the California Air Resources Board
EMIGMA	Emissions Inventory for Greater Manchester
Emission Function	EF as a function of variables related to the traffic or individual vehicles
EMIT (EM)	Emissions Inventory Toolkit – sub-model of ADMS
EMME (RTM)	Produced by INRO
ENEA	Italian National Agency for New Technologies, Energy and Sustainable Economic Development
EnViVer (EM)	Environment VISSIM and VERSIT+ – produced by TNO and PTV
EPA	USA national government's Environmental Protection Agency
ER	Emission Rate (e.g. gCO_2/s)
ESC (EM)	Emission Specific Characteristics – produced by Nesamani *et al.* (2007)
EU	European Union
Euro 1-6	EU standards to limit atmospheric emissions from LDVs
Euro 1-4	EU standards to limit atmospheric emissions from two-wheel vehicles
Euro I-VI	EU standards to limit atmospheric emissions from HDVs
FCV	Fuel Cell Vehicle
F-gases	Fluorinated gases
FHWA	USA national government's Federal Highway Administration
gCO_2	Grams of carbon dioxide
GHG	Greenhouse Gas
GLA	Greater London Authority

GMCA	Greater Manchester Combined Authority
GVM	Gross Vehicle Mass – maximum operating mass of a vehicle as specified by the manufacturer
HBEFA (EM)	Handbook of Emission Factors – coordinated by INFRAS
HC	Hydrocarbon
HCC	Hampshire County Council
HCSE	Heteroscedastic-Consistent Standard Error estimator
HDV	Heavy Duty Vehicle
HEV	Hybrid Electric Vehicle
HGV	Heavy Goods Vehicle – a sub-category of HDV
ICE	Internal Combustion Engine
ICT	Information and Communication Technology
IEM (EM)	Instantaneous Emissions Model
ILD	Inductive Loop Detector
Intersection	A junction between two (or more) road sections
IoWC	Isle of Wight Council
ITS	Intelligent Transport Systems
Kerb mass	Vehicle unladen mass
LAEI	London Atmospheric Emissions Inventory
LDV	Light Duty Vehicle
LEP	Local Enterprise Partnership
LEZ	Low Emission Zone
LGA	Local Government Authority – local government for sub-national administrative areas
LGV	Light Goods Vehicle – a sub-category of LDV
LHA	Local Highways Authority
Link	Uni-directional road section between two intersections
LINSIG (RTM)	Signal-controlled intersection analysis – Produced by JCT Consultancy
LOO CV	Leave-One-Out Cross Validation
LPG	Liquefied Petroleum Gas
LSTF	Local Sustainable Transport Fund
LUT	Look-Up Table
MAF	Mean Accuracy Factor
MAPE	Mean Absolute Percentage Error

MCC	Manual Classified Counts
MCO	Moving Car Observer
MEET	Methodologies to Estimate Emissions from Transport – European Commission 4th Framework project
MLP	Multilayer Perceptron neural network
MLR	Multiple Linear Regression
MOBILE (EM)	Produced by the EPA
MODEM (EM)	Modelling of Emissions and Consumption in Urban Areas – produced during DRIVE
MoU	Memorandum of Understanding
MOVES (EM)	Motor Vehicle Emission Simulator – produced by the EPA
MRO	Mass in Running Order – vehicle unladen mass, plus driver mass
MTC	Manual Traffic Count
N_2O	Nitrous oxide
NAEI	National Atmospheric Emissions Inventory
NEDC	New European Driving Cycle – test used for type approval of new cars
NEMO (EM)	Network Emissions Model – produced during ARTEMIS
NI	National Indicator
NO_2	Nitrogen dioxide
NO_X	Oxides of nitrogen
NTM	National Transport Model – DfT's strategic transport model
NUIDAP (EM)	Newcastle University Integrated Database and Assessment Platform
O_3	Ozone
OGV	Other Goods Vehicle
OLS	Ordinary Least Squares
Optimal EM complexity	Point beyond which decreasing accuracy of input data begins to offset any accuracy gains through increasing model complexity
PARAMICS (RTM)	Parallel Microscopic Simulation – Q-PARAMICS produced by Quadstone and S-PARAMICS produced by SIAS Limited
PCC	Portsmouth City Council
PEMS	Portable Emissions Measurement System
PHEM (EM)	Passenger car and Heavy duty Emission Model – developed during ARTEMIS and coordinated by Technische Universität Graz
PHEV	Plug-in Hybrid Electric Vehicle

PICADY (RTM)	Priority Intersection Capacity and Delay (now called Junctions 8) – produced by TRL
PITHEM (EM)	Platform for Integrated Transport, Health and Environmental Modelling – produced by Newcastle University
PKM	Passenger-Kilometre
PM	Particulate Matter
PPM	Parts Per Million
PSV	Public Service Vehicle
PTE	Passenger Transport Executive
PTV	Planung Transport Verkehr AG
QUADRO (RTM)	Road works cost appraisal – produced by TRL
r	Pearson linear correlation coefficient
R^2	Coefficient of determination
RFID	Radio Frequency Identification Device
rho	Spearman (non-parametric) linear correlation coefficient
RM	Reference Mass – MRO, minus driver mass, plus 100kg
RSI	Roadside Interview
RTFO	Renewable Transport Fuel Obligation
RTM	Road Traffic Model
RTMS	Remote Traffic Microwave Sensor – also known as SDR
SATURN (RTM)	Simulation and Assignment of Traffic to Urban Road Networks – developed at the University of Leeds and distributed by Atkins Limited
SCATS	Sydney Coordinated Adaptive Traffic System – UTC system developed by Roads and Maritime Services, a New South Wales Government agency in Australia
SCC	Southampton City Council
SCF	Speed Correction Factor
SCOOT	Split, Cycle and Offset Optimisation Technique – UTC system developed by Imtech Traffic & Infra UK, Siemens and TRL
SDR	Speed Detection Radar – also known as RTMS
SIGSIM (RTM)	Produced by Newcastle University
SRN	Strategic Road Network
SSF (EM)	Stepwise Speed Function – produced by Kuwahara *et al.* (2013)
SS_R	Sum of squared residuals

SUV	Sports Utility Vehicle
TCI	Traffic Congestion Index
TDS	Traffic Data Sensor – specialist sensor used in CARBOTRAF
TEE-KCF (EM)	Traffic Energy and Emissions-Kinematic Correction Factor – produced by ENEA
TEE-REC (EM)	Traffic Energy and Emissions-Reconstructed – produced by ENEA
TfGM	Transport for Greater Manchester
TfL	Transport for London
TfSH	Transport for South Hampshire (now called Solent Transport)
TNO	Netherlands Organisation for Applied Scientific Research
TPI	Traffic Performance Index
TRANSYT (RTM)	Traffic Network and Isolated Intersection Study Tool – produced by TRL
TRICS	UK database for trip generation analysis
TRIPS (RTM)	Transport Improvement Planning System – produced by MVA Consultancy (MVA Consultancy are now called Systra)
TRL	Transport Research Laboratory
TSAF	TRL Speed-specific Adjustment Factor
TUBA	Transport User Benefit Appraisal – software application for road and multi-modal scheme appraisal produced by the DfT and Atkins Limited
UK	United Kingdom of Great Britain (England, Scotland and Wales) and Northern Ireland
UKTCM	UK Transport Carbon Model
UNECE	United Nations Economic Commission for Europe
UNFCCC	United Nations Framework Convention on Climate Change
UROPOL (EM)	Urban Road Pollution – produced by Matzoros and Van Vliet (1992)
UTC	Urban Traffic Control
VDM (EM)	VSP Distribution Model – produced by Song *et al.* (2014)
VERSIT+ (EM)	VERkeers SITuatie (Traffic Situation) – produced by TNO
VeTESS (EM)	Vehicle Transient Emissions Simulation Software – produced during DECADE
VISSIM (RTM)	Produced by PTV
VISUM (RTM)	Produced by PTV
VITO	Vlaamse Instelling voor Technologisch Onderzoek (Flemish Institute for Technological Research)
VKM	Vehicle-Kilometre

VMS	Variable Message Sign
VOEM	VITO’s On Road Emissions and Energy Measurement system
VSP	Vehicle Specific Power
WebTAG	Web Transport Analysis Guidance – DfT guidance on conducting transport studies, including methods for calculating road traffic emissions
WLS	Weighted Least Squares
WLTC	Worldwide Light-duty Test Cycle
WLTP	Worldwide harmonised Light vehicle Test Procedure

Chapter 1 INTRODUCTION

1.1 PROJECT AIM AND OBJECTIVES

The aim of this project was to provide a more accurate representation of road traffic carbon dioxide (CO_2) emissions in urban areas, whilst remaining within limited Local Government Authority (LGA) resource budgets. This aim was accomplished through completion of the following four objectives:

1. Determine the factors that influence the road traffic CO_2 emissions modelling process, with an emphasis on the trade-off between Emissions Model (EM) accuracy and resource consumption.
2. Determine current LGA attitudes and practices concerning the road traffic emissions modelling process, and discover the EM detail level considered to be practical within limited resources.
3. Develop an EM useable by all (or the majority of) LGAs based on readily available traffic variables that improves accuracy through explicitly including the influence of congestion, without substantially increasing resource use.
4. Compare the prediction accuracy of the newly developed EM with that of the next-best alternative available to LGAs.

1.2 RESEARCH QUESTIONS SUMMARY

Formulated in response to the research gap identified through the literature review (refer to Section 2.6.5), the three research questions that constituted the framework for this project are summarised as follows:

1. What data and models are currently used by LGAs for road traffic CO_2 emissions modelling, and what are their attitudes to the issues of resource use and prediction accuracy?
2. Is it possible to identify traffic variables as indicators of congestion that have a consistent relationship with CO_2 emissions from road traffic, and that are readily available to LGAs?
3. By virtue of being readily available, is it possible to use such traffic variables, in addition to traffic average speed, to explicitly include congestion influence and improve the accuracy of urban network CO_2 emissions predictions compared to predictions from EMs based solely on average speeds, whilst avoiding a substantial increase in model complexity and remaining a tractable tool for use by LGAs in transport intervention assessments?

1.3 REPORT STRUCTURE

Chapter 1 (this chapter) establishes the importance of the problem of CO_2 emissions from road traffic in congested urban areas, and describes the responsibility that LGAs have for facilitating the mitigation of such emissions. Chapter 2 presents a contemporary review of the literature concerning the factors that influence road traffic CO_2 emissions, potential sources of road traffic data for use in the emissions modelling process, and the practicalities of the use of such data by LGAs in EMs. The research gap, and associated research questions, identified for further investigations are outcomes of this literature review. Chapter 3 provides a brief overview of the entire project methodology in order to assist the reader in understanding how the constituent parts of the project fit together. Chapter 4 details a survey conducted to establish current attitudes and practices of British LGAs concerning the road traffic CO_2 emissions modelling process. Chapter 5 explains the methodology employed in developing a new EM for predicting urban network-level CO_2 emissions, termed the Practical Emissions Model for Local Authorities (PEMLA), and in comparing PEMLA with the next-best alternative available to LGAs. Chapter 6 details results from the development and comparison of PEMLA. Chapter 7 discusses these results, leading to a chosen version of PEMLA being recommended for use by LGAs and a discussion of the wider context of PEMLA application. Finally, project conclusions are presented in Chapter 8.

1.4 THE PROBLEM OF ROAD TRAFFIC EMISSIONS IN URBAN AREAS

More than half the world's population now lives in urban areas; and, by 2030, the number of urbanites is expected to reach almost 5 billion (UNFPA 2007). The high population density of urban areas presents challenges, not least of which is servicing requirements for transportation, both of passengers and freight. This concentrated travel requirement can often overwhelm the transport system leading to congestion on urban road networks during peak periods. As an example of the situation in a typical developed nation, according to the United Kingdom[1] (UK) national government Department for Transport (DfT) (2012), the national total of 420bn vehicle-kilometres[2] (VKMs) travelled in England in 2010 was split approximately evenly between those driven in urban areas (216bn VKMs = 51%) and those driven outside urban areas (204bn VKMs = 49%). However, congestion is a much bigger problem in urban areas, with 14% (29.2bn) of VKMs being driven in very congested conditions[3],

[1] The United Kingdom constitutes Great Britain (England, Scotland and Wales) and Northern Ireland.
[2] One VKM is achieved when one vehicle travels one kilometre.
[3] Very congested conditions were defined as occurring when a road was at greater than 80% of theoretical capacity.

compared to just 2% (4.1bn) outside urban areas. It should be noted that the industrial sponsor for this EngD project was Southampton City Council (SCC), the LGA responsible for the city of Southampton[4] in southern England. Consequently, project investigations are primarily considered from a UK (or British) perspective. However, the situation in the UK will often have parallels in other countries, particularly other developed nations.

The large number of vehicles using urban road networks has damaging environmental impacts. One cause of such impacts is atmospheric emissions from vehicle tailpipes, including both greenhouse gases (GHGs) and pollutants detrimental to air quality (AQ emissions). High traffic densities lead to large amounts of emissions, with the problem exacerbated by the stop-and-go nature of congestion increasing emissions yet further (DfT 2013a). Consequently, urban areas produce a disproportionate amount of road traffic emissions compared to their geographic size (Grote *et al.* 2016a), and should be a focus for efforts to mitigate such emissions as part of overall strategies to reduce anthropogenic GHG emissions and improve air quality. Indeed, SCC already provides a forecasting service for poor air quality to individuals with respiratory disease to reduce preventable admissions to hospital; this has been evaluated by McLaren and Williams (2015).

Once again using the UK as an example of a typical developed nation, the transport sector contributes approximately 26% of total anthropogenic GHG emissions; consisting of 19% from domestic transport and 7% from international aviation and shipping, as shown in Figure 1-1 (DECC 2015; DfT 2015c). A discussion by the author of the problem of CO_2 emissions from civil aviation can be found in Grote *et al.* (2014). In Figure 1-2, the 19% of GHG emissions from domestic transport are sub-divided according to transport mode, demonstrating that road traffic is responsible for the vast majority (92%) (DfT 2015c). GHG emissions from transport are CO_2, methane (CH_4), nitrous oxide (N_2O), and fluorinated gases (F-gases) (Kahn Ribeiro *et al.* 2007). However, CO_2 is by far the most significant contributor. For example, CO_2 constitutes approximately 99% of GHG emissions from transport in the UK on a CO_2e basis[5] (DECC 2015). The UK figures are broadly similar to the global situation, where transport's contribution to

[4] Southampton is an urban area on the south coast of England with a population of 236,900 according to the last national census in 2011.

[5] CO_2-equivalent is the amount of CO_2 emitted that would cause the same time-integrated radiative forcing, over a given time horizon, as an emitted amount of another GHG.

total CO_2 emitted from fuel combustion is 23%, of which road traffic is responsible for three-quarters (IEA 2015).

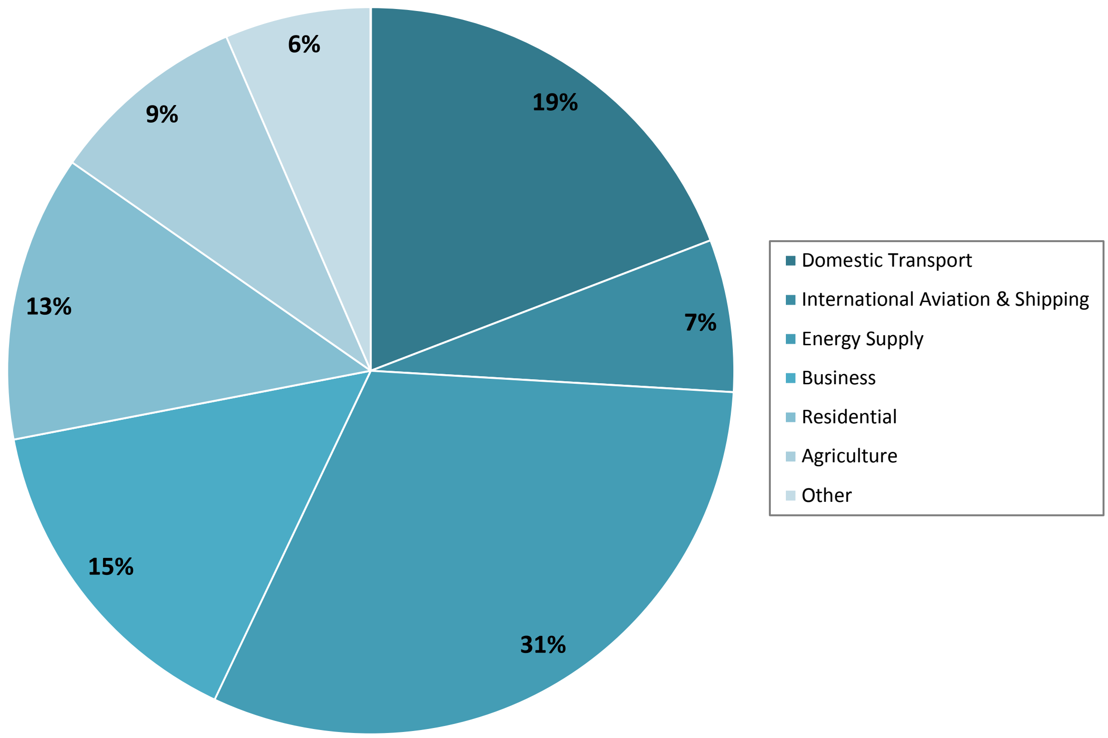

Figure 1-1: Total UK GHG emissions disaggregated by sector for 2013.

- Total emissions were 609.7 million tonnes CO_2e.
- Responsibility for an emission is allocated to the source that directly produces the emission.
- GHG emissions from international shipping and international aviation (based on estimated fuel sold from UK fuel supplies) have been added to domestic emissions to give a UK total.
- 'Other' is public bodies, industrial processes, waste management, and land-use and land-use change and forestry (LULUCF).
- Sources: DECC (2015) and DfT (2015c).

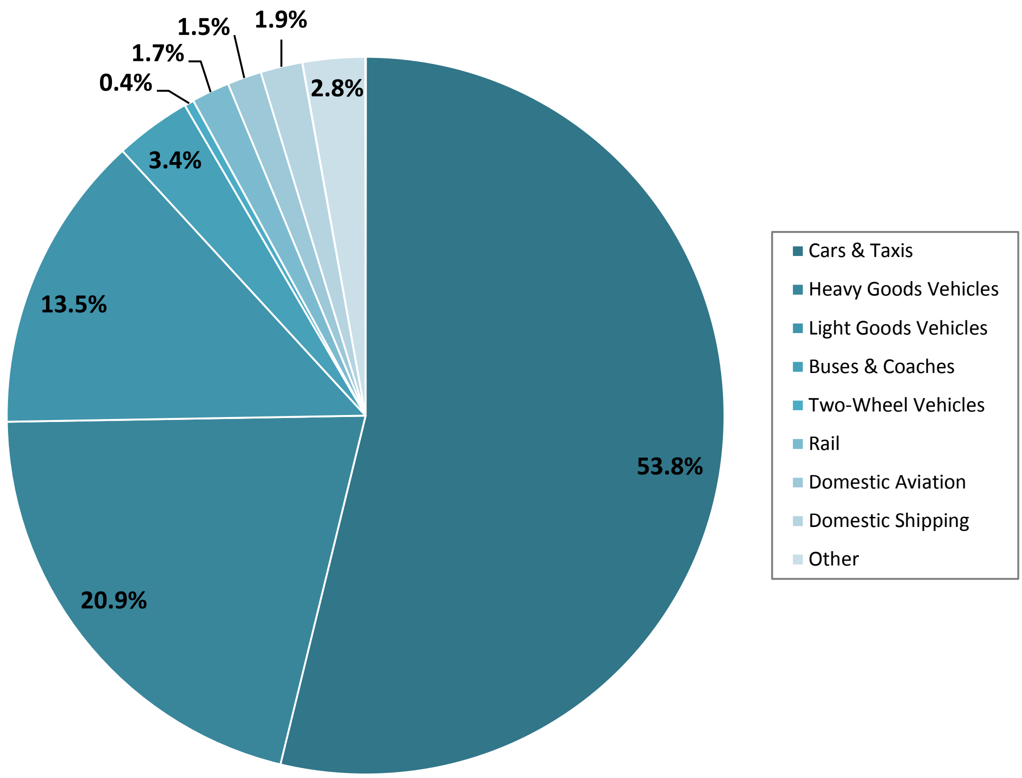

Figure 1-2: UK domestic transport GHG emissions disaggregated by mode for 2013.

- Total emissions were 116.8 million tonnes CO_2e, which is 19% of the total UK GHG emissions shown in Figure 1-1.
- Responsibility for an emission is allocated to the source that directly produces the emission. So, for example, electrified rail transport would have zero GHG emissions. Emissions produced in generating electricity for rail-use would not appear in Figure 1-2 because they are allocated to the 'Energy Supply' sector rather than the 'Domestic Transport' sector. If emissions from both fuel processing and electricity generation used by rail were to be included, rail GHG emissions would rise from 2.0 to 4.2 million tonnes CO_2e.
- 'Other' is mainly military aircraft and shipping, aircraft support vehicles, stationary combustion by the railway sector, and road vehicles running on liquefied petroleum gas (LPG).
- Source: DfT (2015c).

Worldwide, an estimated one billion people in urban areas are continuously exposed to health hazards from air pollution (Smit *et al.* 2008a). Most of the detrimental human health effects associated with AQ emissions are related to respiratory and cardiovascular disease, whilst some are also carcinogenic (Uherek *et al.* 2010). Harmful pollutants include particulate matter (PM), oxides of nitrogen (NO_X), carbon monoxide (CO), and the secondary pollutant ozone (O_3) (Nejadkoorki *et al.* 2008). Road traffic is often the dominant anthropogenic source of AQ emissions in urban areas (Silva *et al.* 2006; Smit *et al.* 2008a; Franco *et al.* 2013), and poor local air quality in the vicinity of busy roads is of particular concern (Uherek *et al.* 2010), especially as emissions occur in close proximity to people (Smit *et al.* 2008a). It has been suggested that road traffic is likely to remain a major contributor to poor urban air quality over the coming decades (Franco *et al.* 2013).

1.5 LOCAL GOVERNMENT AUTHORITY RESPONSIBILITIES

Ultimately, governments are responsible for providing road infrastructure, and for achieving agreed GHG emission reduction targets and maintaining local air quality to within established safe limits. Many of these responsibilities are devolved from national government to LGAs.

1.5.1 Local Government Authority Responsibilities for Roads

Typically, motorways and major trunk-roads are administered by national government agencies, whilst responsibility for other roads is devolved to LGAs. For example, in Great Britain, motorways and major trunk roads are known as the Strategic Road Network (SRN), with the SRN administered by Highways England, Transport Scotland and the Welsh Government in England, Scotland and Wales, respectively. Responsibility for all other adopted[6] roads is devolved to LGAs. For comparison, the national total of 417bn VKMs travelled in England in 2012 was split between 33% (136.3bn VKMs) carried by SRN roads and 67% (280.7bn VKMs) carried by non-SRN roads (DfT 2013a).

Those British LGAs responsible for non-SRN roads are known as Local Highways Authorities (LHAs)[7]. Under the complex system of local government in Britain (particularly England), not all LGAs are LHAs. Only first tier LGAs (County Councils) and single tier LGAs (Unitary Authorities, London Borough Councils and Metropolitan District Councils) are LHAs. Second tier LGAs (District Councils, Borough Councils and those City Councils that are not Unitary Authorities) are not responsible for the roads in their region, with the appropriate first tier LGA being responsible instead. The result of this system is that – excluding Combined Authorities (refer to next paragraph) and Single Purpose Authorities (e.g. National Park Authorities, Waste Authorities and Fire Authorities) – approximately half of British LGAs (206 out of a total of 407) are also LHAs (DECC 2014; DCLG 2015).

At intermediate level between national government and LGAs there is a layer of regional partnerships, collaborations and authorities whose main function is to coordinate regional

[6] In contrast to private roads, adopted roads (which constitute the vast majority of British roads) are those maintained at public expense.

[7] In this thesis, LGA is used in preference to LHA because it is a more typical term used to describe local government institutions. However, where LGA is used, this implies a local authority with responsibility for non-SRN roads in their area of administration.

transport strategy. For example, the Greater London Authority's (GLA) London-wide transport strategy is implemented by Transport for London (TfL) in cooperation with the individual London Borough Councils. The GLA is responsible for some of the more major (non-SRN) roads in London, with TfL being the LHA for approximately 5% of the road network (DCLG 2015). Outside London, the six largest conurbations in England are Greater Manchester, Merseyside, South Yorkshire, Tyne and Wear, West Midlands and West Yorkshire. Each of these regions has established a Combined Authority (CA), which is a statutory body responsible for transport policies (principally public transport) affecting the individual LGAs that constitute each CA. Alongside each CA, there is a Passenger Transport Executive[8] (PTE) responsible for delivery of the CA's policies. For example, the delivery arm of the Greater Manchester Combined Authority (GMCA) is the Transport for Greater Manchester (TfGM) PTE. CAs are not limited to the six conurbations mentioned, and legislation provides for any neighbouring LGAs to form CAs if they so wish, with the establishment of others currently under discussion. Local Enterprise Partnerships (LEPs) were introduced in the UK national government's Department for Communities and Local Government (DCLG) 2010 White Paper[9] 'Local Growth: Realising Every Place's Potential'. There are currently (September 2016) 39 LEPs throughout England, bringing together LGAs, business leaders and educational institutions within their boundaries to discuss the priorities for investment in transport, buildings and facilities in the area. In Scotland, seven Regional Transport Partnerships have been established covering the whole of the country, and bringing together their constituent LGAs to better achieve the planning and delivery of regional transport. A similar role in Wales is fulfilled by four Regional Transport Consortia. Many other examples of regional transport collaborations exist across Britain. As an example, Solent Transport[10] consists of a partnership between SCC, Hampshire County Council (HCC), Portsmouth City Council (PCC) and Isle of Wight Council (IoWC), and was established to plan transport improvements for the South Hampshire sub-region. A disadvantage of this complex intermediate layer of regional collaboration and partnership is that boundaries of different partnerships can often be overlapping, with LGAs simultaneously being members of several partnerships that could potentially have competing interests.

[8] West Yorkshire PTE (called Metro) has now been abolished and its functions absorbed into the West Yorkshire CA. West Midlands PTE (called Centro) has now been abolished and its functions provided by Transport for West Midlands, the delivery arm of the West Midlands CA.

[9] White Papers are government documents setting out details of future policy, allowing an opportunity to gather feedback before policies are formally put before the UK Parliament as a Bill.

[10] Solent Transport was previously known as Transport for South Hampshire (TfSH).

Further actors worthy of note in the context of LGA responsibilities for roads are external expert transport consultants. In situations where in-house expertise needs to be supplemented, LGAs may engage external consultants from the private sector to assist with the generation of the evidence database required to support their transport policies and decisions. As well as for short-term contracts, engagement of external consultants can be on a longer-term, strategic basis under framework agreements[11]. For example, SCC signed the Southampton Highways Service Partnership contract with Balfour Beatty in 2010 which covers provision of highways transportation planning and asset management services over a 10 year period (with an optional 5 year extension). The layer of regional partnerships and the use of external consultants both complicate and influence the framework within which LGAs make decisions concerning their road network. However, ultimately LGAs are the highways authorities responsible for the non-SRN roads within their areas of administration, and consequently are responsible for facilitating mitigation of road traffic emissions. LGAs are also responsible (possibly collaboratively) for deciding on the necessity of expending resources to engage external consultants. Therefore, the role of LGAs in mitigating road traffic emissions was selected as the principal concern for this project.

1.5.2 Local Government Authority Responsibilities for Reducing Emissions

1.5.2.1 Greenhouse gas emissions

In common with many other countries, the UK is a signatory to the United Nations Framework Convention on Climate Change (UNFCCC), and the associated Kyoto Protocol and recent (2015) Paris Agreement. Obligations under the UNFCCC translated into UK law with national government passing the Climate Change Act 2008, which is a statutory commitment to an 80% reduction in net UK GHG emissions by 2050, compared to a 1990 baseline. Also established in the Act, the strategy for achieving this reduction is through a series of increasingly stringent 5-yearly carbon budgets (beginning with 2008-2012) for net UK GHG emissions, such that the annual equivalent of the carbon budget for the period including 2050 is 80% lower than the 1990 baseline.

However, this statutory requirement to cut GHG emissions has not been devolved to LGAs, who are not mandated to have GHG emissions reduction targets, although some do voluntarily set such targets (DECC 2014). For example, SCC (a Unitary Authority and therefore also the

[11] Framework agreements are typically implemented when one party requires the services of another party but is unsure of the extent or schedule of the services.

LHA responsible for Southampton's non-SRN road network) has an ambition for Southampton to become a world-leading low carbon city, as set out in the Low Carbon City Strategy (LCCS), which includes a target to reduce the city's CO_2 emissions by 34% by 2020, compared to a 1990 baseline (SCC 2011b; SCC 2011c). As of 2012, a reduction of 14.8% had been achieved, and SCC felt they were on-track to meet their target (SCC 2012). The voluntary emissions reduction target contained in the LCCS will inform decisions concerning future changes to the transport system (i.e. transport interventions) in Southampton.

Pre-dating the Climate Change Act 2008, the Nottingham Declaration on Climate Change was launched in 2000 and signed by over 300 (out of 353) English LGAs (Scottish and Welsh LGAs signed their own versions) pledging to work with national government and systematically address the causes of climate change at a local level. However, the Declaration did not include any reduction targets or commit LGAs to actually take firm action.

In 2011, the DfT published their transport White Paper 'Creating Growth, Cutting Carbon – Making Sustainable Local Transport Happen'. The White Paper recognised that transport plays a key role in enabling economic growth; but at the same time, it recognised that transport must build on current progress in reducing CO_2 emissions if the UK is to meet its commitment under the Climate Change Act 2008. As a way to cut transport CO_2 emissions, the White Paper identified that two-thirds of all trips in the UK were less than five miles in length, many of which could easily be cycled, walked or undertaken by public transport. The DfT believe a substantial proportion of drivers would be willing to drive less, particularly for shorter trips, if practical alternatives were available. A key policy introduced in the White Paper was the establishment of the Local Sustainable Transport Fund (LSTF), with the objective of funding interventions aimed at making travelling on foot, by bike or on public transport more attractive[12]. LGAs were able to competitively bid for money from the LSTF to finance such interventions within their administrative areas. For example, SCC was involved in two successful bids. The first bid was for a project called '*Southampton Sustainable Travel City*', with a total cost of £5.72 million spread over 4 years from 2011 to 2015, of which £3.96 million was from the LSTF (this project was subsequently extended until 2016 with an extra £1 million

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[12] In general, the interventions are aimed at improving facilities for walking, cycling and public transport. For example, schemes such as provision of bus/cycle lanes or cycle/walking routes, improving interchange nodes, more convenient timing of connections, provision of cycle hire schemes, provision of real-time public transport information, and smart/integrated public transport ticketing.

of funding from the LSTF). The geographic area for interventions funded by this project extends beyond Southampton into the neighbouring urban areas of Eastleigh, Totton and Hythe, covering a population of 417,000 (SCC 2011d). The second bid was as part of what was then TfSH (now Solent Transport), which bid for funding for a project called '*A Better Connected South Hampshire*', with a total cost of £31.16 million spread over 3 years from 2012 to 2015, of which £17.84 million was from the LSTF. The geographic area for this project extended across south Hampshire covering a population of 1,019,300 (TfSH 2011).

Also in 2011, a Memorandum of Understanding (MoU) was signed between the UK national government's Department of Energy & Climate Change[13] (DECC) and the Local Government Group (now the Local Government Association[14]) establishing that the parties will cooperate to encourage LGAs to set ambitious GHG reduction targets, to take action to reduce GHG emissions from their own estates and operations, and to reduce GHG emissions from homes, businesses and transport infrastructure. However, the MoU is not a binding agreement and does not create legal obligations on the parties.

Launched in 2012 by the Local Government Association, Climate Local is an initiative to drive, inspire and support LGA action on climate change in England and Wales. Climate Local is seen as the successor to the Nottingham Declaration, and is the only initiative of its type in the UK. As of January 2016, 113 (out of 353 English + 22 Welsh = 375) LGAs had signed-up to this voluntary initiative, which is far less signatories than previously achieved by the Nottingham Declaration.

In general, policy debates over GHG emissions reductions take place at global and national level, whereas actions to reduce emissions are usually required at local level (Dodman 2009). However, responsibility for taking the necessary actions is contested because of tensions between national and local government (Walker *et al.* 2014), with a consequence being that there is little systematic approach to implementing policies aimed at reducing transport's GHG emissions (Marsden and Rye 2010). In the UK, despite the various declarations, legislation, policies, agreements and initiatives that have been established over the past 15 years, the fact

[13] Following the recent (July 2016) appointment of a new Prime Minister in the UK, this national government department has been abolished and its functions transferred to other departments, notably the new Department of Business, Energy and Industrial Strategy.

[14] The Local Government Association is the national organisation representing LGAs in England and Wales.

remains that there is currently no explicit statutory obligation for LGAs to reduce GHG emissions, and any emissions reduction targets that are set remain voluntary in nature.

However, there are many instances where LGAs do need to assess the GHG emissions impact of transport interventions. For example, national government may provide incentive schemes for LGAs to tackle such emissions (e.g. the ring-fencing of national government funds in the LSTF), and in order to benefit from such schemes LGAs need to demonstrate the efficacy of their interventions. Additionally, LGAs are likely to want to monitor their progress towards achieving (albeit voluntary) emissions reduction targets. Furthermore, there are circumstances where LGAs may have a statutory obligation to assess a transport intervention's GHG emissions impact. For example, deriving from a European Commission directive translated into UK law, Environmental Impact Assessments (EIAs) are required for certain types of development and can include assessment of the GHG emissions impact. Large road traffic interventions (e.g. construction of motorways or trunk roads, or construction of new roads with 4 or more lanes over 10 or more kilometres) always require a statutory EIA regardless of location. Such large interventions are unlikely to be the responsibility of LGAs because they are likely to form part of the SRN. Smaller transport interventions (e.g. urban development, or construction of new roads) which are likely to have significant environmental effects due to their size or location in an environmentally sensitive area will require screening to decide if a statutory EIA is required. Such smaller interventions could well be the responsibility of LGAs. In general, even where statutory EIAs are not necessary, good practice dictates that adequate environmental assessment (including GHG emissions impact) is required to establish the significance of any environmental issues and inform the decision making process concerning implementation of transport interventions.

1.5.2.2 Air quality emissions

As part of their duties under the Environment Act 1995 and the Environment (Northern Ireland) Order 2002, UK LGAs are obliged to conduct regular review and assessment of air quality in their areas of administration. Where LGAs consider that air quality objectives for pollutants are not being met, then an area must be designated an Air Quality Management Area (AQMA); with road traffic emissions being the reason for such designations in 90% of cases (Bell *et al.* 2013). LGAs must then implement a remedial Action Plan to improve air quality in the AQMA, and submit annual Action Plan Progress Reports to national government (DEFRA 2009b). According to the latest UK air pollution report, as of August 2015, 248 LGAs have designated one or more AQMAs (DEFRA 2015a), which represents almost 60% of UK LGAs (total of 418).

This percentage increased from 31% in 2003 to 60% in 2011, and has remained nearly constant at approximately 60% ever since (DEFRA 2007; DEFRA 2009a; DEFRA 2010; DEFRA 2011; DEFRA 2012; DEFRA 2013b; DEFRA 2014a). SCC has designated ten AQMAs in Southampton, which are all related to heavy and congested road traffic conditions. In this respect Southampton is not unusual (although Southampton has been identified as having a particular problem with air quality, refer to Section 4.4), and a similar situation can be found in other nearby urban areas. For example, Portsmouth City Council has designated five AQMAs, and Winchester City Council has one AQMA covering the whole of the city centre.

1.6 PROJECT SCOPE

In their capacity as LHAs, much of the responsibility for facilitating mitigation of road traffic emissions is borne by LGAs. Consequently, this project's scope was limited to the role of LGAs in discharging this responsibility (refer to Section 1.5.1). Further to this, whilst mitigation of AQ emissions is obviously important, this project's scope was also limited to GHG emissions, more specifically CO_2 because it is by far the largest constituent of transport's GHG emissions, e.g. 99% on a CO_2e basis in the UK (refer to Section 1.4). That said, with certain caveats, it is generally acknowledged that well designed, integrated strategies to reduce GHG emissions and AQ emissions will often result in significant co-benefits (DEFRA 2009b; EEA 2009; King *et al.* 2010; Tiwary *et al.* 2013), and it is likely that methodologies developed in this project could be extended to include AQ emissions through further work.

From the perspective of European countries, any emissions modelling processes developed in other regions of the globe have a significant drawback in terms of transferability. This is because vehicle category classifications can be markedly different, and cannot be easily mapped onto the European system of classification. This project is UK-focused because it is sponsored by SCC. EMs involving vehicle categories that are substantially different from those commonly found on UK roads are of limited direct interest or use to SCC, and are only reviewed in this project to provide a complete overview of the different methods used worldwide in the emissions modelling process.

The harmful nature of CO_2 manifests as a global phenomenon (i.e. through its properties as a GHG contributing to global warming). Hence, it is the overall effect of a transport intervention (or combined effect of many small diffuse interventions) on emissions of CO_2 which is more important than any localised effects. Therefore, this project is concerned with estimating emissions for an urban road network (or substantially large parts of a network) as a whole.

This situation would be reversed for AQ emissions. Rather than the network-level, it is localised emissions that are likely to be more important because the detrimental impacts on human health are localised in the area close to the source of emissions.

1.7 UNIQUE AND NOVEL CONTRIBUTION STATEMENT

As part of this project a survey was conducted to establish what data and models are currently used by British LGAs for road traffic CO_2 emissions modelling, and what their attitudes are to the issues of resource use and prediction accuracy. Based on the new knowledge generated by the survey, in combination with results from a review of relevant literature, a research gap was identified which required an investigation of the feasibility of predicting network-level road traffic CO_2 emissions in urban areas based on traffic variables readily available to LGAs from both Urban Traffic Control (UTC) systems and Road Traffic Models (RTMs). The investigation ultimately led to the development of a new EM (PEMLA), the performance of which was then compared with the next-best alternative EM available to LGAs. The methodology employed to undertake this investigation was a novel endeavour, with no prior examples of the same method being found in the existing literature.

1.8 DATA ACCESS STATEMENT

The dataset used in this project is managed by the University of Southampton. All data sharing must meet the terms of existing project ethics approvals and participants' consent forms. The terms of the ethics approval and participants' consent form for the LGA road traffic emissions modelling survey (Research Ethics Committee number 13144) prevent the sharing of data in this instance. Data collected and used to support the development of the new EM created during this project (Research Ethics Committee number 16720) are openly available from the University of Southampton repository at http://dx.doi.org/10.5258/SOTON/400894.

Chapter 2 ROAD TRAFFIC EMISSIONS MODELLING: A REVIEW

2.1 INTRODUCTION

A contemporary review was conducted of the literature concerning the factors that influence road traffic CO_2 emissions, the potential sources of road traffic data for use in the emissions modelling process, and the practicalities of the use of such data by LGAs in EMs. Details of the literature review have been divided into six main sections. Section 2.2 explains the requirement for EMs in assessing transport interventions. Section 2.3, Section 2.4 and Section 2.5 critically review the literature concerning factors influencing emissions, road traffic data and road traffic EMs, respectively. A discussion of the findings of the literature review, including identification of the research gap, is presented in Section 2.6, before conclusions are detailed in Section 2.7. (An abridged version of the research detailed in this chapter can be found in the published journal article by Grote *et al.* (2016a), which is included as Appendix A).

2.2 REQUIREMENT FOR EMISSIONS MODELS

2.2.1 Assessing the Impact of Transport Interventions

When instigating transport interventions, critical to the decision making and design process is the ability to assess environmental impacts, including the impact on road traffic emissions. To analyse this impact, it is necessary to quantify an intervention's effect on emissions. However, it is impractical to measure real-world emissions at network-level due to the large number of vehicles and traffic conditions involved (Smit 2006; Smit *et al.* 2010); and measurement is impossible when hypothetical scenarios are considered. Consequently, there is a requirement for EMs, which can offer a practical (and less expensive) alternative to real-world measurements (Grote *et al.* 2016a).

2.2.2 Emissions Modelling with Limited Resources

In their role as LHAs, LGAs are responsible for facilitating the mitigation of road traffic emissions. Consequently, it is typically LGAs that must find the necessary resources for modelling the emissions impact of transport decisions. However, public funds are limited, and governments must finance provision of many services, of which road infrastructure is just one. The global financial crisis of 2008 and subsequent austerity measures have increased the constraints on public funds, with many governments forced to make budget cuts. In the UK for example, LGAs are seen as having felt the "brunt of the austerity measures", with LGA spending in England (excluding police, schools and housing benefit) having fallen by approximately 30% in real terms between 2008 and 2015 (Fitzgerald and Lupton 2015), and similar dramatic budget cuts are being enforced across much of Europe (Lowndes and McCaughie 2013). Therefore, LGA resources are under intense pressure and financial savings need to be made wherever possible, meaning funds for modelling are scarce.

Models used by LGAs must strike a difficult balance. On the one hand, EMs must not be so simplistic that they fail to capture the majority of the emissions impact of potential interventions. On the other hand, there is a need to avoid model complexity. More complexity entails more time and expertise in building and running models and collecting the necessarily detailed input data. Such time and expertise is generally expensive, and beyond LGA budgets and decision-making timescales. Modelling expertise is not the core business of LGAs, and increasing complexity increases the likelihood that LGAs will be forced to engage external expert consultants. Engaging consultants involves expense, which means the frequency with which LGAs can undertake the modelling process is limited and may be less than desired.

Another factor in the accuracy/complexity trade-off is that, although more complex models are generally more accurate than less complex models, they also require more detailed input data (Smit *et al.* 2006). Finely detailed input data are more susceptible to errors in estimation, measurement, or assumptions. Therefore, a lack of quality input data may offset any accuracy gained through increased model complexity (Smit *et al.* 2010; Ramos *et al.* 2011; Zhu and Ferreira 2013). This is illustrated by Alonso (1968) who distinguished between two error sources. Firstly, specification error which arises due to models being simplified representations of real-world phenomena; and secondly, measurement errors in input data. Total model error is the sum of these two sources. Figure 2-1 shows there is an optimal model complexity where total prediction error is minimised (at the point where the gradients of curves e_m and e_s are equal and opposite).

The measurement error curve (e_m) in Figure 2-1 represents the error in input data assuming a given level of resources allocated by the LGA for the data collection effort. If more resources were available for data collection or data collection became easier (e.g. through technological advances), it is reasonable to assume that measurement error could be reduced. Figure 2-2 shows that, if measurement error is reduced by a given percentage (curve e_{m2}) the optimal model complexity is shifted to the right and aligns with a more complex model. In other words, optimal EM complexity is dependent on the resources that LGAs can afford to deploy to minimise measurement error during input data collection.

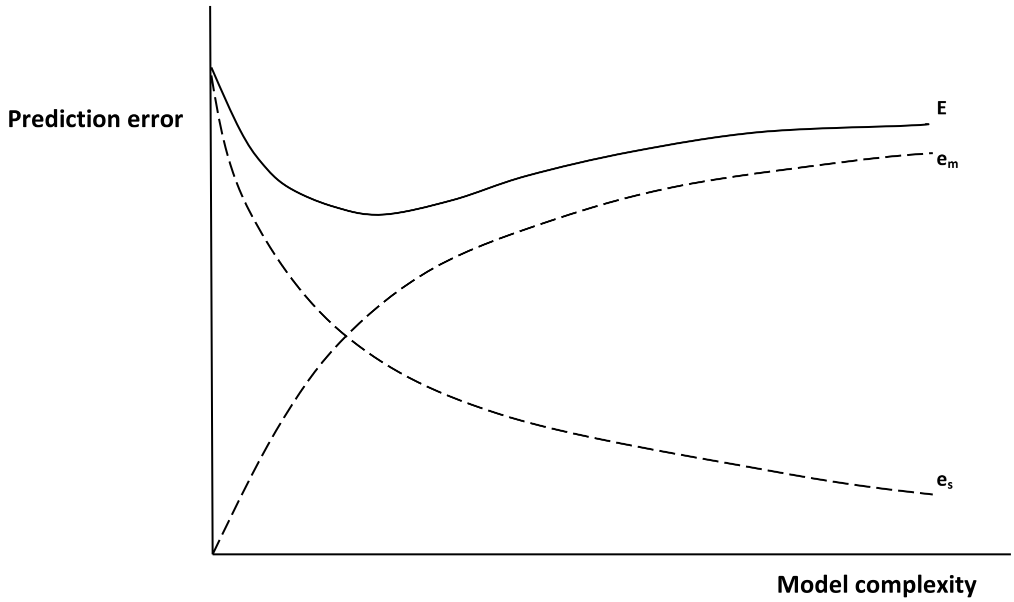

Figure 2-1: Model complexity and model prediction error.

- E is total prediction error.
- e_m is measurement error.
- e_s is specification error.
- Source: adapted from Alonso (1968).

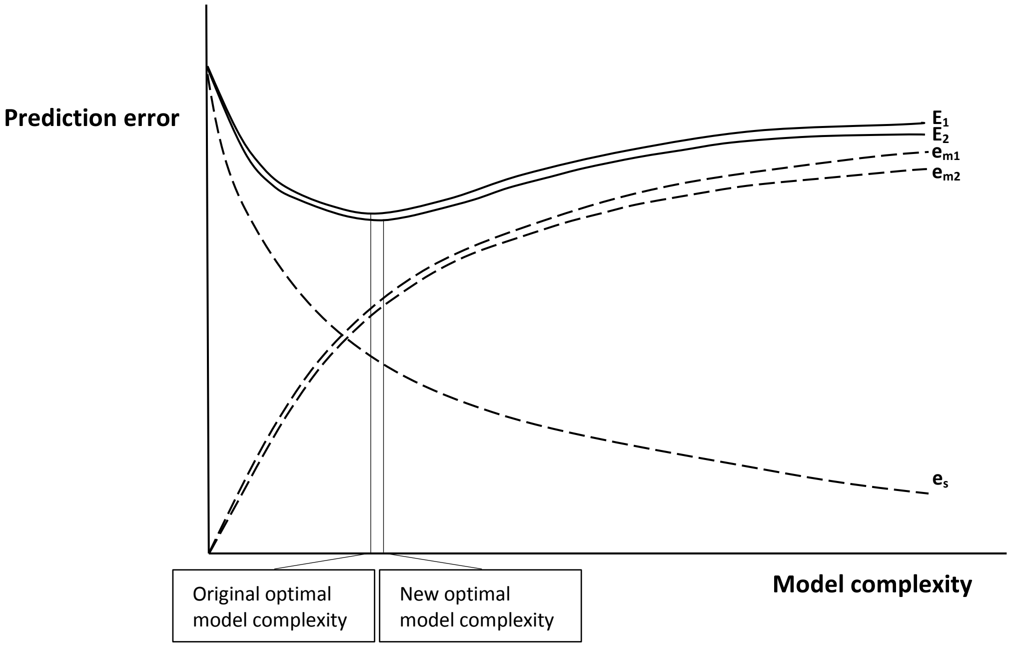

Figure 2-2: Model complexity and model prediction error, with two different measurement error curves.

- E_1 is total prediction error with e_{m1}.
- E_2 is total prediction error with e_{m2}.
- e_{m1} is measurement error with original resources for input data collection.
- e_{m2} is measurement error with increased resources for input data collection.
- e_s is specification error.
- Source: adapted from Alonso (1968).

2.3 FACTORS INFLUENCING EMISSIONS

This section explains the influence various factors have on CO_2 emissions from road vehicles, and outlines the approaches adopted in this project to account for these influences. In the final sub-section (Section 2.3.14) the justification is provided for project focus on explicitly[15] accounting for congestion, whilst implicitly[16] accounting for most other factors.

2.3.1 Lifecycle Assessment

It is acknowledged that lifecycle emissions are an important consideration in the full environmental impact of any transport system (Chester and Horvath 2009). Lifecycle assessments (LCAs) of road traffic typically demonstrate that, whilst vehicle operation is usually the majority contributor to lifecycle emissions, the emissions contributed by other phases of vehicle, fuel and infrastructure lifecycles are non-negligible. For example, a LCA study of transport in the USA reported results for road vehicles as shown in Table 2-1. The LCA

[15] Explicit: within model user control, with values specified for use as EM inputs.
[16] Implicit: outside model user control, but may be included through underlying EM assumptions.

encompassed 17 components, not all of which made significant contributions to lifecycle GHG emissions. The principal non-operational contributors were found to be vehicle manufacturing and maintenance, road construction and maintenance, street lighting, parking construction and maintenance, and petroleum production (Chester 2008). Inspection of Table 2-1 reveals that vehicle operation constitutes 60-70% of total lifecycle GHG emissions, and it is these direct emissions (commonly called Tank-To-Wheel emissions) that form the scope of this project.

Table 2-1: Comparison of GHG emissions from operational and non-operational phases of road vehicle lifecycles.

Road Vehicle	Saloon	SUV	Pickup	Bus (Off-Peak)	Bus (Peak)
Example of Type	Ford Focus Saloon	Ford Explorer	Ford F-Series	40-Foot Bus	40-Foot Bus
Weight	1,450 kg	2,085 kg	2,340 kg	11,340 kg	11,340 kg
Average Lifetime	16.9 years	15.5 years	15.5 years	12 years	12 years
Average Annual Distance	17,700 km	17,700 km	17,700 km	67,600 km	67,600 km
Average Occupancy	1.58	1.74	1.46	5 passengers	40 passengers
Fuel Type	Petrol	Petrol	Petrol	Diesel	Diesel
Operational GHG Emissions gCO_2e/PKM (% of Total Lifecycle GHG Emissions)	143 (61%)	168 (60%)	261 (68%)	292 (69%)	37 (70%)
Non-operational GHG Emissions gCO_2e/PKM (% of Total Lifecycle GHG Emissions)	93 (39%)	112 (40%)	124 (32%)	131 (31%)	16 (30%)
Total Lifecycle GHG Emissions gCO_2e/PKM	236	280	385	423	53

- SUV is sports utility vehicle.
- PKM is passenger-kilometre (One PKM is achieved when one passenger travels one kilometre).
- Results based on data from the USA.
- Source: Chester (2008).

2.3.2 Distance, Speed and Vehicle Category

Considering only the vehicle operation phase, tailpipe emissions (i.e. Tank-To-Wheel emissions from fuel combusted in-vehicle) from road traffic are typically estimated through multiplying activity data by Emission Factors[17] (EFs) (Smit *et al.* 2010). For example, emissions of CO_2 are commonly calculated using the following equation:

Equation 1

CO_2 emissions (g) = distance travelled (VKMs) x gCO_2/VKM

Where: distance travelled is activity data

gCO_2/VKM is an EF

Hence, from inspection of Equation 1, distance travelled by a vehicle (VKMs) has a large influence on emissions (i.e. greater activity gives greater emissions). Vehicle speed is another important influence on emissions, because road traffic EFs are strongly dependent on speed (Smit *et al.* 2008b; Abou-Senna and Radwan 2013). Vehicle category also has a considerable influence on emissions. Different vehicle categories have different EF profiles due to factors such as vehicle mass, fuel specification, engine size, aerodynamics, and emissions control technology.

To account for the influence of vehicle category on emissions, the road vehicle fleet must be disaggregated into categories, each with a different associated EF profile. In Europe the most detailed level of disaggregation is according to Euro Emission Standard compliance. Euro Standards are a series of increasingly stringent regulations, which have been introduced over the years to limit the amount of certain regulated pollutants (CO, NO_X, PM and Hydrocarbons (HC)) that road vehicles are permitted to emit. The current (September 2016) standards to which new vehicles[18] must comply are Euro 6 for Light Duty Vehicles[19] (LDVs), Euro VI for

[17] Emission Factor (EF) is used in a general sense in this thesis to cover any factors that relate emissions to different measures of activity data (e.g. g/VKM; g/second; g/hour; g/litre of fuel; g/kWh of electricity). In contrast, where Emission Rate (ER) is used this specifically means amount of emissions released per unit of time (e.g. g/second; g/hour).

[18] When a new Euro Standard comes into force, initially it applies to new type approvals only, where type is defined by the EU as vehicles which do not differ in respect of manufacturer, manufacturer's type designation, and essential aspects of construction and design such as chassis, floor plan or power plant (e.g. internal combustion, battery or hybrid). Then typically a year later the Euro Standard will apply to all new registrations.

[19] For Euro Standard purposes, the distinction between LDVs and HDVs is based on Reference Mass (RM), with LDVs having RM ≤2610kg and HDVs having RM >2610kg. RM is defined as Mass in Running Order (MRO), minus the mass of the driver (75kg), plus 100kg; i.e. RM = MRO + 25kg. MRO is defined as the mass of the unladen vehicle, plus the mass of the driver (75kg), fuel (90% filled), other liquids (e.g. oils and coolant), and standard equipment (e.g. tools and spare wheel).

Heavy Duty Vehicles (HDVs), and Euro 3 for two-wheel vehicles[20]. CO_2 is not a regulated pollutant under Euro Standards. However, disaggregation according to Euro Standard is the universally adopted method (in Europe) for classifying vehicle category because of its relevance to the estimation of emissions of other pollutants. Due to the substantial impact on emissions of VKMs, vehicle speed and vehicle category, these three factors were explicitly included in this project's investigations.

2.3.3 Importance of Congestion

Congestion is the deterioration of smooth, free-flowing traffic conditions due to increased travel demand and/or reduced traffic movement capacity (Smit *et al.* 2008a), i.e. travel demand exceeding the supply of road capacity. Traffic movement capacity is dictated by factors such as network characteristics (e.g. link[21] length, number of lanes, link curvature, intersection types and layouts, number of intersections per kilometre, pedestrian crossing types, speed limits, roadside land-use), traffic management strategies (e.g. traffic signal control, rerouting, dynamic speed limit systems), or adverse weather (e.g. heavy rain, fog, snow). It is commonly accepted that under the stop-and-go traffic conditions associated with congestion there is an increase in the number of acceleration and deceleration events experienced by vehicles, which results in increased emissions (Chen and Yu 2007; Barth and Boriboonsomsin 2008; Smit *et al.* 2008a; Madireddy *et al.* 2011). Congestion has been repeatedly identified as a major factor when estimating road traffic emissions (Smit *et al.* 2008a), and ranks alongside VKMs, vehicle speed and vehicle category, as one of the most important influences (De Haan and Keller 2000; Int Panis *et al.* 2006; Smit *et al.* 2008a; Smit *et al.* 2008b).

Barth and Boriboonsomsin (2008) compared CO_2 emissions from cars during steady-state activity (i.e. constant speed) to emissions during real-world activity (i.e. including dynamics due to congestion) having the same average speed. According to results, the increase in emissions between steady-state and real-world activity at an average speed of 45 km/h, a typical average speed for cars on major urban roads[22] (DfT 2011a), was approximately 40%. This study assumed that all the dynamics of real-world driving patterns[23] were due to congestion. This is a reasonable assumption because the important issue is to capture as much

[20] For motorcycles, currently (2016) the Euro 4 Standard applies to new type approvals only, and will apply to all new registrations from January 2017. For mopeds (<50 cubic centimetres engine capacity), Euro 4 Standards will apply to new type approvals from January 2017, and to all new registrations from January 2018.

[21] A link is a uni-directional road section between two intersections.

[22] The average speed for cars on major urban roads in the South-East region of England during peak period is 47.2 km/h.

[23] Fine grained time series (e.g. 1Hz) of speed points for an individual vehicle, also called a speed-time profile.

as possible (within resource constraints) of the influence of vehicle dynamics, regardless of whether or not they are labelled as congestion. For example, even a vehicle in uncongested traffic conditions would be unable to maintain a completely constant speed (i.e. steady-state activity) whilst travelling across an urban road network; and the inevitable dynamics of the vehicle's driving pattern will influence its emissions and should (ideally) be fully captured by an EM. In effect, the term congestion is used as a proxy for vehicle dynamics, regardless of source.

Smit and McBroom (2010) reported a much greater influence of congestion on emissions, although the study was limited to eight different types of typical Australian LDVs. Compared to European countries, the Australian LDV fleet is characterised by a larger proportion of vehicles with large engine capacities, automatic transmissions or 4-wheel drive. Hence, extension of the results to the UK should be treated with caution. The CO_2 emissions from the eight vehicles were calculated for six different urban driving cycles[24] representative of real-world conditions, with varying levels of congestion. From the least congested driving cycle (density: 0-35 vehicles/km.lane, link average speed: 30-45 km/h) to the most congested driving cycle (density: 70-125 vehicles/km.lane, link average speed: <15 km/h), the percentage increase in the sum of the CO_2 emissions from all eight vehicles was found to be approximately 150%; although this was not a comparison between congested and uncongested conditions with the same average speed, so a proportion of the increase will be due to the change in average speed.

Congestion can be considered at multiple scales, for example around a single intersection, along a certain corridor (series of links and intersections), or for a network as a whole. Assessment of the emissions impact of transport interventions at these different scales may require LGAs to use different types of road traffic data and EMs. However, the scope of this project is predicting the impact of interventions on CO_2 emissions at the network-level (refer to Section 1.6), and it is explicit inclusion of the influence of congestion at this scale that formed the focus of investigations.

2.3.4 Driver Behaviour and Gear-Shift Strategies

Driver behaviour can be classified into three types to investigate the influence on emissions: calm, normal and aggressive. Calm driving implies anticipating other road users' movements and avoiding sudden or high acceleration or braking. Normal driving implies moderate

[24] Standardised driving pattern over which a vehicle's emissions are measured during a laboratory emissions test.

acceleration and braking. Aggressive driving implies sudden and high acceleration and heavy braking (De Vlieger 1997; Ericsson 2001). For car drivers in urban areas, aggressive driving was found to increase fuel consumption (which is directly proportional to CO_2 emissions) by 20-40% compared to normal driving. In contrast, calm driving gave a 5% reduction in fuel consumption compared to normal driving (De Vlieger 1997; De Vlieger *et al.* 2000; Ericsson 2001).

Part of the work conducted during the ARTEMIS[25] project examined the effect of gear-shift strategies on emissions from cars. Five gear-shift strategies were tested – gear-shift pattern included in the design of the driving cycle; gear-shift criteria defined by engine speed; gear-shift pattern defined by vehicle speed; gear-shift pattern as recorded during real-world data collection; and gear-shifts as decided by the laboratory test driver. Results showed variation between the strategies of up to 15% for CO_2 emissions (Joumard *et al.* 2006; Boulter *et al.* 2009a). The least polluting strategy was found to be 'vehicle speed', the reason being that this strategy corresponded to a very calm driving style (akin to an eco-driving style), with gear-shifts at low engine speeds. The most polluting strategy was found to be 'engine speed', the reason being that this strategy corresponded to a very aggressive driving style, with up-gear-shifts at very high engine speeds. The study authors felt that neither of these two extremes represented real-world driving that well because they don't allow for driver anticipation of traffic conditions. For example: when decelerating to a stop, drivers in the real-world often block change from third or second gear to neutral; or when accelerating to overtake, drivers often maintain a lower gear to ensure the manoeuvre is completed expeditiously (André *et al.* 2003).

More complex EMs, which calculate emissions for individual vehicles, can have inputs that allow the influences of driver behaviour and gear-shift strategies to be explicitly modelled. Less complex EMs include these factors implicitly, through the assumption that emissions tests (the data from which are used as the basis for EM construction) adequately represent the real-world distributions of driver behaviours and gear-shift strategies; and this was the approach adopted for this project.

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[25] Assessment and Reliability of Transport Emission Models and Inventory Systems (ARTEMIS) – a European Commission 5th Framework project.

2.3.5 Road Gradient

As positive (uphill) road gradient increases, so does the engine power required to keep the vehicle at a constant speed due to the increasing force of gravity opposing vehicle motion. Increases in engine power require greater fuel consumption, resulting in greater emissions. The opposite effect is found on negative (downhill) road gradients, where gravity acts to accelerate the vehicle, reducing engine power demand, fuel consumption and emissions (Wyatt *et al.* 2014). Therefore, road gradient influences emissions. For example, Boriboonsomsin and Barth (2009) evaluated the effect of gradient on LDV fuel consumption (and hence CO_2 emissions), measuring a 15-20% rise in fuel consumption for hilly routes compared to a flat route.

As gradient can vary continuously along a vehicle's route, to be fully included its effects need to be accounted for over short distances. More detailed EMs, which calculate emissions for individual vehicles, require a value for road gradient for each second of a vehicle's motion. However, this approach adds considerable complexity to the calculation of emissions. An alternative would be to include gradient as an average over longer distances (e.g. link length), but this begins to render its inclusion meaningless. For example, the two links shown in Figure 2-3 have their start points at the same elevation, and also their end points at the same elevation. Hence their gradients calculated using these points would be the same. However, the same vehicle travelling down each link would be likely to have different emissions due to the continuously varying gradient of link B.

Figure 2-3: Side elevation of two links with equal average end-to-end gradients.

A further alternative would be to assume 0% gradient for all links. When calculating emissions from vehicles on road networks as a whole (in contrast to small-scale calculations for solitary intersections or links) increases in emissions due to uphill gradients will be, to a certain extent (although not entirely), offset by reductions in emissions due to downhill gradients. This will act to increase the validity of the assumption of 0% gradient. For example, a recent study compared predictions for CO_2 emissions from a LDV performing a circular test route around Leeds, UK. Including 1Hz road gradient inputs resulted in a 1% increase in CO_2 emissions compared to when gradient was assumed to be zero. The increase in emissions due to road gradient inclusion was small because the test route started and finished at the same point. In other words, average gradient was zero, and positive gradient effects had been offset by negative gradient effects (Wyatt *et al.* 2014). An assumption of 0% gradient for all links was the approach adopted in this project.

2.3.6 Vehicle Load

As vehicle mass increases, greater engine power is required for reasons such as accelerating, overcoming increased rolling resistance or overcoming road gradient. Increases in engine power require greater fuel consumption, resulting in greater emissions. Vehicle load therefore influences emissions. Emissions tests on cars are usually conducted on a chassis dynamometer, with dynamometer load settings representative of the combined mass of vehicle and driver under typical normal use. Additionally, the load range for cars is small in comparison to that of an HDV. Hence, the typical assumption used for cars is that the influence of vehicle load is small and adequately included in the emissions test data (Hickman *et al.* 1999).

For HDVs (and to a lesser extent LGVs), the influence of load becomes more important. This is because payload can constitute more than 50% of a vehicle's total mass (Rexeis *et al.* 2005). For example, the average speed for HGVs on major urban roads in the South-East region of England during peak period is 46.5 km/h (DfT 2011a). Using this speed in the 'load correction factor function' established during the European MEET[26] project (Hickman *et al.* 1999) gives the following estimates of the increase in CO_2 emissions when fully loaded compared to unloaded (at 0% road gradient):

- Maximum HGV mass 3.5-7.5 tonnes: 13%
- Maximum HGV mass 7.5-16 tonnes: 22%
- Maximum HGV mass 16-32 tonnes: 26%
- Maximum HGV mass 32-40 tonnes: 41%

One approach for including the influence of HDV load on emissions is to assume a constant percentage load for all HDVs. For example, this is the approach taken in the EM produced by the Transport Research Laboratory (TRL) in 2009 (refer to Section 2.5.5.1), where all HGVs were assumed to be 56% loaded (the average HGV load in the UK) and all buses and coaches were assumed to be 50% loaded, with percentage load measured by mass rather than by

[26] MEET is Methodologies for Estimating air pollutant Emissions from Transport.

volume (Boulter *et al.* 2009b; Barlow 2009). More detailed EMs, which calculate emissions for individual vehicles, have inputs that allow the effects of vehicle load to be explicitly modelled. The approach adopted in this project was that all vehicles (LDVs and HDVs) were assumed to be 50% loaded (available choices were unladen, half-laden or fully-laden, refer to Section 5.3.5.3).

2.3.7 Cold-Starts

Before a vehicle reaches full running temperature, emissions are elevated because of reasons such as increased viscous friction due to low lubricant temperatures and increased rolling resistance from cold tyres. Cold-Start Excess Emissions (CSEEs) are defined as the amount of pollutant emitted over and above that which would be emitted by a vehicle at its normal running temperature (Boulter and McCrae 2007), illustrated graphically in Figure 2-4, and are typically quoted as excess emissions per start (g/start) (Weilenmann *et al.* 2005a). Research has shown that CSEEs are characterised by five parameters: vehicle Emission Standard; vehicle average speed; distance travelled (because if a trip is short, the excess emissions associated with a start may not all be emitted); ambient temperature; and engine stop time (also called parking time, which affects how far a vehicle's engine temperature has fallen towards ambient) (André and Joumard 2005; Favez *et al.* 2009; Weilenmann *et al.* 2009). CSEEs can be a significant proportion of total emissions (Boulter *et al.* 2012), and are particularly important in urban areas because most car trips start there (Weilenmann *et al.* 2005a).

A study by Weilenmann *et al.* (2009) investigated CSEEs for Euro 4 cars using emissions tests on a chassis dynamometer at ambient temperatures[27] of -20, -7 and 23°C, with the vehicles completely cooled to ambient temperature prior to testing. The INRETS Urbain Fluide Court 15 (IUFC15) driving cycle was used, which has an average speed of 19km/h. The results for CO_2 CSEEs from petrol cars were 230, 240 and 75 g/start at -20, -7 and 23°C ambient temperatures, respectively. The corresponding results for diesel cars were 400, 360 and 140 g/start. Diesel cars produce greater CO_2 CSEEs because their higher engine mass and higher fuel efficiency cause a slower warm-up (Weilenmann *et al.* 2005a). The explanation given for the slight increase (230 to 240 g/start) observable for petrol cars between -20 and -7°C is that the vehicles have incomplete combustion below -7°C leading to greater emissions of CO at the expense of reduced CO_2 emissions.

[27] 23 and -7°C were chosen because certification testing is conducted at these ambient temperatures, and -20°C was chosen as a representative lower limit for European ambient temperature.

To be able to calculate percentage increases due to cold-starts, a measure of hot emissions is required. Obviously, as trip length increases hot emissions become a larger proportion of total emissions. Therefore, for indicative purposes, the average distance of all trips in the UK in 2011 (approximately 11km) was selected (DfT 2013b). Hence, hot emissions are calculated using the average hot EF (g/km) for the fleet of tested cars over the IUFC15 driving cycle used in the study, multiplied by a distance of 11km. This gives the following increases due to cold-starts for Euro 4 petrol cars: 7%, 8% and 3% at -20, -7 and 23°C ambient temperatures, respectively. The corresponding figures for Euro 4 diesel cars are: 15%, 16%, and 6%.

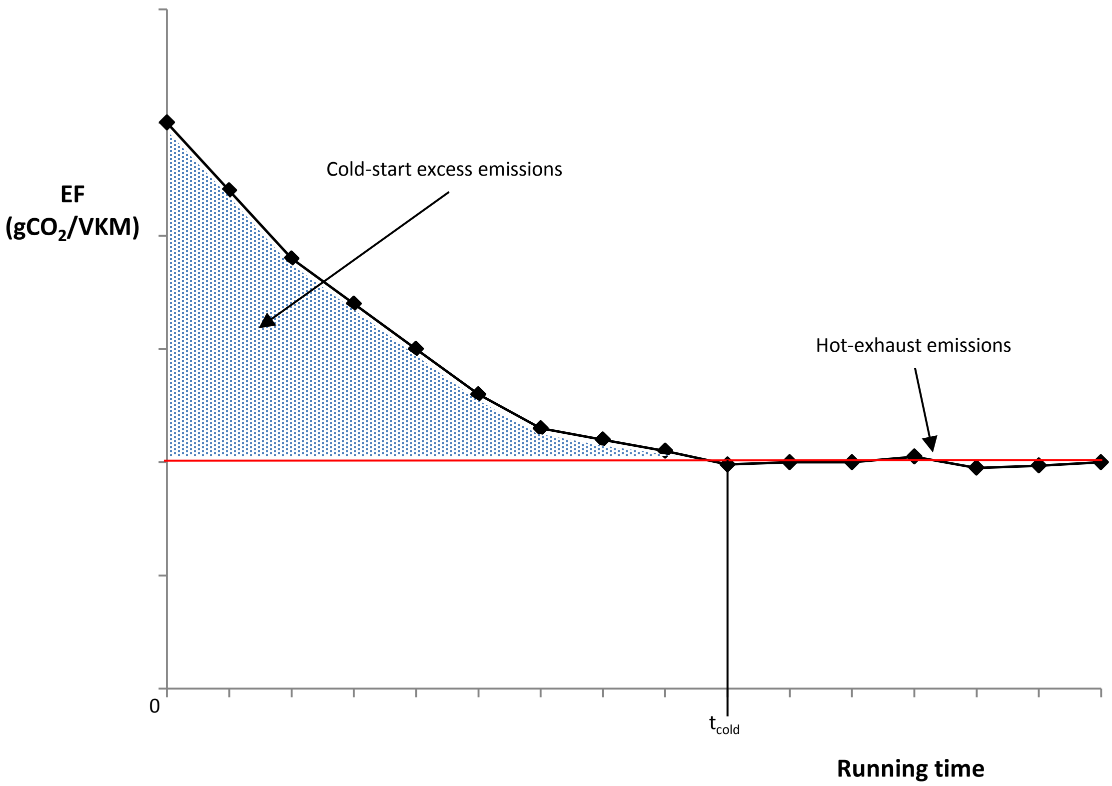

Figure 2-4: Evolution of an EF with increasing engine temperature.

- The engine reaches full running temperature at t_{cold}.
- An idealised emission-profile is shown. During a driving cycle involving a succession of varying vehicle and engine speeds, the emission-profile would be more complex.
- Source: adapted from Boulter and McCrae (2007).

The scope of this project is limited to estimation of hot CO_2 emissions (i.e. emissions at normal running temperature). Therefore, for a full estimate of network emissions including CSEEs, LGAs would need to use a separate cold-start EM. An example of a cold-start EM that offers a potential option for LGAs (i.e. a suitable balance between accuracy and complexity) was developed during the ARTEMIS project. This EM predicts European-average CSEE EFs (in g/VKM) as a function of vehicle category, traffic average speed, ambient temperature, time of day (which gives parking time distribution), and the season (which gives trip length distribution) (Boulter *et al.* 2009c).

2.3.8 Ambient Temperature

As well as influencing cold-start emissions, ambient temperature also affects hot emissions. As ambient temperature goes down, internal friction in the engine and transmission goes up, which increases emissions. This effect was investigated during the ARTEMIS project, where emissions tests were conducted on cars at three different ambient temperatures: -20°C, -7°C and 23°C, with each driving cycle test being carried out with a hot-start. On average, over all the tested driving cycles, the ratio between CO_2 emissions at -10°C and emissions at 20°C was found to be 1.05 and 1.04 for petrol cars and diesel cars, respectively (Joumard *et al.* 2006).

To account for the influence of ambient temperature, this project assumed that emissions tests are conducted at a range of ambient temperatures that are representative of the real-world. Additionally, any errors due to unrepresentative ambient temperatures are likely to be small because variations in CO_2 emissions with ambient temperature are small, with only a 5% increase as temperature decreases from 20°C to -10°C. For comparison, the UK annual mean temperature for 2006 was 9.7°C (Boulter *et al.* 2009b).

2.3.9 Vehicle Age and Maintenance

2.3.9.1 Vehicle age

The influence of vehicle age on emissions can be divided into two components. The first component is due to vehicle accumulated mileage because, in general, older vehicles will tend to have higher accumulated mileages. Increasing accumulated mileage tends to increase emissions. For example, the air pollutant emission inventory guidebook produced by the European Environment Agency (EEA) includes scaling factors to be applied to baseline EFs to account for this influence. Scaling factors are provided for Euro 1 to Euro 4 petrol LDVs[28] for emissions of CO, NO_X and HC, with the scaling factors increasing linearly with increasing mileage up to a maximum beyond which the scaling factor is assumed to remain constant (120,000km for Euro 1 and Euro 2, and 160,000km for Euro 3 and Euro 4) (EEA 2014; Borken-Kleefeld and Chen 2015). These scaling factors are also included in COPERT (EEA 2014; Borken-

[28] Scaling factors are not provided for other vehicle categories. Instead, baseline EFs are assumed to be representative of a vehicle fleet constituting a typical range of accumulated mileages (fleet average accumulated mileage of between 30,000 to 60,000km) (EEA 2014).

Kleefeld and Chen 2015), which is an Average Speed EM widely used across Europe (refer to Section 2.5.5.4). However, the literature suggests that increasing accumulated mileage does not affect emissions of CO_2 (Samaras and Ntziachristos 1998; Ntziachristos and Samaras 2000; Rexeis *et al.* 2005; Samaras and Geivanidis 2005; Boulter *et al.* 2009c; Borken-Kleefeld and Chen 2015), so this component of vehicle age was disregarded in this project.

The second component is that, when vehicles are new, they must comply with emissions regulations that have become increasingly stringent over time. Therefore, older vehicles will have higher emissions due to compliance with the more lax emission legislation that was in force when they were new. For example, in Europe, disaggregating vehicle categories according to Euro Standard is a convenient method for EMs to include the influence of this component of vehicle age on emissions. Euro Standards do not apply to CO_2 emissions, but other EU legislation does place similar, increasingly stringent limits on its emission. The fleet average limit[29] to be achieved by all new cars was 130 gCO_2/VKM in 2015 (average EF from the New European Driving Cycle (NEDC) emissions test), reducing to 95 gCO_2/VKM in 2021, which represent reductions of 18% and 40%, respectively, compared with the fleet average of 158.7 gCO_2/VKM in 2007. The fleet average limit to be achieved by all new LGVs will be 175 gCO_2/VKM in 2017, reducing to 147 gCO_2/VKM in 2020, which represent reductions of 3% and 19%, respectively, compared with the fleet average of 180.2 gCO_2/VKM in 2012. However, there is no such EU legislation to restrict CO_2 emissions from HDVs (EC 2015). To account for the influence of this component of vehicle age, project investigations disaggregated vehicle categories according to Euro Standard. Whilst Euro Standards do not apply to CO_2 emissions, they do provide a convenient way to distinguish between vehicles of different ages that is consistent with the vehicle category classification typically found in emissions tests results and in other EMs.

2.3.9.2 Vehicle maintenance

Much of the research into the effects of vehicle age and maintenance on emissions has been conducted using roadside remote sensing equipment developed at the University of Denver called the Fuel Efficiency Automobile Test (FEAT) system. An explanation of this equipment can be found in Bishop and Stedman (1996) and in Bishop and Stedman (2008). Examples of the use of roadside remote sensing equipment in UK urban areas are the collection of a

[29] Only the average for a manufacturer's fleet is regulated, so manufacturers can produce vehicles with emissions above the limit, provided these are offset by vehicles below the limit.

dataset[30] of measurements obtained using equipment similar to FEAT in London during 2008 (Rhys-Tyler *et al.* 2011; Rhys-Tyler and Bell 2012), and the collection of a dataset[31] obtained using the FEAT system itself (hired from the University of Denver) in London during 2012 (Carslaw and Rhys-Tyler 2013).

Virtually all the literature centres on three species of AQ emissions, namely CO, HC and NO_X. Emissions of these pollutants do tend to increase with vehicle age, but older vehicles do not contribute significantly to total fleet emissions, mainly because of the small number of older vehicles in the fleet and the low VKMs they undertake. Newer vehicles make a much larger contribution to total fleet emissions, but this is due to the small minority that are high-emitters (top 20% of emitters) as a result of poor maintenance, rather than the vast majority that have low emissions (Muncaster *et al.* 1996; Revitt *et al.* 1999). The general conclusion of the literature is that emissions differences between well and badly maintained vehicles are considerably larger than the effects of vehicle age (Revitt *et al.* 1999; Zhang *et al.* 1995). Put simply, maintenance is a far more important factor than vehicle age (Guenther *et al.* 1994).

A preliminary investigation by Smit and Bluett (2011) compared the results of laboratory emissions tests with data from roadside remote sensing. The comparison indicated that high-emitting vehicles may not be adequately captured in laboratory test data. The study went on to develop suggested correction factors, for application to emissions predictions based on laboratory emissions tests, which account for the increase in fleet emissions due to high-emitters. However the authors identified a need for further validation of laboratory emissions test results to confirm the correction factors, prior to the factors being recommended for use.

The quantitative results for AQ emissions found in the literature are not applicable to CO_2 emissions. That said, it is recognised that high-emitters of AQ emissions also tend to have poorer fuel economy (Zhang *et al.* 1995). Therefore, due to the direct relationship between fuel consumption and CO_2 emissions, the research findings are likely to give an indication of the situation for CO_2.

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[30] The dataset was compiled from 29 survey days (approximately 08:30 to 18:30) at 13 urban sites (30mph speed limit) from March to August in 2008 giving 54,599 observations with valid emissions measurements and vehicle identification. Vehicle identification was obtained by matching licence plate photographs with vehicle registration records (Rhys-Tyler *et al.* 2011; Rhys-Tyler and Bell 2012).

[31] The dataset was compiled from weekday survey days (approximately 08:00 to 18:00) at 4 urban sites from May 21st to July 2nd in 2012 giving 72,712 observations with valid emissions measurements and vehicle identification. As in the 2008 dataset, vehicle identification was obtained by matching licence plate photographs with vehicle registration records (Carslaw and Rhys-Tyler 2013).

In general, high-emitters require further investigation to improve estimation of their emissions (André and Rapone 2009) before the effects of maintenance can be fully included in EMs. This is particularly true in the case of CO_2 emissions because nearly all the existing research concerns AQ emissions instead. Hence, this project included the influence of high-emitters only insofar as they feature in the emissions test data, which is likely to be an under-representation because owners of high-emitting vehicles are unlikely to volunteer for emissions testing (Pokharel *et al.* 2002).

2.3.10 Ultimate CO_2 emissions

There is a direct relationship between fuel consumption and ultimate CO_2 emissions, in accordance with the carbon content of petrol and diesel. The relationship is based on the principle that all carbon in the fuel will ultimately end up as CO_2, even if a small proportion is initially emitted from the tailpipe in other forms, such as CO, HC or PM (AEA 2009). Typically, the difference between tailpipe CO_2 emissions and ultimate CO_2 emissions is very small for modern vehicles. For example, for modern petrol and diesel cars, the effect is an increase of 1% or less. However, for older vehicles (e.g. pre-Euro 1 petrol cars) the effect can be larger (Boulter *et al.* 2009b). This project investigated the estimation of ultimate CO_2 emissions, because it is the total CO_2 emitted that is of concern with respect to climate warming impacts.

2.3.11 Auxiliaries

The use of auxiliary systems, such as air conditioning, headlights, windscreen wipers, or in-vehicle entertainment, can have a considerable impact on vehicle emissions (Boulter and McCrae 2007). However, the most important auxiliary system is air conditioning, which represented the single largest auxiliary load by almost an order of magnitude in 2000 (Farrington and Rugh 2000). The number of vehicles using energy intensive in-vehicle entertainment and comfort systems (such as seat heating) has increased since then (Mock *et al.* 2013), but air conditioning remains the second largest energy consumer after driving itself (Weilenmann *et al.* 2010), and this is where much research has focused.

For example, a study of six Euro 3 petrol cars investigated the extra CO_2 emissions due to air conditioning using emissions tests on a chassis dynamometer at ambient temperatures of 13, 23, 30, and 37°C, either with or without simulated solar radiation (i.e. sun or shade). The desired temperature of the car interior was set to 23°C. The maximum average extra CO_2 occurred during urban driving at 37°C with the sun shining, and was a 26% increase. The average extra CO_2 during urban driving at 13°C was 7%. The extra was not zero at 13°C because air-conditioning continued to run to prepare dry air for potential de-misting of the windscreen, rather than for cooling the car interior (Weilenmann *et al.* 2005b). The equivalent results for a subsequent similar study of six Euro 4 diesel cars were a 40% increase for urban driving at 37°C, and a 4% increase for urban driving at 13°C (Weilenmann *et al.* 2010).

For vehicle fleets as a whole, the penetration rate of air conditioning systems has increased significantly over time, with nearly all new vehicles in the EU now equipped with air conditioning (Mock *et al.* 2013). A European Climate Change Programme working group predicted that, under average European conditions, the use of air conditioning will cause an increase in fuel consumption (and associated CO_2 emissions) of between 4% and 8% for car fleets in 2020 (EC 2003).

Laboratory emissions test data are unlikely to represent real-world use of auxiliaries, as much testing is conducted with auxiliary systems switched off. For example, the NEDC type approval test for cars does not include the use of air conditioning (Mock *et al.* 2013). Models to correct for the influence of auxiliaries on emissions have been advanced. For example, the ARTEMIS project developed a model to calculate excess emissions due to air conditioning in cars as explained in Roujol and Joumard (2009). However, such detailed and complex methods to include the influence of auxiliaries were outside the scope of this project. Instead, the influence of auxiliaries was included through the use of scaling factors (refer to Section 7.2.3.5).

2.3.12 Alternative Drivetrains or Fuels

Potential low carbon alternatives to conventionally fuelled (i.e. mineral petrol and diesel) Internal Combustion Engine (ICE) road vehicles include Battery Electric Vehicles (BEVs), Plug-in Hybrid Electric Vehicles (PHEVs), Hybrid Electric Vehicles (HEVs), Fuel Cell Vehicles (FCVs), biofuels, Compressed Natural Gas (CNG), and Liquefied Petroleum Gas (LPG). However, none of these vehicle categories are expected to make any significant contribution to reducing road traffic CO_2 emissions in the short term (next 10 years). The main reasons for this are that alternative low carbon drivetrains and large scale production of alternative low carbon fuels both have significant challenges to overcome, and that the impact of new vehicle technologies is constrained by fleet lifetimes of 12-15 years (King *et al.* 2010). As an example, the use of CNG in the UK is negligible, with only 559 CNG vehicles on the road in 2011 (NGVA 2013). Similarly, few vehicles run on LPG. There are no reliable figures available for total numbers of LPG vehicles in the UK, but energy use data indicate consumption of LPG is around 0.3% of the total for petrol and diesel (Passant *et al.* 2013). For electric vehicles, the UK government is committed to progressive electrification of the passenger car fleet, but see this policy for decarbonising road traffic as being effective over the longer term (DfT 2011c).

The UK's National Atmospheric Emissions Inventory (NAEI) acknowledge that these alternative vehicle categories are used in some areas (particularly captive fleets), and that their share of the national fleet will grow over the next 20 years (NAEI 2012). The NAEI national fleet model includes data for some alternative vehicle categories (NAEI 2014), and their fraction of national VKMs in 2016 is shown in Table 2-2, which reveals the small fraction of total VKMs constituted by these alternative vehicle categories. In their guidance on EFs for alternative vehicle categories, the NAEI explain that the primary purpose of including alternative vehicle categories in fleet projections is to allow more accurate calculation of NO_X and PM emissions; and, to that end, alternative vehicle category EFs for these two pollutants are tabulated in the guidance (NAEI 2013). However, no information is provided regarding EFs for CO_2 emissions. In general, there is a scarcity of emissions data (for all pollutants) for vehicle categories using alternative drivetrains or fuels, with a consolidated set of EFs not being available (NAEI 2013).

Due to their small fraction of total national VKMs (and associated contribution to CO_2 emissions, which is likely to be even smaller because their EFs will be lower than conventional vehicles, otherwise they would not be low carbon alternatives), coupled with the scarcity of emissions data (particularly for CO_2), the influence of vehicle categories using alternative drivetrains or fuels (except for biofuel detailed in the next section) was excluded from this project. If (when) a low carbon alternative successfully penetrates the mass market this decision would have to be revisited.

Table 2-2: Fractions of VKMs for alternative vehicle categories on urban roads in England (outside London) provided in the NAEI national fleet model projections for 2016.

Alternative Vehicle Category	Percentage of Aggregate Category VKMs	Percentage of Total VKMs
Car BEV	0.12% of Car	0.10%
Car Petrol HEV	1.02% of Car	0.84%
Car Petrol PHEV	0.08% of Car	0.06%
Car Diesel HEV	0.16% of Car	0.13%
LGV BEV	0.96% of LGV	0.13%
LGV Petrol HEV	0.00% of LGV	0.00%
LGV Petrol PHEV	0.00% of LGV	0.00%
LGV Diesel HEV	0.02% of LGV	0.00%
Bus HEV	0.78% of Bus	0.01%
Bus BEV	0.02% of Bus	0.00%
Bus CNG/LPG	0.04% of Bus	0.00%
Coach HEV	0.78% of Coach	0.00%
Coach BEV	0.02% of Coach	0.00%
Coach CNG/LPG	0.04% of Coach	0.00%
	Combined total	1.27%

- Table entries showing 0.00% are too small to register at two decimal places.
- Source: NAEI (2014).

2.3.12.1 Biofuel

The Renewable Transport Fuel Obligation (RTFO) requires that a percentage of total road transport fuel supplied in the UK is sustainable biofuel, i.e. fuel derived from biomass (HMG 2007; DfT 2014a). According to the DfT statistical release for the year 2014/15 (the latest year for which full statistics are available), renewable fuel supplied amounted to 3.29% of total fuel volume, against a 4.75% obligation target (DfT 2016a).

The two main types of biofuel available in the UK for road transport are biodiesel blended with fossil diesel, and ethanol blended with fossil petrol. Biodiesel is typically produced from rapeseed, soybean, sunflower, palm or other vegetable oils, and has the chemical name Fatty Acid Methyl Ester (FAME). Ethanol is typically produced by fermentation of the sugar in crops such as sugar cane, sugar beet or wheat (Boulter and Latham 2009). There is no requirement for scaling factors to account for the influence of biofuel blends on CO_2 emissions, because it has been found that blends of biofuel below 10% (as in the RTFO) with petrol or diesel do not affect emissions (Boulter and Latham 2009).

However, some emissions reduction benefit is gained due to the CO_2 absorbed by the biofuel feedstock as it is grown. In fact, for incorporating the effects of the RTFO, the DfT recommend assuming that biofuels produce zero CO_2 emissions when combusted, as the carbon released during combustion is entirely offset by the carbon absorbed during feedstock growth (DfT 2014c). In other words, calculated emissions should be reduced by a percentage equivalent to the percentage of the biofuel blend, and that was the approach adopted in this project.

It should be noted that the DfT recommended assumption applies to the combustion phase of the biofuel lifecycle (i.e. tank-to-wheel emissions, which are the scope of this project). If other lifecycle phases are considered, CO_2 emissions produced by biofuels are unlikely to be zero. For example, land-use changes from wetlands, rainforests, peatlands, savannahs, and grasslands to cultivation of biofuel crops could involve net increases in GHG emissions. Also, nitrous oxide (N_2O), emitted as a result of biofuel crop production, is a GHG and may negate any CO_2 savings. Overcoming problems such as these could potentially be achieved by using other sources of biomass feedstock, such as waste biomass or algae (Grote *et al.* 2014).

2.3.13 Retrofitting of Emissions Control Technology

There are a number of current policy initiatives aimed at reducing AQ emissions from road traffic. For example, the introduction in many cities across Europe and the UK of areas where high emitting vehicles are charged to enter or banned altogether (typically called Low Emission Zones (LEZs), refer to Section 2.5.12) (Holman *et al.* 2015; DEFRA 2015b). Emissions from older, diesel HDVs (i.e. compliant with earlier, less strict Euro Standards) have been identified as a particular concern, and it is often necessary for these vehicles to have emissions control technology retrofitted to their exhaust systems in order to comply with the latest emissions restrictions (DEFRA 2015b). Two technologies commonly retrofitted to diesel HDVs are Selective Catalytic Reduction (SCR)[32] for the reduction of NO_X emissions, and Diesel Particulate Filters (DPF) for the reduction of PM emissions (Murrells and Pang 2013). For example, Transport for London (TfL) recently (2014) completed the retrofitting of SCR to over 1000 buses in London (Font and Fuller 2015).

Despite the (small) mass penalty of the equipment (e.g. approximately 120kg), retrofitting SCR has been reported as causing no discernible increase in fuel consumption (which is directly

[32] Further details of the operation of SCR systems can be found in Footnote 142 in Section 5.5.4.3. The details of the operation of DPF systems are (as the name implies) fairly self-explanatory.

proportional to CO_2 emissions) (Lambert *et al.* 2004; AMEC 2011). However, retrofitting DPF can lead to increased exhaust backpressure (MECA 2009), which has been found to increase fuel consumption by up to 4% (Stevens *et al.* 2005). That said, the influence of retrofitting emissions control technology on overall CO_2 emissions from the vehicle fleet as a whole is relatively small. Therefore, for reasons of simplicity and practicality, the influence was excluded from this project.

2.3.14 Focus on Congestion

The focus of this project is to investigate methods to explicitly include the influence of congestion on CO_2 emissions for urban road networks as a whole, which are sufficiently simple to be used within LGA resource constraints. The justification for this focus on congestion, rather than other factors, is that congestion (arguably) ranks alongside VKMs, vehicle category, and vehicle speed as one of the most important influences on CO_2 emissions; and, therefore, should also be explicitly included in EMs. In general, the influences of other factors are smaller than that of congestion. That said, it is acknowledged that all factors should be included in EMs where possible, although the manner and detail of their inclusion can vary substantially. Indeed, the influences of most other factors <u>are</u> usually included to some extent, typically through assumptions, either of a constant value (e.g. zero road gradient), or that emissions tests, the data from which are used as the basis for EM construction, cover (albeit imperfectly) the real-world distribution of values these factors can take (e.g. vehicle age). However, methods to <u>explicitly</u> include the influence of other factors are subjects beyond the scope of this project.

This project is concerned with estimation of emissions at network-level (or substantially large parts of a network, e.g. >1km^2). Therefore, the validity of the assumptions used to include other factors is strengthened because random errors introduced by not fully accounting for vehicle-specific values should (to a certain extent) average-out (Smit *et al.* 2008b). For example, negative gradients will offset positive gradients and lighter than average vehicle loads will offset heavier than average vehicle loads. A final point is that, in general, LGAs have more influence over congestion than for example gradient, vehicle loading, ambient temperature, use of auxiliaries, etc., and it is interventions affecting congestion in which LGAs are most interested.

2.4 ROAD TRAFFIC DATA

2.4.1 Road Traffic Data Sources

The emissions modelling process requires road traffic data as inputs which describe the category and motion of vehicles travelling on road networks. Such data are available from numerous sources. Traffic counts (manual or automatic) record numbers of vehicles passing a location, and can include vehicle category data (i.e. car, LGV, HGV, bus, etc.). Manual Traffic Counts (MTCs) are done by people located at the roadside, and are often known as Manual Classified Counts (MCCs) when vehicle category data are also included. Automatic Traffic Counts (ATCs) can be done by various methods, including pneumatic tubes, piezoelectric pressure sensors and Speed Detection Radar (SDR) traffic classifiers (a SDR can also be known as a Remote Traffic Microwave Sensor (RTMS) (Econolite 2012)). Pneumatic tubes are the simplest method, being both cheap and easy to install. A hollow tube is stretched across the road and is sealed at one end, with the other leading to a pressure switch contained in a roadside box. Each time the tube is compressed by a vehicle's wheel, the pulse of air is registered by the pressure switch. Hence, the tube counts axels, and a correction factor must be applied to the raw data (average number of axels per vehicle) to estimate the number of vehicles. Piezoelectric pressure sensors are installed under the road surface and are usually permanent, but can be temporary. An electrical signal is produced as a vehicle's wheel passes over the sensor. Therefore, similar to pneumatic tubes, the sensors count axels. SDR traffic classifiers are relatively easy to install, with the sensor being pole-mounted at the roadside, avoiding the need to intrude on the road surface. A microwave radar system is used to automatically count traffic, recording each vehicle's arrival time, speed, and length.

Automatic Number Plate Recognition (ANPR) data are generated by fixed or mobile cameras that record a photograph of each vehicle and read the vehicle's licence plate allowing vehicle category to be determined, and journey time data to be produced from the time taken for vehicles to travel between different camera locations. A long-established source of road traffic data is the Moving Car Observer (MCO) method, where average trip time and traffic flow are derived from observers in a test vehicle recording their trip time, along with the number of slower vehicles overtaken and the number of faster vehicles which overtake them (Wright 1973).

Roadside Interview (RSI) surveys are performed manually by stopping a sample of the vehicles passing a survey site and interviewing the occupants. Their main purpose is in providing origin and destination data for use in the traffic modelling process. Queue length surveys manually record the number of queueing vehicles or queue length in metres, and often include associated delay times. Their main purpose is in the calibration and validation of Road Traffic Models (RTMs).

In the UK, there used to be a requirement (abolished in 2010) for National Indicators (NIs) to be reported annually by LGAs to national government. However, LGAs are still encouraged by national government to collect those NIs beneficial for monitoring and evaluation purposes (SCC 2011a), and some are measures of road network performance. For example, in their respective Local Transport Plans (LTPs), SCC has committed to producing figures for average trip time per mile along key road traffic routes through the city (SCC 2011a) and Hampshire County Council has committed to reporting average total vehicle delay (vehicle.h/h) for fifty representative links across the county during the AM and PM peak periods (HCC 2013). An advantage of this data source is that NIs are produced anyway by LGAs, and would not incur additional resources for use in emissions modelling.

The utility of the sources listed in the previous paragraphs for predicting emissions can be limited, either because their availability is typically restricted to only a few locations (spatially and also sometimes temporally) within a network (i.e. they lack continuous link-by-link resolution), or because they involve resource-intensive data acquisition, or both. However, these sources can be a useful addition to the emissions modelling process, either in combination with other data or through providing data for the calibration and validation of models. For example, ANPR data could be used to provide supplementary information on how a local vehicle category fleet mix may differ from a national fleet model.

The data sources already mentioned are relatively simple and self-explanatory; however, a few data sources require a more detailed explanation and are described in the following sections. It is also worth noting here that the characteristics of the road network itself will obviously influence the movement of traffic through the network because of their relation to supply of road capacity. Therefore, the definition of road traffic data was extended to include network characteristics. These characteristics have the advantage of being fairly easily measured by (or on behalf of) LGAs; and having been measured once, are not subject to change very often.

Furthermore, network characteristics have been defined as traffic variables[33] for the purposes of this project because they typically apply to all vehicles together rather than on an individual basis.

2.4.2 Fleet Models

Typically a fleet model of vehicle categories particular to a given nation (or sub-national region) is maintained by that country's government (or other delegated authority). For example, a detailed classification of the categories in the UK road vehicle fleet is provided by the NAEI national fleet model, which at the finest level of disaggregation distinguishes according to Euro Standard (Figure 2-5). The model supplies activity data in terms of the fraction of total national VKMs travelled by each vehicle category in urban areas, rural areas and on motorways. These fractions are projected on a yearly basis up to 2035 (NAEI 2014).

[33] Traffic variables are variables describing the movement of traffic as an aggregate whole, for example: traffic average speed (km/h); traffic flow (vehicles/h); traffic density (vehicles/km); traffic average delay rate (seconds/vehicle.km); traffic average travel time (minutes/km); and average queue length (m).
In contrast, cycle variables are variables describing the movement of an individual vehicle (i.e. describing an individual vehicle's driving pattern), for example: vehicle average speed (km/h); vehicle maximum speed (km/h); time spent accelerating (s); time spent cruising (s); time spent decelerating (s); time spent idling (s); average acceleration (m/s^2); number of stops per km (stops/km); and average distance between stops (m).

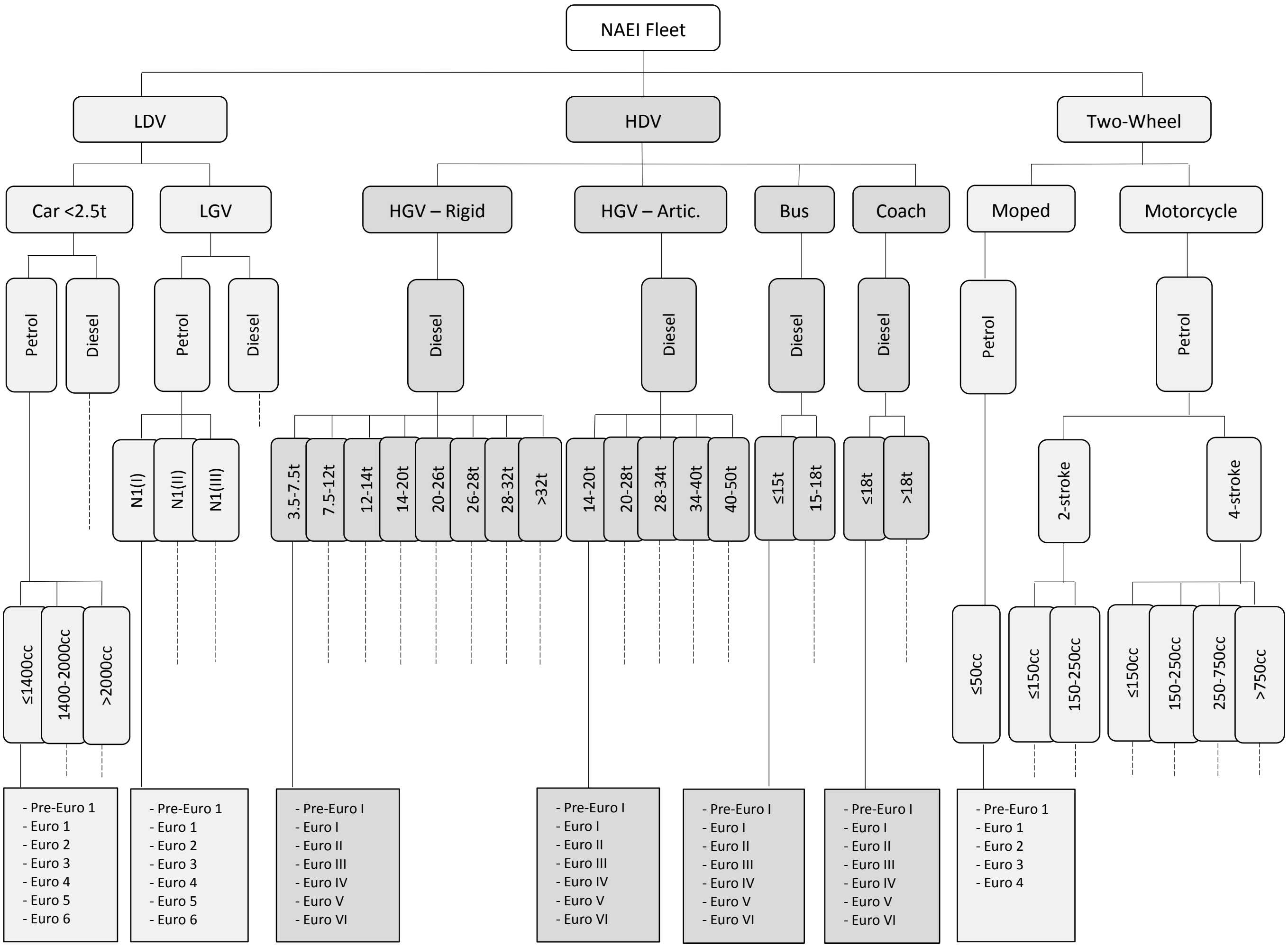

Figure 2-5: NAEI national fleet model for the UK (outside London).

- LDV is Light Duty Vehicle; HDV is Heavy Duty Vehicle; LGV is Light Goods Vehicle; HGV is Heavy Goods Vehicle.
- Artic denotes articulated HGVs.
- Vehicle mass in tonnes (t) is Gross Vehicle Mass (GVM), the maximum operating mass of the vehicle as specified by the manufacturer.
- Engine capacity is shown in cubic centimetres (cc).
- NAEI projections for national fleet mix assume that all cars are <2.5t as there is no information available on cars of 2.5-3t.
- NAEI projections for national fleet mix assume that the Bus>18t category applies only to articulated buses, which are assumed to be absent from the bus fleet outside London.
- NAEI projections for national fleet mix assume that, outside London, taxis are included within the Car categories.
- The boundaries for mass and cc bands are: greater than the lower limit, but include the upper limit. For example 3.5-7.5t means: >3.5t to ≤7.5t.
- The N1 category (LGVs) covers vehicles with GVM ≤3.5t, and is further subdivided by Reference Mass (RM). N1(I), N1(II) and N1(III) have RM bands: ≤1305kg; >1305kg to ≤1760kg; and >1760kg, respectively (for an explanation of RM, refer to Footnote 19 in Section 2.3.2).
- Vehicle categories with alternative drivetrains or fuels are not shown.
- Source: NAEI (2014).

2.4.3 Intelligent Transport Systems Technologies

Intelligent Transport Systems (ITS) are defined as any application of Information and Communication Technology (ICT) to transport (refer to Section 2.5.11 for more details), which includes several technologies that can serve as sources of road traffic data via vehicle telematics[34]. Vehicle tracking data can be collected from in-vehicle devices using Bluetooth, GPS, mobile telephony or Wi-Fi technologies[35]. These devices can provide information on traffic flow, average speeds, delays, travel times, and (at the most detailed resolutions) driving patterns. A drawback of vehicle tracking data is the issue of privacy. Gathering identifiable data requires driver permission, which may not be forthcoming from private citizens. Installing devices on captive fleets could be more practical, but resistance may still be encountered from reluctant work forces or business owners. The problem of privacy leads on to another problem in terms of penetration, i.e. the number of vehicles from which data can be gathered compared to the total number of vehicles. A small sample size decreases the likelihood that the samples will be representative of the traffic conditions on all parts of a network because the frequency of tracked vehicles traversing a given link is likely to be lower (De Kievit *et al.* 2014b).

An example of the use of vehicle tracking data can be found in the compilation of the 2010 London Atmospheric Emissions Inventory[36] (LAEI). In a change from previous methodologies, traffic average speeds for roads defined as major were based on a combination of GPS and MCO speeds, rather than on MCO speeds alone (data for other roads were provided by TfL's London Transportation Studies model). The GPS data were provided by a company called Trafficmaster[37]. Traffic average speed was estimated at link level, averaged for the following daily periods: overnight (22:00-07:00), AM peak (07:00-10:00), inter-peak (10:00-16:00), PM peak (16:00-19:00) and evening (19:00-22:00). The data were from observations during 2009/10, and GPS data were available for approximately 62% of the major roads. For the

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[34] Telematics can be broadly defined as the integration of telecommunications with ICT to send and store information relating to remote objects such as vehicles.

[35] GPS devices include mobile telephones (e.g. real-time Google Traffic available in Google Maps), satellite navigation devices (e.g. Tom Tom or Garmin) and fleet tracking devices (e.g. Teletrac Inc. fleet tracking services). GPS devices can be passive (GPS location recorded by the device) or active (GPS location transmitted to a central tracking system in real-time). For Bluetooth and Wi-Fi devices, signals emitted by the devices are received by road side detectors allowing the unique Media Access Control (MAC) address of a device to be identified. Mobile telephony is the tracking of mobile telephones based on a device's location relative to the mobile telephone network base stations (i.e. cell towers).

[36] An emissions inventory is an account of the amount of pollutant(s) emitted from all source categories, within a specified geographic area, within a specified time period. The LAEI is an inventory of all atmospheric emissions sources in the Greater London area.

[37] Trafficmaster became a division of Teletrac Inc. in 2013. Teletrac is one of the largest fleet companies in the UK and USA, and (among other services) provides GPS fleet tracking services to assist organisations in managing their vehicle fleets.

remaining major roads, where GPS data were not available, MCO data were used instead (GLA 2014).

Automatic Vehicle Identification (AVI) using Radio Frequency Identification Devices (RFID) provides similar data to ANPR cameras. Vehicles are fitted with RFID tags (sometimes called transponders), typically in the form of labels attached to the windscreen or licence plate, which pass the vehicle's details to a roadside tag reading unit. Unlike ANPR cameras, AVI is not sensitive to ambient adverse weather conditions. However, vehicle identification is limited to those carrying transponders (De Kievit *et al.* 2014b).

Based on the vehicle telematics data available from ITS, Traffic Congestion Indices (TCIs) (also known as Traffic Performance Indices, TPIs) can be produced using methods such as comparison of measured travel times with free-flow measured travel times or, less commonly, comparison of the marginal cost of congestion[38] with the average cost of congestion[39] (Goodwin 2004; Grant-Muller and Laird 2006; Grote *et al.* 2016a). For example, TomTom produce a Traffic Index for 218 cities worldwide based on GPS data. INRIX also produce global congestion data for urban areas (e.g. the Urban Mobility Scorecard Annual Report), and the Texas A&M Transportation Institute produce similar data for the USA. In the UK, Mott MacDonald produce Strat-e-gis Congestion which provides historic congestion data based on GPS technology, with this data source often used by UK LGAs to monitor performance against NIs.

2.4.4 Road Traffic Models

Road Traffic Models (RTMs) are often used as a source of EM input data because they offer a practical method to generate a full complement of type and trajectory information for all vehicles on all (or mostly all) roads in a modelled network (Smit 2006). RTMs represent how travel demand (i.e. desire for goods and people to move between origins and destinations) is satisfied by the road network, with demand generally expressed in the form of an origin-destination (O-D) demand matrix, populated by the number of trips between each pair of defined origin and destination zones (Grote *et al.* 2016a).

[38] Typically defined as the economic cost of one additional VKM (i.e. the difference between the total economic cost of congestion before and after one additional VKM is performed).
[39] Typically defined as the total economic cost of congestion divided by the total number of VKMs.

RTMs are usually classified according to scale; although it is worth noting that the scale of RTMs is a continuum, and there is no clearly specified and agreed demarcation between the different scales. Macro-RTMs typically consider road traffic as an aggregated flow, with the flow of traffic through links and intersections described by relationships between traffic variables such as traffic density (vehicles/km), traffic average speed (km/h) and traffic flow (vehicles/h) (Lighthill and Whitham 1955; Kotsialos *et al.* 2002). Demand is assigned to the network iteratively, aimed at finding an equilibrium solution that replicates route choice through the network. Demand, and the resulting values for each link's density, speed and flow, are assumed to be constant for the entire modelled period which is not a very realistic assumption for congested networks (Ortúzar and Willumsen 2011), particularly over longer time periods (e.g. a peak period).

Micro-RTMs consider the motions and interactions of individual vehicles based on combining detailed network characteristics with detailed driver behaviour sub-models (car following, lane choice, and gap acceptance) (Papacostas and Prevedouros 2005; Ortúzar and Willumsen 2011; Ramos *et al.* 2011). Hence, driving patterns for each vehicle are available as outputs. However, RTMs (including micro-RTMs) are typically calibrated and validated for aggregate traffic measures (i.e. traffic variables such as traffic average speed, traffic flow, average delay, and queue length), rather than for driving patterns of individual vehicles (Hirschmann *et al.* 2010; Song *et al.* 2012; Toffolo *et al.* 2013; Song *et al.* 2013). Therefore, driving pattern outputs from micro-RTMs are rarely validated properly, and do not necessarily accurately represent real-world driving patterns (Song *et al.* 2012; Song *et al.* 2013). For example, when functioning at micro-scale (it also functions at meso- and macro-scales), Anya *et al.* (2014) found that the driving patterns simulated by AIMSUN[40] were not representative of real-world driving patterns when default settings were used. To generate more realistic driving pattern outputs, the parameters of the car following sub-model within AIMSUN had to be calibrated using measurements from real-world driving patterns.

Meso-RTMs are a third classification often distinguished between micro-RTMs and macro-RTMs. Vehicle motions and interactions are considered, but in less detail than in micro-RTMs.

[40] Advanced Interactive Microscopic Simulator for Urban and Non-Urban Networks (AIMSUN) is produced by Transport Simulation Systems.

For example, SATURN[41] groups vehicles into platoons, and uses a platoon-dispersion module[42] to simulate the movement of vehicles between signal controlled intersections accounting for interaction with vehicles entering/exiting the road and different drivers' preferred speeds (Papacostas and Prevedouros 2005; Ortúzar and Willumsen 2011). As another example, when functioning at meso-scale, AIMSUN considers the motions of individual vehicles (using less detailed driver behaviour sub-models than at micro-scale), but only calculates entry and exit times for each link, rather than calculating full driving patterns (Grote *et al.* 2016a).

The resources (costs, labour, and computer runtimes) demanded by RTMs increase with network size. Hence, for a given resource constraint, as the size of network to be modelled increases, the detail of traffic data generated is effectively reduced. For large urban road networks, the outputs of RTMs are usually limited to data for the traffic on each link, rather than for individual vehicles (Smit *et al.* 2008b). In other words, micro-RTMs provide finely detailed data (e.g. individual vehicles), over short time period resolutions (e.g. 1Hz), but are limited to micro-scale geographic areas (e.g. several links and intersections). As network scale increases, meso-RTMs and macro-RTMs are used instead, providing less detailed output data.

2.4.5 Urban Traffic Control Data

Urban Traffic Control (UTC) systems can provide road traffic data in the form of traffic variables. UTC systems coordinate traffic signals to achieve good progression for vehicles through urban road networks. An example of a widely used system is SCOOT[43], which operates in over 250 cities and towns worldwide (Bretherton *et al.* 2011). Signal control data are generated by Inductive Loop Detectors (ILDs) installed beneath the road surface, with the ILD for an intersection usually located 10-15 metres downstream from the previous intersection[44] (Bretherton *et al.* 2011). ILDs send updates of vehicle presence every 250 milliseconds in the form of 1s and 0s (denoting occupied or unoccupied, respectively), which

[41] Simulation and Assignment of Traffic to Urban Road Networks (SATURN) was developed at the Institute for Transport Studies, University of Leeds and distributed by Atkins Limited.

[42] A platoon-dispersion module simulates how a platoon of vehicles released by a green traffic signal disperses as the vehicles progress through the network.

[43] Split, Cycle and Offset Optimisation Technique (SCOOT) was developed by Imtech Traffic & Infra UK, Siemens and TRL.

[44] As well as their use in UTC systems, ILDs are also used as detectors in other traffic control systems. For example, ILDs are used in the Microprocessor Optimised Vehicle Actuation (MOVA) system, which is distributed by TRL and designed to control traffic signals at isolated intersections. Another example is the Motorway Incident Detection and Automatic Signalling (MIDAS) system, which is a network of traffic sensors (mainly ILDs spaced at 500m intervals, although SDR sensors have also been used as part of the system in more recent years) installed on over 1000kms of England's busiest motorways that detects early indications of traffic congestion and automatically sets upstream signs with messages aimed at reducing the risk of serious congestion (e.g. advisory speed limits, queue ahead, queue caution, etc.). However, this project is concerned with prediction of emissions from vehicles on urban road networks. It is therefore ILDs installed as part of UTC systems that are more relevant.

are then processed by the UTC system. The data used by UTC systems are typically stored in a database. For example, data used by SCOOT are automatically stored in the ASTRID[45] database.

An advantage of UTC data is that it can be considered a by-product of the traffic signal control system (Marsden *et al.* 2001), allowing EM input data to be collected without using additional resources (Reynolds and Broderick 2000). Another advantage is that UTC data provide an 'on the ground' picture of the real-world situation, in contrast to RTM outputs which are a modelled representation of the real-world. However, a disadvantage is that data availability is limited to certain point locations on the network, i.e. data are only available where ILDs are installed. Another disadvantage is that, where traffic average speed is required as an EM input, this is typically space-mean-speed[46] (i.e. based on average travel time over longer distances, e.g. link length or longer, refer to Section 2.5.5), whereas ILDs provide estimates of time-mean-speed (i.e. average of vehicle spot speeds). Also, because UTC data are real-world measurements, the data are not available for assessment of hypothetical scenarios (although simulated ILDs can be include in a network modelled using a RTM). In other words, UTC data can be used to assess the effect of transport interventions post-implementation through comparison of before and after emissions estimates, but cannot assess the effect of an intervention prior to implementation (Reynolds and Broderick 2000). For further details concerning the accuracy of data generated by ILDs refer to Section 5.4.4.

Enhanced ILDs (as distinct from conventional ILDs) can provide vehicle category data alongside their primary function of detecting vehicle presence. Enhanced ILDs rely on the resulting change in inductance due to the passage of a vehicle over the detector being distinct for different vehicle categories. To further assist with vehicle category classification, enhanced ILD data can be supplemented with axel count data (from pneumatic tubes or piezoelectric sensors). However, whilst enhanced ILDs can typically distinguish between two-wheel vehicles, LDVs, rigid HGVs, articulated HGVs and buses/coaches, they cannot further disaggregate vehicle categories (e.g. by fuel type, mass, compliance with different Euro Standards, or vehicle age). Additionally, enhanced ILDs are not universally installed, and upgrading existing,

[45] ASTRID is Automatic SCOOT Traffic Information Database.

[46] Space-mean-speed is calculated from the arithmetic mean of measured travel times over a measured distance of all vehicles during a given survey period. In contrast, time-mean-speed is the arithmetic mean of measured speeds (i.e. spot speeds) over a short measured distance of all vehicles during a given survey period.

conventional ILDs would involve expense and time. Therefore, vehicle category data from this source are not universally available to LGAs (Grote *et al.* 2016a).

2.4.6 Indicators of Congestion

This project is concerned with explicitly including the influence of congestion on CO_2 emissions. To achieve this, an obvious requirement is collection of road traffic data indicative of congestion levels. The detailed influence of congestion on vehicle motion can be captured through collection of driving patterns. However, collecting and processing driving patterns for each vehicle on a network is resource-intensive. An alternative option is to use traffic variables, which provide a less detailed representation of congestion than driving patterns, but have the advantage of being less resource-intensive to collect. A comprehensive discussion of over 40 different Congestion Indicators (CIs) used in traffic engineering can be found in a study by Smit (2006). From this extensive list, some of the more common examples of traffic variables widely used as CIs include traffic average speed (km/h), traffic density (vehicles/km), traffic average delay rate (seconds/vehicle.km), and average travel time (minutes/km). The Smit (2006) study also identified 'good' CIs as those which "show a consistent and unambiguous relationship with the level of congestion in a traffic stream". An example of an ambiguous traffic variable that should not be used as a CI is traffic flow (vehicles/h), which can be low in congested or uncongested situations.

2.5 ROAD TRAFFIC EMISSIONS MODELS

The term 'Emissions Model' is used loosely in this section to encompass a range of methods for predicting emissions from road traffic, from academic studies into a particular method, through to examples of proprietary EM software applications.

2.5.1 Construction of Emissions Models

EMs are typically constructed based on data from laboratory testing of sample vehicles over various standardised driving cycle emissions tests (Smit and Bluett 2011; Barlow and Boulter 2009). Many emissions tests are conducted as part of the type approval process for new vehicles. For LDVs, type approval tests are conducted by testing the entire vehicle on a chassis dynamometer. This is the case for the New European Driving Cycle (NEDC), which is the type approval test for cars within the EU. HDV engines can be coupled to many different chassis types. Therefore, as it would be impractical to test all possible combinations, type approval tests are conducted on the engine alone using an engine dynamometer (Franco *et al.* 2013). Extensive additional laboratory emissions testing has also been conducted for the purposes of research projects and EM development, which has included testing on an entire vehicle basis for HDVs (Boulter *et al.* 2009a; Franco *et al.* 2013). Hence, a large body of emissions test results has been compiled. As this is the most abundant source of emissions data, with the advantage of being highly accurate standardised measurements recorded under laboratory conditions, it is laboratory emissions test data that are typically used as the basis for EM construction (Franco *et al.* 2013).

The disadvantage of reliance on laboratory emissions test results is that they may not accurately replicate real-world emissions. In particular, the driving resistance values used in chassis dynamometer tests to simulate road load (combined effect of rolling resistance, aerodynamic resistance, gradient resistance and acceleration resistance) are often obtained from vehicle coast-down tests under overly favourable conditions, leading to lower emissions in comparison to real-world results (Franco *et al.* 2013; Kadijk and Ligterink 2012). Additionally, whilst some driving cycles attempt to replicate real-world driving patterns, others can be quite unrepresentative. For example, past investigations have found that the NEDC is not representative of real-world driving patterns and tends to under-estimate CO_2 emissions, with it often criticised for being too smooth and under-loaded compared to typical vehicle operation (Sileghem *et al.* 2014; Kousoulidou *et al.* 2013a). A recent study by Ntziachristos *et al.* (2014), of 924 cars measured over a wide range of real-world driving conditions, found in-use fuel consumption (which is directly proportional to CO_2 emissions) to be 16% and 11% greater than NEDC type approval values for diesel and petrol cars, respectively. The Worldwide Light-duty Test Cycle (WLTC) is an example of a new driving cycle[47] that more accurately represents real-world driving patterns, with one of the objectives of the WLTC being a more realistic measurement of CO_2 emissions (Sileghem *et al.* 2014; Ntziachristos *et al.* 2014). To account for driving cycles and laboratory conditions not necessarily being representative of real-world driving, the typical EM construction process is to calibrate a model using laboratory emissions test results, and then to validate the model using real-world emissions measurements (Ropkins *et al.* 2009).

[47] Being developed as part of the Worldwide harmonised Light vehicle Test Procedure (WLTP) under the United Nations Economic Commission for Europe (UNECE), aiming at worldwide harmonisation of vehicle testing. In the EU, the WLTP is planned to replace the NEDC in 2017.

Notwithstanding the previous paragraphs, a recent trend has been the use for EM construction of data from Portable Emissions Measurement Systems[48] (PEMS) fitted to vehicles driven in the real-world. Over the years, PEMS have improved, and they are now considered to be reliable and accurate to use on a wide variety of vehicles. In fact, advanced PEMS have been found to measure emissions with a similar quality to that found in emissions certification laboratories (Kousoulidou *et al.* 2013a). PEMS provide straightforward estimates of real-world emissions, and it has been suggested that EMs based on PEMS data are likely to predict emissions closer to the actual on-road values than EMs based on laboratory emissions test data (Ligterink *et al.* 2012).

2.5.2 Validation Methods for Emissions Models

The accuracy of EMs is assessed by validation, whereby model predictions are compared to independent observations. However, there are a number of general difficulties associated with the validation process. For instance, it is not possible to validate an EM at network-level in the strict scientific sense because it is not possible to measure true emissions for a network due to the large number of vehicles and traffic conditions involved (Namdeo *et al.* 2002; Smit 2006). Instead, only partial validation is possible for specific localised situations over relatively short time periods (Smit 2006). Generally, there are four main approaches for measuring the real-world emissions to be used in partial validation: (1) PEMS can be fitted to probe vehicles to measure emissions during specific vehicle trips; (2) during road tunnel studies, the difference between pollutant concentrations measured at the outlet and inlet of a tunnel can be used to derive real-world EFs for the tunnel traffic; (3) remote sensing can be used to analyse the exhaust plumes of vehicles passing a specific roadside point; and (4) inverted pollutant dispersion models can be applied to measurements of ambient pollutant concentrations to derive EFs for traffic, although this method makes the assumption that all the ambient pollution is emitted by the traffic (Barlow and Boulter 2009; Smit *et al.* 2010; Kousoulidou *et al.* 2013a; Franco *et al.* 2013). All four of these approaches are time consuming and costly processes, and it is unlikely that any of them could be conducted with enough regularity or consistency to ensure the continued accuracy of EMs over time (Barlow and Boulter 2009).

[48] In this thesis PEMS is used generically to encompass all Portable Emissions Measurement System equipment designed to be carried aboard road vehicles during real-world emissions tests on a test track or on public roads; as opposed to static laboratory emissions measurement equipment used during laboratory emissions tests (DfT 2016b).

Assessment of the accuracy of EMs has also been conducted by comparing the predictions of different EMs with each other. However, whilst similarities in the predictions between EMs tend to improve the confidence with which those EMs can be viewed (Barlow and Boulter 2009), it is important to note that model comparison is not the same as model validation – results from two different EMs may be similar but still differ substantially from reality (Smit *et al.* 2010). It is also worth noting that similarities in the predictions of EMs may occur due to the considerable amount of data that is shared between EMs in Europe (i.e. different EMs are calibrated based on the same emissions test results), rather than the similarities being an indicator of model accuracy (Barlow and Boulter 2009).

2.5.3 Inclusion of Congestion in Existing Emissions Models

As this project is concerned with explicitly including the influence of congestion on CO_2 emissions, it was informative to review the methods by which existing EMs include this influence. To provide structure for the review, EMs were classified according to type. At the broadest level, EMs were divided into two groups: (1) the Traffic EM Group, which calculate emissions for the traffic as an aggregate whole; and (2) the Vehicle EM Group, which calculate emissions for each individual vehicle within the traffic. These two groups were then further subdivided into EM types in accordance with the road traffic data required as inputs, which is consistent with the system of EM classification published in the journal article by Smit *et al.* (2010). However, it is acknowledged that there is no definitive, universally agreed classification system; and that under any given system some examples of EMs may defy easy classification. To illustrate each type of EM, specific examples have been selected because of their relevance to this project and/or because they are a widely used example of a type. Types of EM are broadly dealt with in order of complexity, moving from simple EMs to the more complex, as depicted in Figure 2-6.

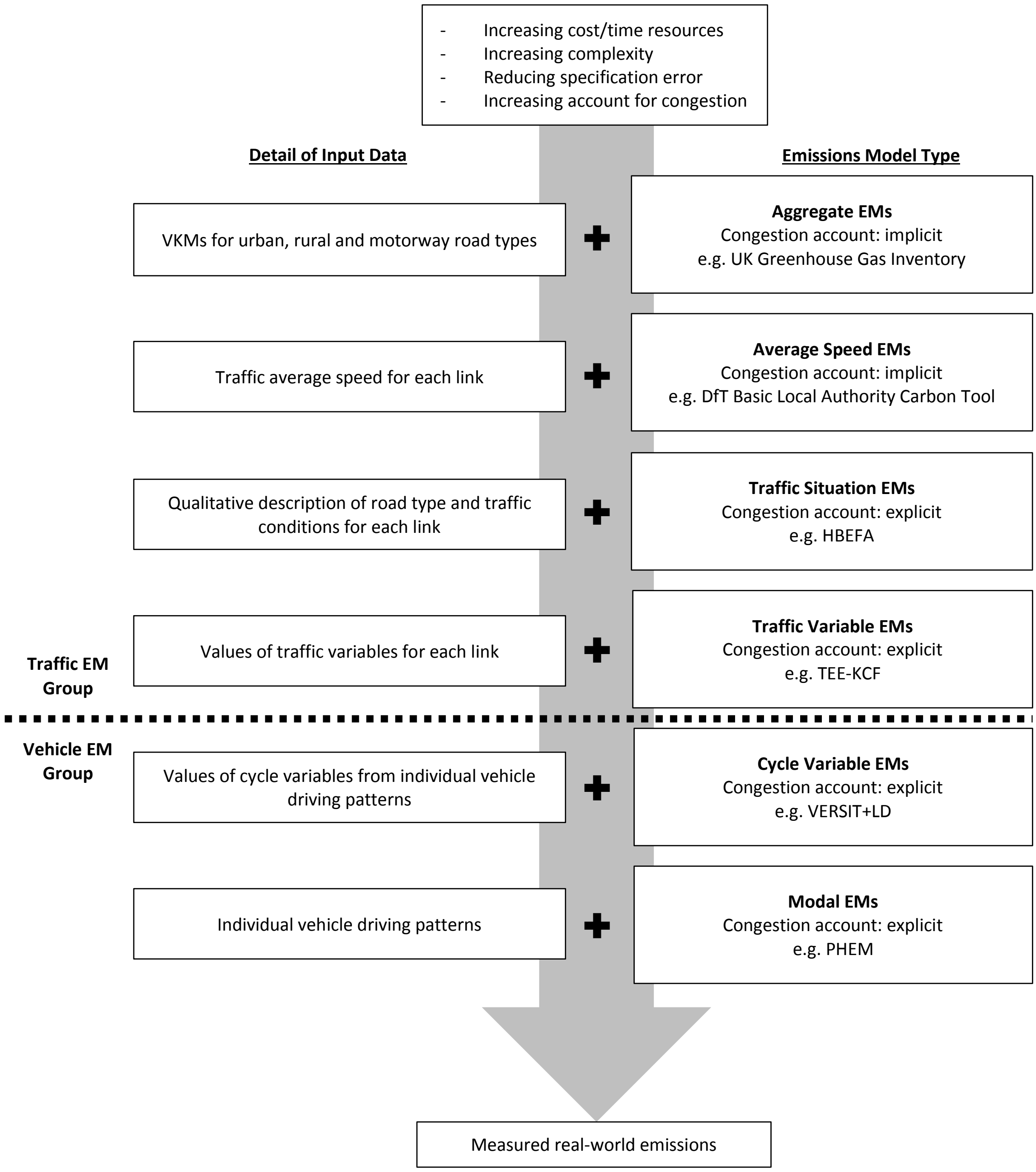

Figure 2-6: Emissions Model classification on a scale of resource consumption, complexity, accuracy, and account for congestion.

- The system of EM classification selected to provide a framework for the review is that published in Smit *et al.* (2010).

2.5.4 Aggregate Emissions Models

Aggregate EMs are the simplest and least detailed type of EM. A single, fixed EF is used for a given category of vehicle travelling on a given type of road, with the typical distinction between road types being urban, rural or motorway. Aggregate EMs are usually applied on large spatial scales to regional or national emission inventories because their simplicity means they are often the only type of EM that can be practically applied on such large scales.

2.5.4.1 UK Greenhouse Gas Inventory (GHGI)

The bottom-up methodology employed in the UK's GHG Inventory[49] uses an Aggregate EM. An average speed for traffic on each road type is used in conjunction with equations[50] that relate fuel consumption (which is directly proportional to CO_2 emissions) to average speed for each vehicle category to generate fuel consumption factors. For example, the fuel consumption factors for a Euro 5 petrol car are 44.7, 41.2 and 47.4 g/km for urban, rural and motorway road types, respectively. Total fuel consumed calculated by the bottom-up methodology is then normalised to agree with total fuel consumed calculated by the top-down methodology, which is based on the total fuel sold in the UK as published by the DECC in the Digest of UK Energy Statistics (DUKES), with the DUKES figures considered to be known with high accuracy (Webb *et al.* 2014).

An Aggregate EM such as the GHGI can provide an aggregate distribution of emissions between urban, rural and motorway road types, and between vehicle categories on those road types. Also, some implicit account for congestion is taken because the average speeds for the different road types will be influenced by congestion. However, the fuel consumption factors are fixed for a given road type, so the effects of transport interventions that vary local (e.g. link level) average speeds cannot be analysed.

2.5.5 Average Speed Emissions Models

Average Speed EMs calculate EFs for each vehicle category as a function of traffic average speed (i.e. average speed emission functions). Most road traffic EMs are currently based on average speed (Boulter *et al.* 2012). A suggested reason for this prevalence is that, particularly for larger urban networks, readily available data are often restricted to estimates of traffic average speed for each link (Smit *et al.* 2008b). Average speed emission functions are generated based on results from driving cycle emissions tests. For a given vehicle category, the average EF varies according to the average speed during a driving cycle. Therefore, when a vehicle category is tested over a number of different driving cycles, the results from each cycle will yield an average speed and an associated average EF. Figure 2-7 shows typical results from a number of driving cycles plotted as data points on a graph of average EF against average speed. A curve can then be fitted to the data points, and the equation of the curve is the average speed emission function for the vehicle category concerned (Boulter *et al.* 2012). An

[49] Compiled for submission under the United Nations Framework Convention on Climate Change (UNFCCC).
[50] Developed as part of the TRL EFs 2009 Average Speed EM (refer to Section 2.5.5.1).

important point to note is that, due to being developed based on vehicle average speeds over the length of driving cycles, the appropriate traffic average speeds to use as inputs to Average Speed EMs are space-mean-speeds rather than time-mean-speeds.

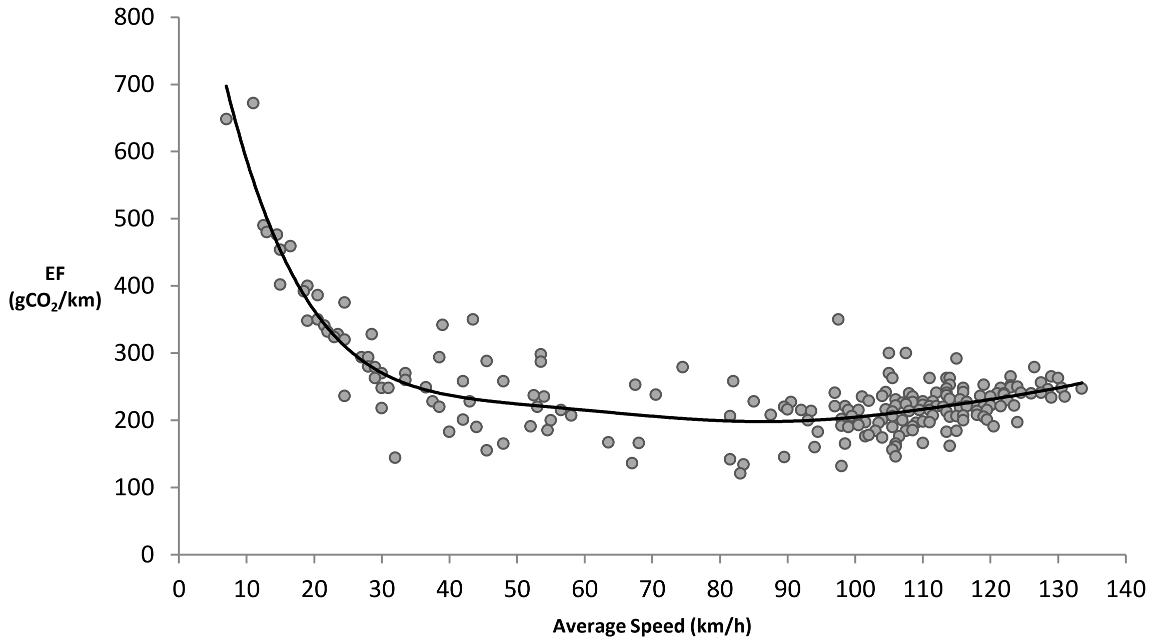

Figure 2-7: Generic CO_2 average speed emission function.

- Each data point (grey circle) represents the average speed and EF resulting from an emissions test.
- The black line is a continuous average speed emission function fitted to the data points.
- Source: adapted from Barth and Boriboonsomsin (2009).

A limitation of Average Speed EMs is that they cannot account for the fact that trips with differing vehicle operation characteristics (e.g. accelerations, decelerations, and time spent stationary) will all have differing emissions, but could all result in the same average speed (Int Panis *et al.* 2006; Boulter *et al.* 2009a; Toffolo *et al.* 2013). This is a particular problem at low average speeds, such as those in congested urban areas where the possible range of operational characteristics for a given average speed is large (Ramos *et al.* 2011; Boulter *et al.* 2012). However, when applied to a whole network (or substantially large parts of a network) this inaccuracy should be subject to a certain amount of averaging out, i.e. the increase in emissions due to stop-and-go conditions at particular network locations (model under-estimating) is offset by the decrease in emissions from free-flowing conditions at other locations (model over-estimating).

Average Speed EMs do implicitly account for some congestion influence because the driving cycles used in vehicle emissions tests that generate the data from which EMs are developed will have a dynamic speed-time profile. In other words, each data point is derived from a dynamic driving cycle with an associated average speed and average EF, rather than each data point being representative of the EF at a given steady-state average speed. However, the driving cycles used during model development are fixed and cannot be varied by the model user so as to reflect a particular congested situation of interest (Smit *et al.* 2008a).

Average Speed EMs are based on results averaged over an entire driving cycle. The simulated distance travelled during a driving cycle is typically representative of a series of links (i.e. a trip). For example, the 256 driving cycles in TRL's 'Reference Book of Driving Cycles'[51] have a mean and median distance of 11.1km and 6.7km, respectively (Barlow *et al.* 2009; Boulter *et al.* 2009a), which are both longer than typical urban road links. Therefore, the minimum spatial resolution for application of Average Speed EMs should ideally be trip-based average speed (space-mean-speed). However, they are often applied to link-based average speed (space-mean-speed), or even average spot speeds (time-mean-speed), because of the ready availability of such data.

2.5.5.1 TRL Emission Factors 2009 (TRL EFs 2009)

The Average Speed EM most relevant to the UK is the comprehensive set of average speed emission functions, reviewed by the TRL in 2009 (commissioned by the DfT), for the road vehicle fleet as classified in the NAEI national fleet model, which are the officially recognised formulae recommended for use in the UK[52] (Boulter *et al.* 2009b; Brown 2016). Due to its relevance to the UK, this example of an Average Speed EM is described in the greatest detail. The basic emission functions calculate emission factors for ultimate CO_2 (all pollutants subsequently oxidised to CO_2 in the atmosphere are included), and are of the form shown in Equation 2.

[51] Compiled during the development of TRL EFs 2009 Average Speed EM (refer to Section 2.5.5.1), with emphasis placed on those driving cycles most relevant to the UK.

[52] All the analyses performed in this project were carried out during a time when the CO_2 EFs officially recommended by the UK government were the TRL EFs 2009 (e.g. used as the basis for methodologies by the NAEI, the DfT Basic Local Authority Carbon Tool (refer to Section 2.5.5.2), and WebTAG (refer to Section 2.5.5.3)). Therefore, where required for analysis in this project, the TRL EFs 2009 have been used. Subsequent to the work carried out in this project, the NAEI are currently (during 2016) in the process of changing their methodology for CO_2 emissions from being based on TRL EFs 2009 to being based on COPERT (refer to Section 2.5.5.4). This indicates a forthcoming transition of the officially recommended CO_2 EFs from TRL EFs 2009 to COPERT. A likely reason for this transition is that TRL EFs 2009 requires direct investment by the UK government to update, whereas COPERT can be purchased 'off-the-shelf' and is updated on an on-going basis by Emisia (a spin-off company of the Laboratory of Applied Thermodynamics at Aristotle University, Greece).

Equation 2

$$EF\ (gCO_2/VKM) = k.(a + b.v + c.v^2 + d.v^3 + e.v^4 + f.v^5 + g.v^6)/v$$

Where: v is vehicle average speed in km/h.

k is an adjustment factor.

a, b, c, d, e, f and g are coefficients defined for each vehicle category.

For cars, the basic emission functions are based primarily on type approval data from NEDC tests, which tend to under-predict real-world emissions. The principal reason for using NEDC data is that the database of measurements for the NEDC is much larger than the database for other driving cycles more representative of the real-world. Opting to base the emission functions on NEDC data was justified by arguing that CO_2 emissions are less susceptible to differences between NEDC and real-world driving cycles than other pollutants. However, to account for real-world effects such as use of auxiliaries and level of maintenance, a recommended 15% uplift factor to NEDC-based emission functions has been agreed between the DfT and the UK national government's Department for Environment Food & Rural Affairs (DEFRA) (Boulter *et al.* 2009b; DEFRA 2013a), which is consistent with Ntziachristos *et al.* (2014) who found real-world CO_2 emissions from cars to be 11-16% greater than NEDC values (refer to Section 2.5.1). For small LGVs in the N1(I) category, basic emission functions are based on those for cars with a small adjustment added to allow for the higher vehicle weight of an in-use van. For larger LGVs in the N1(II) and N1(III) categories, emission functions were generated for those vehicle categories with existing data, and then modified by assumptions for the remaining categories (Boulter *et al.* 2009b). As with cars, a 15% uplift is recommended to account for real-world effects (DEFRA 2013a). Basic emission functions for HDVs are based on those developed during the ARTEMIS[53] project. The emission functions for HGVs assume 0% road gradient and 56% vehicle load (the average HGV load in the UK), and for buses and coaches assume 0% road gradient and 50% vehicle load, with percentage load measured by mass rather than volume (Boulter *et al.* 2009b; Barlow 2009). For two-wheel vehicles, basic emission functions for mopeds were taken from COPERT 4 (refer to Section 2.5.5.4), which is another widely used European Average Speed EM. The basic emission functions used for motorcycles were those developed during the ARTEMIS project (Boulter *et al.* 2009b).

[53] Assessment and Reliability of Transport Emission Models and Inventory Systems (ARTEMIS) – a European Commission 5th Framework project.

To the basic emission functions, consideration was given to the application of scaling factors to account for the effects of increasing vehicle accumulated mileage, future improvements in fuel and vehicle technologies, and the use of biofuels. For increasing vehicle accumulated mileage, it was concluded that the literature suggests CO_2 emissions are not affected. For improvements in fuel and vehicle technologies, scaling factors were unnecessary because the basic emission functions already included assumptions to account for improvements in technology leading to better fuel economy and the voluntary agreements between the European Automobile Manufacturers Association (ACEA) and the EU to reduce CO_2 emissions (Boulter 2009) (now enacted into European Legislation, refer to Section 2.3.9.1). Regarding the use of biofuels, it was found that “exhaust CO_2 emissions appear not to be greatly affected”, and hence scaling-factors to account for their use were not required in the UK (Boulter *et al.* 2009c; Boulter 2009).

When deriving the basic emission functions, LDV emissions test results were normalised to 10°C as the UK annual mean temperature, i.e. the emission functions are correct for 10°C ambient temperature. In contrast, HDV emissions test results were not processed in a similar fashion. Therefore, HDV emission functions are based on the assumption that the distribution of ambient temperatures used in the underlying emissions tests is representative of UK temperatures (Boulter *et al.* 2009c). However, when using the emission functions, there is no input or scaling factor to correct for measured ambient temperature, which is a potential (small) source of error.

Validation of the EM was conducted by comparison with real-world measurements from PEMS, road tunnel studies, remote sensing, and inverted pollutant dispersion models. Generally, whilst acknowledging the difficulties inherent in the validation process, the results were seen to indicate that the EM probably provides “a reasonably accurate characterisation of total emissions from road transport”; although emission functions for some specific vehicle categories (e.g. NO_X emissions from HDVs) were associated with a high degree of uncertainty. The majority of the validation was concentrated on pollutants other than CO_2. The only validation to include CO_2 was completed using PEMS fitted to a single Euro 3 petrol car, which found comparable results between EM predictions and measured values. However, it was recognised that this was a very limited piece of work (Boulter *et al.* 2009c).

2.5.5.2 *DfT Basic Local Authority Carbon Tool*

The DfT Basic Local Authority Carbon Tool is a spreadsheet-based Average Speed EM built on the CO_2 emission functions from the TRL EFs 2009. The user inputs an average speed (which should be space-mean-speed), acquired from any convenient traffic data source, for both the pre- and post-intervention scenarios. The spatial scale over which the speeds should be averaged is not specified, and the LGA can use an average for a link, a series of links, or a network, depending on data availability. Alternatively, the Carbon Tool includes default values for national average speeds based on time period, road type, area, region, and year. The EM also includes the NAEI national fleet model as the default mix of vehicle categories, although the user has the option to vary the mix if required by local conditions. EFs are then calculated by inputting average speeds into vehicle categories' emission functions. To calculate emissions, EFs are then multiplied by VKM inputs (DfT 2011a; DfT 2011b).

For HGVs, the Carbon Tool applies a scaling factor to the original TRL EFs 2009 emission functions. The DfT collects road freight statistics from UK haulage firms that include the average miles per gallon fuel efficiency for different categories of HGVs. These data are based on a large sample of real-world HGV operations, compared to the TRL emission functions which were based on data from emissions tests on a few individual vehicles. Therefore, scaling factors are used to normalise the TRL emission functions to agree with the haulage firm statistics through multiplication of the emission functions by 1.351 and 1.023 for rigid HGVs and articulated HGVs, respectively[54] (AEA 2009; DfT 2011a).

For LDVs running on LPG and CNG fuels, the Carbon Tool applies a correction factor to the relevant petrol vehicle TRL average speed emission function of 0.9 and 0.8, respectively. This is based on Energy Savings Trust estimates that vehicles running on LPG and CNG emit 10% and 20% less CO_2 than a petrol vehicle of equivalent engine size, respectively. For cars that are PHEVs or BEVs, the DfT Carbon Tool applies aggregate EFs (i.e. not dependent on vehicle speed) of 97.3 gCO_2/VKM and 53.4 gCO_2/VKM respectively (DfT 2011a).

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[54] The scaling factor for articulated HGVs in the AEA (2009) reference is actually 1.025, which has been updated to 1.023 in the DfT Basic Local Authority Carbon Tool.

Use of biofuel under the RTFO is accounted for through calculated CO_2 emissions being discounted by the percentage of biofuel supplied (DfT 2011a). This discount is based on the assumption that biofuels produce zero emissions when combusted (refer to Section 2.3.12.1).

2.5.5.3 WebTAG

Whilst WebTAG is not an EM in itself, it constitutes the DfT's transport analysis guidance, which includes general advice on calculating the emissions impact of transport interventions. The method employed estimates the combined GHG emissions (in CO_2e) of CH_4, N_2O and CO_2 (DfT 2014c). Initially, fuel consumption for each vehicle category is estimated as a function of average speed using Equation 3 which was derived using results from the TRL EFs 2009 (DfT 2014b).

Equation 3

$$L = a/v + b + c.v + d.v^2$$

Where: L is fuel consumption (litres/VKM).

v is average speed (km/h).

a, b, c and d are coefficients defined for each vehicle category.

For any electric vehicles, it is assumed that energy consumption is proportional to distance, but independent of speed. In other words, 'b' is the only non-zero coefficient in Equation 3, resulting in a constant value for 'L' (kWh/VKM). The vehicle categories are very aggregate in comparison to the NAEI national fleet model, with coefficient values provided for petrol car, diesel car, petrol LGV, diesel LGV, OGV1, OGV2 and PSV[55] (DfT 2015d). Once fuel (and electricity) consumption has been calculated using VKM data, EFs ($kgCO_2e$/litre or $kgCO_2e$/kWh) for the different fuels are applied to estimate CO_2e emissions. These EFs include the blending of biofuels in accordance with the RTFO and the assumption that biofuels produce zero emissions when combusted (i.e. there is no requirement to reduce the calculated total emissions by the percentage of blended biofuel) (DfT 2014c). Where the DfT's TUBA[56] software application is used to carry out an economic appraisal of a transport intervention, the methodology used by the software to estimate CO_2e emissions from road traffic is consistent with the advice presented in WebTAG (DfT 2014c).

[55] Other Goods Vehicle 1 (OGV1) is rigid vehicles over 3.5 tonnes Gross Vehicle Mass (GVM) with two or three axles; Other Goods Vehicle 2 (OGV2) is rigid vehicles with four or more axles, and all articulated vehicles; and Public Service Vehicle (PSV) is buses and coaches over 3.5 tonnes GVM.

[56] Transport User Benefit Appraisal (TUBA) is a cost-benefit analysis software application for road and multi-modal schemes produced by the DfT and Atkins Limited.

2.5.5.4 Computer Programme to calculate Emissions from Road Transport (COPERT)

COPERT (latest version COPERT 5 released in 2016) is an Average Speed EM software application widely used across Europe. Development of COPERT is coordinated by the European Environment Agency (EEA), with scientific development managed by the European Commission's Joint Research Centre. The main purpose of the software is to assist in the compilation of national emission inventories, but it can also be used for smaller networks such as cities or regions. COPERT is based on average speed emission functions for practically all vehicles in the European fleet, derived from the work of research institutes across Europe. Vehicle categories are disaggregated at a similar level of detail to that found in the NAEI national fleet model, i.e. disaggregated according to Euro Standard at the finest level of detail (Ntziachristos *et al.* 2009).

A recent validation study (Kousoulidou *et al.* 2013a) compared COPERT predictions to PEMS measurements for cars, finding that in general CO_2 emissions correlated "fairly well". Six cars were fitted with PEMS, consisting of three diesel and three petrol vehicles, from Euro 3 to Euro 5 Standard. All the cars were driven on real-world test routes in Italy that included sections of urban, rural and motorway roads. COPERT predictions for fuel consumption (which is directly proportional to CO_2 emissions) varied between +33% (over-estimation) and -14% (under-estimation) of PEMS measurements depending on fuel type, Euro Standard and road type (Kousoulidou *et al.* 2013b).

2.5.5.5 Emissions Factors Toolkit (EFT)

The EFT (latest version 7.0 released in 2016) is an Average Speed EM developed by DEFRA with the principal purpose of allowing LGAs to monitor their progress in tackling poor air quality within AQMAs. The EFT is similar to the DfT Basic Local Authority Carbon Tool, in that they are both spreadsheet-based Average Speed EMs. The EFT provides estimates for emissions of NO_X and PM based on average speed emission functions taken from COPERT 4 v.11. The EFT also has the facility for estimating CO_2 emissions, with calculations based on the average speed emission functions from TRL EFs 2009 (DEFRA 2016).

For each link in the area of interest, the user inputs the following data: traffic average speed; traffic flow (number of vehicles over a specified time period, which can range from 1 to 24 hours); and link length. The EFT includes a default mix of vehicle categories consisting of the NAEI national fleet model for roads outside London and the TfL fleet model for roads within London, although the user can vary the fleet mix if required by local conditions. EFs are then calculated by inputting average speeds into vehicle categories' emission functions. To calculate emissions, EFs are then multiplied by VKMs (calculated from number of vehicles in the specified time period multiplied by link length). The EFT also has the facility to account for the reduction in CO_2 emissions from vehicles with alternative drivetrains, which is achieved using scaling factors applied to the EFs for conventional vehicles, with the scaling factors taken from the London Atmospheric Emissions Inventory (LAEI) (GLA 2016; DEFRA 2016).

2.5.5.6 Direct Energy-use and Emissions Model (DEEM)

DEEM is the emissions sub-model within the UK Transport Carbon Model (UKTCM). The UKTCM is a strategic model of the transport sector's energy use and CO_2 emissions in the UK, based on inputs such as forecasts for GDP, number of households, population's inclination to travel, energy prices, costs for different transport modes, and mix of technologies in the UK's vehicle fleet (all transport vehicles, not just road vehicles). The road traffic element of DEEM is an Average Speed EM, based on average speed emission functions taken from sources such as COPERT, MEET and the NAEI (Brand *et al.* 2012).

2.5.5.7 Vehicle Specific Power Distribution Model (VDM)

Research by Song *et al.* (2014) illustrates a slightly different approach for Average Speed EMs based on Speed Correction Factors (SCFs). Rather than expressing EFs directly as a function of average speed (average speed emission functions), SCFs are determined for each average speed (or, more typically, each average speed bin) such that the EF at a particular average speed is given by the SCF at that speed multiplied by a constant baseline EF, as shown in Equation 4. In other words, an average speed SCF function can be produced through dividing an average speed emission function by a constant baseline EF. Similar to the development of average speed emission functions, once a convenient baseline EF has been selected, the average speed and average EF results from driving cycle emissions tests can be used to calculate SCFs for each average speed bin, which was (for example) the method adopted in the development of MOBILE[57] (Brzezinski *et al.* 2001).

Equation 4

$EF_V = SCF_V \times EF_B$

Where: EF_V is Emission Factor at average speed v (g/VKM).

SCF_V is Speed Correction Factor for average speed v (dimensionless).

EF_B is a constant baseline Emission Factor (g/VKM).

[57] MOBILE is an Average Speed EM and was the USA national government's Environmental Protection Agency (EPA) official model for estimating emissions from road vehicles until recently (2010) replaced by MOVES (a Modal EM, refer to Section 2.5.9.1).

However, Song *et al.* (2014) propose a different method for determining SCFs based on Vehicle Specific Power (VSP) distributions. VSP (kW/tonne) is calculated based on a vehicle's instantaneous speed and acceleration (Abou-Senna and Radwan 2013), and represents the instantaneous power demand placed on a vehicle (by rolling resistance, aerodynamic resistance, acceleration resistance, and road gradient resistance) divided by vehicle mass (Ritner *et al.* 2013). The general form of the equation for a vehicle's instantaneous VSP is shown in Equation 5 (Wyatt *et al.* 2014), although in practice the equation is often simplified by assuming values representative of a typical LDV or HDV. For emissions modelling purposes, VSP is typically handled using a binning method, with instantaneous VSP values assigned to relevant VSP bins (e.g. 1kW/tonne intervals). A VSP distribution defines the amount of time a vehicle spends in each VSP bin during its operation, and can be calculated from a vehicle's driving pattern.

Equation 5

$$VSP = v[a(1+\epsilon_i) + (g.grade) + (gC_R)] + (v/m)[0.5\rho C_D A(v+v_w)^2]$$

Where: v is instantaneous speed (m/s).

a is instantaneous acceleration (m/s^2).

ϵ_i is equivalent translational mass of the rotational motion of power train components (tonne).

g is acceleration due to gravity (m/s^2).

grade is road gradient (dimensionless).

C_R is rolling resistance coefficient (dimensionless).

ρ is ambient air density (kg/m^3).

C_D is aerodynamic drag coefficient (dimensionless).

A is vehicle frontal area (m^2).

v_w is headwind velocity (m/s).

m is vehicle mass (tonne).

Driving patterns from 22 LDVs driven on urban, restricted-access roads (i.e. accessed only via on-ramps) in Beijing, were collected using GPS loggers and divided into 60-second trajectories. The average speed for each trajectory was calculated, allowing it to be assigned to an average speed bin (from 3km/h to 71km/h in intervals of 2km/h). Based on all the assigned trajectories, the VSP distribution for each average speed bin was calculated using a version of Equation 5 simplified by assuming values representative of a typical LDV. Average speed bins and their associated VSP distributions were all stored in a database, called the VSP Distribution-database (VD-db). These data were then analysed to develop a model that could predict VSP distributions based on average speeds, i.e. the VSP Distribution Model (VDM). In fact, it was necessary to develop two different models for predicting VSP distributions, one for average speeds higher than 20km/h (VDM-high) and one for average speeds less than 20km/h (VDM-low).

The Emission Rate (ER) (g/h) associated with each VSP bin was derived from a database of PEMS tests conducted on 52 petrol LDVs. Hence, an average ER could be calculated for each average speed bin based on its associated VSP distribution. Average ER was then converted to average EF through dividing by average speed, as shown in Equation 6. A constant baseline EF was selected as that calculated from the VSP distribution derived from the NEDC. Therefore, SCFs for each average speed bin could now be calculated using Equation 4.

Equation 6

$EF_V = ER_V/v$

Where: EF_V is Emission Factor at average speed v (g/VKM).

ER_V is Emission Rate calculated from the VSP distribution at average speed v (g/h).

v is average speed (km/h).

SCFs were calculated for each average speed bin based on three methods for deriving its associated VSP distribution: (1) VSP distribution as predicted by VDM-Low, (2) VSP distribution as predicted by VDM-high, and (3) VSP distribution as stored in VD-db. These were compared to SCFs based on a separate VSP distribution database (VD-real), which was constructed by the same method as VD-db, but using GPS driving patterns reserved for validation purposes. SCFs from VD-db were found to be nearly identical (<2% relative difference for all pollutants) to those from VD-real. SCFs from VDM-low and VDM-high were also found to be well-matched to those from VD-real, although a problem was identified in that SCFs from VDM-low and VDM-high were found to be discontinuous at the 20km/h boundary.

The advantage of developing a relationship between average speed and VSP distribution is an ability to calculate SCFs without the costly and time consuming process of emissions tests. However, this presupposes ready access to a source of ER data for VSP bins, with the study only deriving ER data for VSP bins for CO, NO_X and HC emissions from petrol LDVs in the emissions standards categories[58] Pre-Euro 1 to Euro 4. The authors suggest MOVES (refer to Section 2.5.9.1) as an appropriate source for such data, which provides "a huge and comprehensive emission rate database", although this only includes USA-specific vehicle categories. A disadvantage of the VDM is limited application, with the model only being developed to predict VSP distributions for typical LDVs driven on urban, restricted-access roads in Beijing. Other vehicle categories will have different VSP distributions (due to different values in Equation 5) and have different relationships between VSP bin and ER; and for a given average speed, driving patterns (and hence VSP distributions) are likely to vary with road type.

Similar to Average Speed EMs based on average speed emission functions, account for the influence of congestion is implicit. A single, fixed SCF calculated from a single, fixed VSP distribution (predicted by either VD-db or VDM in the case of this particular study) is associated with each average speed bin and cannot be varied by the user so as to reflect a particular congested situation of interest.

2.5.6 Traffic Situation Emissions Models

In Traffic Situation EMs the parameters of emissions tests, and their associated average EFs, are correlated to specific traffic situations. This results in each traffic situation being referenced to an average EF. Different traffic situations are characterised by road type (e.g. motorway with 120km/h limit, or main road outside built-up area) and a qualitative description of traffic conditions (e.g. free-flowing, or stop-and-go). The user specifies a traffic situation, and then appropriate average EFs for different vehicle categories are weighted according to traffic composition (Smit *et al.* 2010; Boulter *et al.* 2012). Explicit account for congestion influence is achieved through the user-defined qualitative description of traffic conditions.

2.5.6.1 Handbook of Emission Factors for Road Transport (HBEFA)

The most widely used example of a Traffic Situation EM is the HBEFA (latest version HBEFA v.3). Construction of HBEFA was not based directly on emissions test results. Instead it was based on EFs derived from simulated emissions tests conducted using the Passenger car and Heavy duty Emission Model (PHEM), which is a detailed Modal EM that calculates emissions for individual vehicles from their driving patterns (refer to Section 2.5.9.2). The specific driving cycles related to the different HBEFA traffic situations were simulated in PHEM for all the

[58] The emissions standards categories were actually Chinese standards, but these are nearly identical to the equivalent Euro Standard.

various vehicle categories (disaggregated according to Euro Standard at the finest level of detail), rather than the impractical task of trying to find representative data for the numerous combinations of vehicle category and traffic situation from previous emissions test results. Validation of HBEFA v.3 concluded that CO_2 emissions can be predicted “quite accurately” (Hausberger *et al.* 2009). However, a disadvantage of HBEFA is that it is designed specifically for use in Germany, Austria, Switzerland, Sweden, Norway and France, with traffic situations representative of conditions in those countries. Therefore, its application to UK traffic situations would be questionable (Boulter *et al.* 2012; De Kievit *et al.* 2014a).

2.5.7 Traffic Variable Emissions Models

Traffic Variable EMs predict EFs based on traffic variables (Smit *et al.* 2010). The inclusion of other traffic variables (in addition to traffic average speed) as Congestion Indicators (CIs) allows congestion influence to be accounted for explicitly and quantitatively, and overcomes the Average Speed EM limitation of being unable to distinguish between different traffic conditions resulting in the same traffic average speed, i.e. the additional traffic variables can be used to differentiate between different traffic conditions with the same average speed. For this project, the definition of traffic variable was extended to encompass network characteristics because of their influence on traffic movement capacity (refer to Section 2.4.1).

2.5.7.1 Traffic Energy and Emissions-Kinematic Correction Factor (TEE-KCF)

An early example of a Traffic Variable EM is provided by the TEE-KCF developed by ENEA[59], which attempted to overcome the limited ability of Average Speed EMs to account for congestion through use of a KCF. The methodology used to construct the TEE-KCF involved an interim EM called the Traffic Energy and Emissions-Reconstructed (TEE-REC). For 500 different link scenarios, TEE-REC reconstructed a driving pattern based on link values of traffic average speed, traffic density, effective green-time ratio[60] and link length. Then total emissions for each link scenario were calculated in two ways: firstly using traffic average speed and the COPERT III Average Speed EM, and secondly using the reconstructed driving patterns and the MODEM[61] Modal EM. Next a value for the Kinematic Correction Factor (KCF) for each link scenario was determined using Equation 7. Finally, based on analysis of the KCF values

[59] ENEA is the Italian National Agency for New Technologies, Energy and Sustainable Economic Development.

[60] For traffic signals, the ratio of effective green-time (displayed green-time adjusted for time loss due to vehicles accelerating up to speed, and time gain due to vehicles crossing a yellow signal) to signal cycle time (the time required to complete one complete sequence of signal phases).

[61] Modelling of Emissions and Consumption in Urban Areas (MODEM) is an early example (1990s) of a Modal EM (refer to Section 2.5.9), originally developed during Dedicated Road Infrastructure for Vehicle safety in Europe (DRIVE) – a European Commission 2nd Framework project. MODEM calculates emissions as a function of a vehicle’s instantaneous speed and the product of instantaneous speed and acceleration, which were considered the best indicators of engine power.

determined for the 500 link scenarios, a formula was developed for calculating link-specific KCFs from link values of traffic average speed, traffic density, effective green-time ratio, and link length (Smit 2006).

Equation 7

$E_{i\ MODEM} = KCF_i \times E_{i\ COPERT}$

Where: $E_{i\ MODEM}$ is total emissions using MODEM for link scenario i.

KCF_i is the Kinematic Correction Factor for link scenario i.

$E_{i\ COPERT}$ is total emissions using COPERT III for link scenario i.

Application of the TEE-KCF EM involves initially calculating total emissions for each link using traffic average speed and COPERT III. Then link-specific KCFs are calculated from link values of the appropriate traffic variables. Finally, COPERT III emissions are multiplied by the link-specific KCFs. A limitation of the model is that, for a given congested traffic scenario, a single value of the KCF is calculated for each link, which is then used to multiply emissions from every vehicle category. Hence, TEE-KCF cannot account for the possibility that a given congested traffic scenario may have different effects on emissions from vehicles in different categories.

A limited validation of the TEE-KCF was conducted by comparing measured CO concentrations at two sites within a small (approximately 0.16 km^2) road network with concentrations predicted by the combination of TEE-KCF and ADMS[62]. It was found that the TEE-KCF/ADMS combination over-predicted concentrations within a factor of 1.5, although this is obviously assessment of the combined performance of the two models rather than TEE-KCF alone (Smit 2006). However, regardless of previous validation, TEE-KCF is now viewed as somewhat out-of-date due to the dated emissions data on which it is based (Boulter *et al.* 2012), with the most recent emission legislation in MODEM being Euro 1, and COPERT III being superseded by COPERT 4 in 2006 and then COPERT 5 in 2016. Updating TEE-KCF would be a significant undertaking, requiring recalibration of the model using an up-to-date Modal EM (e.g. PHEM) and COPERT 5 Average Speed EM.

2.5.7.2 SATURN built-in emissions model

The meso-RTM SATURN includes a built-in sub-model that calculates emissions (and fuel consumption) resulting from the simulated movement of traffic. Predictions are based on

[62] Atmospheric Dispersion Modelling System (ADMS) is an air pollution dispersion model produced by Cambridge Environmental Research Consultants.

traffic variables such as average cruise travel time (i.e. cruising time), average delay (i.e. idling time), average number of primary stops (where a vehicle arrives at a queue) per vehicle, and average number of secondary stops (where a vehicle stop-starts as it moves up a queue) per vehicle. Traffic is assumed to consist of only one vehicle category, with the coefficients in the equation used to predict CO_2 emissions being based on data for an average British car in 1981 (Atkins Limited 2014; Tate and Bell 2000).

Perhaps unsurprisingly given the lack of traffic disaggregation according to vehicle category, the SATURN user manual itself acknowledges that the built-in EM is extremely crude, and goes on to state that if the EM "gets to within an order of magnitude of the true answer it will be doing well." Furthermore, the manual suggests that both emissions and fuel consumption predictions would be best handled by using a stand-alone EM (Atkins Limited 2014).

2.5.7.3 Average speed distribution

A study by Smit *et al.* (2008b) investigated improving the accuracy of emissions predictions through application of a link-specific average speed distribution, rather than a single traffic average speed. In other words, supplementing traffic average speed with data on how the average speeds of individual vehicles are distributed around the average for the traffic as a whole. This method was seen as being a closer approximation to reality, and so was expected to improve on the accuracy of emissions predictions based solely on traffic average speed.

Initially, a Road Traffic Model (RTM) was used to generate traffic average speeds for each link in the study network. Then a statistical relationship between average travel time (minutes/km, calculated from traffic average speed) and the standard deviation of travel time was used to develop a link-specific average speed distribution representing the number of vehicles that drive at a particular average speed, as shown in the example in Figure 2-8. Once the average speed distributions for each link had been calculated, they were combined with an Average Speed EM (COPERT 4) to calculate emissions. Arguably, this methodology could be classified as an Average Speed EM because the only input required is traffic average speed for each link. However, it is included within Traffic Variable EMs to highlight how the methodology differs from the typical use of Average Speed EMs, in that traffic average speed and a link-specific average speed distribution are used as inputs, rather than traffic average speed alone.

Compared to the typical use of Average Speed EMs, account for congestion influence is improved by allowing for the different average speeds of each vehicle (i.e. the dynamics of individual vehicles are better included). However, account for congestion is implicit because the user cannot vary the link-specific average speed distribution so as to reflect a particular congested situation of interest. The study found that the average speed distribution method predicted higher network CO_2 emissions than the traffic average speed method for all road types (urban, rural and motorway), with the largest increase being 4% for urban networks. Hence, assuming the average speed distribution method is a closer representation of reality, the commonplace application of Average Speed EMs using traffic average speed alone is possibly biased towards under-prediction of network emissions (Smit *et al.* 2008b).

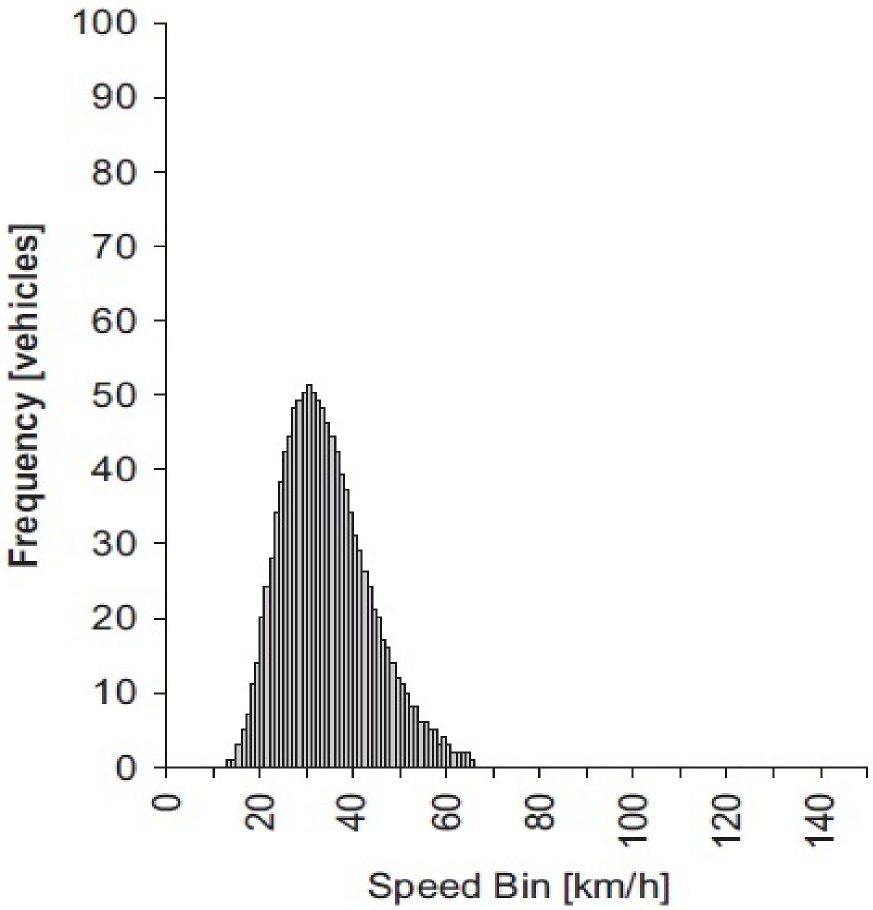

Figure 2-8: Computed average speed distribution for a typical urban road link in Amsterdam.

- Link data: flow = 1,115 vehicles/h; overall link average speed = 34km/h; length = 0.14km; two lanes.
- Flow and average speed were averaged over a 1 hour time period (weekday peak hour 08:00-09:00).
- Source: Smit *et al.* (2008b).

2.5.7.4 Delay Correction Model (DCM)

For predicting emissions from vehicles crossing intersections, Song *et al.* (2015) highlight the lack of a suitable emissions modelling approach. Average Speed EMs are inaccurate because average speed cannot adequately capture the dynamics of vehicle driving patterns as they cross an intersection. More detailed EMs that calculate emissions from individual vehicles based on their driving patterns can capture these dynamics. However, driving patterns lack availability because they are difficult to collect and rarely used in traffic engineering to describe the performance of intersections. Instead, intersection performance is typically assessed in terms of traffic variables. Therefore, the authors developed a Traffic Variable EM to predict emissions from individual vehicles traversing intersections based on traffic variables commonly used to describe intersection performance. The analysis was performed for fuel consumption (which is directly proportional to CO_2), NO_X, HC and CO.

Real-world driving patterns were collected using GPS trackers fitted to seven Euro III buses in Beijing, China, travelling on seven transit lines (total combined length of 176.75 km), crossing a total of 165 signalised intersections. Two types of intersection were defined: arterial/arterial and arterial/collector[63]. For each time a bus crossed an intersection, delay was calculated as the difference between the actual and desired times to cross the intersection. Desired time was considered to be the no-delay case, and was calculated through dividing the intersection length by the desired speed, with desired speed as defined by the Ministry of Housing and Urban-Rural Development of China (arterial/arterial = 60 km/h, arterial/collector = 50km/h).

An interim Modal EM (refer to Section 2.5.9) was initially developed, with the different vehicle operating modes defined by VSP bins at 1kW/tonne intervals. For each time a bus crossed an intersection, its VSP distribution (i.e. time spent in each VSP bin) was calculated using its GPS driving pattern data in a version of the general VSP equation (Equation 5) simplified by assuming values representative of a bus typical of the Euro III types tested. PEMS data (collected at the same time as the GPS data) were used to calculate the ER (g/s) associated with each VSP bin, through dividing the total emissions when in a given VSP bin by the total time spent in that VSP bin. Hence, a Modal EM had been produced that related a vehicle's operating mode (VSP bin) to an associated ER (g/s).

Based on Equation 6, the Modal EM was then used to calculate EFs (g/VKM) for all the VSP distributions (one distribution for each time a bus crossed an intersection). Delay bins of one second interval were defined, and each VSP distribution (and its associated EF) was assigned to

[63] Urban roads are often classified as arterial, collector or local (in decreasing order of significance); with a collector road being one that provides access between local roads and an arterial road.

the appropriate delay bin (i.e. the delay associated with the intersection crossing from which the VSP distribution is calculated). A baseline EF was calculated for the no-delay case by taking an average of the EFs for all VSP distributions in the zero delay bin (i.e. delay=0s). The delay-bin-specific VSP distributions were then further subdivided by number of stops during the intersection crossing (no stop, one stop, or two stops). A stop was defined as two or more continuous points in a driving pattern where speed=0km/h. Average EFs were calculated for each different combination of delay bin and stops from the EFs for the VSP distributions contained in each combination. A Delay Correction Factor (DCF) was calculated for each combination, through dividing the average EF for the combination by the baseline EF.

The final Delay Correction Model (DCM) was developed through linear regression analysis to establish a relationship between delay (predictor variable[64]) and DCF (outcome variable). For each pollutant, six different relationships were established covering the different types of intersection (arterial/arterial, arterial/collector), with each stop case (0 stops, 1 stop, 2 stops). The DCM is applied using delay, stops, and intersection type as inputs, from which a DCF can be calculated. The baseline EF is then multiplied by the DCF to find the EF particular to the situation of interest.

Using GPS driving patterns different from those used during model development, evaluation of model accuracy involved comparing EFs predicted by the DCM with EFs calculated directly from VSP distributions using the Modal EM (which were assumed to be the real-world EFs). The average absolute percentage difference for fuel consumption was found to be 5.6%. This result (and the results for the other pollutants) was taken to indicate that delay and stops are closely related to emissions at intersections.

The DCM in its current form is limited to predicting the emissions of Euro III diesel buses crossing intersections in Beijing. Other vehicle categories will have different VSP distributions (due to different values in Equation 5) and have different relationships between VSP bin and ER. Intersection characteristics specific to Beijing may not be reproduced in other locations (e.g. intersection geometry, which is likely to affect driving patterns; or defined desired speeds used to calculate reference no-delay times). Additionally, the model is only applicable to

[64] There are a number of different terms used in the literature to describe the two types of variables in linear regression analysis. For example: independent and dependent; predictor and outcome; regressor and regressand; and explanatory and explained. A decision was made in this project to adopt the terms predictor and outcome variables.

intersections, and does not predict emissions for vehicles on the links between intersections. Further investigations would be required to extend the DCM to allow prediction of total network emissions (intersections and links), for a full range of vehicle categories, in different geographical locations.

Finally, it is worth noting that the DCM is classified here as a Traffic Variable EM because both delay and stops are available at a traffic level of aggregation (i.e. average delay per vehicle and average stops per vehicle). However, the DCM was developed based on delay and stops for individual vehicles, and also predicts emissions at an individual vehicle level. Therefore, it could be argued that the DCM is actually closer to a Cycle Variable EM.

2.5.8 Cycle Variable Emissions Models

Cycle Variable EMs calculate EFs for individual vehicles as a function of various driving cycle variables, for example: vehicle average speed; time spent idling; average acceleration; number of stops per km; etc. A vehicle's driving pattern is typically required as input, which means congestion influence on emissions is explicitly included. However, in general, the necessary driving patterns for each vehicle can only be acquired from a micro-RTM or by equipping vehicles with GPS devices (Smit *et al.* 2010).

2.5.8.1 VERSIT+LD

VERSIT+[65] has two components: VERSIT+LD for LDVs; and VERSIT+HD for HDVs. VERSIT+LD was originally developed as a Cycle Variable EM, designed to predict EFs for individual LDVs at the most detailed level of vehicle category disaggregation (i.e. Euro Standard). It consisted of statistical models that were constructed using Multiple Linear Regression (MLR) analysis of emissions test data (153 driving cycles used to perform 12,000 emissions tests) to find an empirical relationship between EF (outcome variable) and driving cycle variables (predictor variables) (Smit *et al.* 2007). For each vehicle category, a MLR model was fitted to the average EFs from various emissions tests, allowing the predictor variables that best predict EFs to be determined in the form of a polynomial such as Equation 8.

Equation 8

$$EF = (c_1 \text{ x stops per km}) + (c_2 \text{ x ave. speed}) + (c_3 \text{ x max. accel.}) + (c_4 \text{ x etc.}) + ...$$

Where: c_1, c_2, c_3 and c_4 are predictor variable coefficients.

[65] VERkeers SITuatie (VERSIT+) translates as traffic situation and is produced by the Netherlands Organisation for Applied Scientific Research (TNO).

VERSIT+LD takes a driving pattern as input, from which the predictor variables are calculated, and then used in the polynomial to predict the EF for the driving pattern (Boulter *et al.* 2012). Correction factors for the influence of air conditioning use on CO_2 emissions are also included within VERSIT+LD. On urban roads: for Euro 1 and 2 petrol LDVs the multiplication factor is 1.34; for Euro 3, 4 and 5 petrol LDVs the factor is 1.16; and for all diesel LDVs the factor is 1.39 (Smit *et al.* 2006).

However, VERSIT+LD is now better described as a Modal EM (refer to Section 2.5.9). Ligterink and De Lange (2009) report on version 3 of VERSIT+LD, which entailed major changes to the EM, developing a method for predicting instantaneous emissions dependant on instantaneous values of velocity and acceleration. Initially, a dynamic variable was defined as a linear combination of instantaneous velocity and acceleration. The emissions test data were then re-analysed to determine a relationship to predict instantaneous emissions (g/s) as a function of this dynamic variable.

Madireddy *et al.* (2010) conducted a validation of the modal version of VERSIT+LD by comparing predicted emissions with emissions measured using VITO's[66] On Road Emissions and Energy Measurement (VOEM) system (a PEMS). Predicted and measured emissions were collected for four diesel cars and one petrol car over a 30 minute driving cycle (Mol_30 driving cycle). This cycle was chosen because it is more representative of real-world driving than the NEDC, and constitutes 10 minutes urban driving, 10 minutes suburban driving and 10 minutes motorway driving. The validation found that VERSIT+LD produced good predictions of real-world CO_2 emissions, with the correlation between predicted and measured emissions described by an average value of R^2=.80.

Unlike VERSIT+LD, VERSIT+HD did not begin life as a Cycle Variable EM. Instead it is a Modal EM based on data generated by PHEM (another Modal EM, refer to Section 2.5.9.2), and uses instantaneous emissions maps (refer to Section 2.5.9.2) to predict instantaneous EFs (g/s) for individual HDVs, with vehicle categories disaggregated according to Euro Standard (Velders *et al.* 2011).

[66] Vlaamse Instelling voor Technologisch Onderzoek (VITO) translates as Flemish Institute for Technological Research.

2.5.8.2 EnViVer

EnViVer[67] is a Windows application developed to link driving pattern outputs from VISSIM[68] micro-RTM with VERSIT+micro EM in order to calculate emissions. VERSIT+micro is a simplified version of VERSIT+, with only four aggregate vehicle categories: LDVs; buses; medium HDVs (mass ≥ 3,500kg and 2 axles); and heavy HDVs (mass ≥ 20,000kg and 3 or more axles) (Eijk *et al.* 2013). It should be noted that EnViVer is a Modal EM (refer to Section 2.5.9) because both VERSIT+LD and HD are now Modal EMs, and is only described in the Cycle Variable EM section due to its close relation to VERSIT+.

2.5.8.3 Network Emissions Model (NEMO)

The NEMO was developed during the ARTEMIS project. Emissions for individual vehicles are calculated based on values of the following cycle variables: average speed; maximum and minimum speed; and average acceleration and deceleration (Smit 2006; Palmer 2007). However, rather than using driving patterns for each vehicle as inputs, NEMO is designed to calculate the cycle variables from a single driving pattern representative of all traffic. This simplification was introduced to avoid difficulties associated with collecting driving patterns for every vehicle and to reduce computing time. In this respect, NEMO could arguably be classified as a Traffic Variable EM because a single driving pattern is used to represent all traffic on a link. The values of the cycle variables are used to calculate average engine power for the driving pattern, which is then used to calculate emissions based on the relationship between average engine power and emissions established for each vehicle category; with vehicle categories disaggregated at the finest level of detail (i.e. Euro Standard) (Rexeis *et al.* 2007; Rexeis and Hausberger 2009). The driving pattern input explicitly includes the influence of congestion on emissions, but some detail is lost through using a single driving pattern for the traffic, rather than a driving pattern for each vehicle. NEMO was assessed by comparing predictions of NO_X and PM emissions with predictions from HBEFA (which is model comparison rather than true model validation) for average driving situations in Austria. For urban driving, NEMO predicted NO_X emissions 10-20% higher and PM emissions 5-30% lower than HBEFA (Rexeis and Hausberger 2009).

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[67] Environment VISSIM and VERSIT+ (EnViVer) is produced by TNO and PTV.

[68] Verkehr In Städten Simulationsmodell (VISSIM) translates as Traffic in Cities Simulation Model and is produced by PTV.

2.5.8.4 Velocity and payload emissions model for HGVs

Ligterink *et al.* (2012) developed an EM for HGVs which predicted emissions as a function of vehicle average speed and payload. PEMS and driving pattern data were obtained from seven HGVs (both rigid and articulated, with kerb masses[69] ranging from 5.8-17.8 tonnes), driven on a reference trip including urban, rural and motorway roads. The location of the reference trip is not stated, but the authors are from the Netherlands and the HGVs selected for testing were seen as being representative of the Dutch fleet. Therefore, it seems likely the investigations took place on Dutch roads. The vehicles were all Euro V compliant HGVs, and were driven on the reference trip with various different payloads simulated using water ballast.

The measured data were statistically analysed using a MLR method, with vehicle average speed (km/h) and specific power (kW/tonne) as predictor variables, and EF (g/tonne.VKM) as the outcome variable, where 'tonne' in the units of the EF refers to vehicle laden mass. In this investigation, specific power had a different meaning to VSP as defined in Section 2.5.5.7. Specific power was calculated through dividing the engine rated power by vehicle mass. In contrast, VSP is calculated through dividing the instantaneous power demanded from the engine by vehicle mass. Hence, a vehicle's VSP is constantly changing due to varying resistances that must be overcome (rolling, aerodynamic, acceleration, and gradient), whereas a vehicle's specific power will only change when vehicle mass is altered by changing payload. Specific power was then approximated by a formula based on Gross Vehicle Mass (GVM) and the percentage of maximum payload a vehicle is carrying (% payload). Hence, the EM predicts emissions for a vehicle based on its average speed, GVM and % payload. The PEMS data used to construct the EM were collected from a range of Euro V HGVs (articulated and rigid, with a range of kerb masses, in urban, rural and motorway conditions), so the model is regarded as predicting emissions for a fleet-average Euro V HGV. Validation found that the measured PEMS data corresponded well with emissions predicted by the model. However, this was a comparison between model predictions and PEMS data used in the construction of the EM, rather than comparison with independent measured emissions.

[69] Kerb mass is the mass of the unladen vehicle, full fuel tank, other liquids (e.g. oils and coolant), and standard equipment (e.g. tools and spare wheel). However, in practice, kerb mass is not strictly defined (in contrast to MRO which is defined, refer to Footnote 19 in Section 2.3.2) and some manufacturers include driver mass (75kg), while others exclude driver mass.

2.5.9 Modal Emissions Models

Modal EMs calculate EFs for individual vehicles as a function of vehicle or engine operating modes (Smit *et al.* 2010). A vehicle's driving pattern is typically required as input, which means congestion influence is explicitly included. As was the case for Cycle Variable EMs, a prerequisite for model use is the availability of driving patterns for each vehicle, which usually can only be acquired from a micro-RTM or by equipping vehicles with GPS devices.

For Modal EMs that function at coarser resolutions, a vehicle's driving pattern is defined in terms of a number of operational modes – typically idle, acceleration, deceleration, and cruise. For each mode, the EF for a particular vehicle category is assumed to be constant. Total emissions for an individual vehicle are calculated by weighting each modal EF by the time spent in that mode (Boulter *et al.* 2012). The Urban Road Pollution (UROPOL) model is an example of an EM based on this method (Matzoros and Van Vliet 1992). The latest generation of Modal EMs predict EFs for operating modes at high temporal resolutions (e.g. 1Hz), i.e. a vehicle's mode, and associated EF, is calculated on a second-by-second basis. At this temporal resolution, Modal EMs are typically termed Instantaneous EMs (IEMs). IEMs arguably provide the most accurate estimation of EFs because they offer the most detailed representation of real-world conditions. However, this accuracy comes at some cost in tractability.

2.5.9.1 Motor Vehicle Emission Simulator (MOVES)

MOVES (latest version MOVES2014) has recently (2010) replaced MOBILE (an Average Speed EM) as the EPA's official model for estimating emissions from road vehicles. It is designed to operate at national, regional and project levels, where typical project level analyses would be for intersections or small road networks (Xie *et al.* 2012). MOVES calculates emissions based on the amount of travel time spent in operating modes such as braking, idling, coasting, cruising and accelerating (Abou-Senna and Radwan 2013), with these modes further subdivided to form 23 operating mode bins, each characterised (except braking and idling) by a combination of vehicle speed[70] and VSP (Bai *et al.* 2009), as shown in Table 2-3. Vehicle categories are defined by source bins, each characterised by a combination of vehicle type, fuel type, engine technology (e.g. ICE, HEV, FCV, etc.) and vehicle age (defined by a default national vehicle age distribution) (EPA 2015). For each source bin (i.e. vehicle category),

[70] Vehicle speed was included in the characterisation of the operating mode bins because EPA research found that the VSP-only approach resulted in some bias in predicted ERs at low vehicle speeds, which was thought to be due to engine friction effects (which are relatively large at low speeds) not being included in the VSP calculation. Therefore, vehicle instantaneous speed was included as a readily available proxy for engine friction (Koupal *et al.* 2005).

MOVES contains ERs for each of the operating mode bins shown in Table 2-3 (Koupal *et al.* 2005; Bai *et al.* 2009).

Table 2-3: Speed-VSP operating mode bin numbers as defined in the MOVES Modal EM.

Operating Mode Bin Number	Description	Vehicle Speed (mph)	VSP (kW/tonne)
0	Braking	-	-
1	Idling	-	-
11	Coasting	1-25	<0
12	Cruising/Accelerating	1-25	0-3
13	Cruising/Accelerating	1-25	3-6
14	Cruising/Accelerating	1-25	6-9
15	Cruising/Accelerating	1-25	9-12
16	Cruising/Accelerating	1-25	>12
21	Coasting	25-50	<0
22	Cruising/Accelerating	25-50	0-3
23	Cruising/Accelerating	25-50	3-6
24	Cruising/Accelerating	25-50	6-9
25	Cruising/Accelerating	25-50	9-12
27	Cruising/Accelerating	25-50	12-18
28	Cruising/Accelerating	25-50	18-24
29	Cruising/Accelerating	25-50	24-30
30	Cruising/Accelerating	25-50	>30
33	Cruising/Accelerating	>50	0-6
35	Cruising/Accelerating	>50	6-12
37	Cruising/Accelerating	>50	12-18
38	Cruising/Accelerating	>50	18-24
39	Cruising/Accelerating	>50	24-30
40	Cruising/Accelerating	>50	>30

- VSP is Vehicle Specific Power.
- Source: Ritner *et al.* (2013).

Within MOVES, a link's operating mode distribution defines the amount of time vehicles spend in each operating mode bin (Speed-VSP bin) when passing along the link. A driving pattern is used to calculate instantaneous values of speed and VSP, with VSP being calculated using a version of the general VSP equation (Equation 5) simplified using typical LDV values. Then the operating mode distribution can be determined based on the time spent in each Speed-VSP bin. Finally, in combination with the mix of vehicle categories (and associated ERs) within the traffic on the link, the operating mode distribution is used to calculate emissions.

Operating mode distributions are based on VSP values for LDVs. Therefore, in order that operating mode distributions are also relevant for calculating HDV emissions, HDV ERs are referenced to a combination of speed and Scaled Tractive Power (STP) (i.e. Speed-STP bins rather than Speed-VSP bins), where STP is calculated in a similar way to VSP but includes a scaling factor to ensure HDVs fit into the existing VSP operating mode framework (EPA 2012).

There are three options for determining a link's operating mode distribution: (1) Average Speed and Road Type, which associates a default driving pattern with a user-defined speed, road type and road gradient. The default driving pattern is then used to calculate the operating mode distribution; (2) Link-Drive Schedule, which allows the user to define a driving pattern. This is then used to calculate the operating mode distribution; and (3) Direct Operating Mode Distribution, which does not calculate an operating mode distribution from a driving pattern. Instead, the user defines the operating mode distribution directly (Zhao and Sadek 2013).

It should be noted that in all three options, a single operating mode distribution is assumed to apply to all vehicles on a link. This is because (unlike other Modal EMs) MOVES is principally designed to calculate emissions for links, rather than individual vehicles (Zhao and Sadek 2013). Hence, similar to the NEMO EM, MOVES could arguably be classified as a Traffic Variable EM because a single driving pattern is used to represent all traffic on a link. However, it is possible to calculate emissions for individual vehicles in MOVES (e.g. by creating 'artificial' links for the driving patterns of each vehicle), but this then requires individual vehicle driving patterns as inputs.

Examples of validation include a study by Fujita *et al.* (2012), which compared emissions predicted by MOVES with two sources of measured emissions: a road tunnel study and roadside remote sensing. There was found to be reasonable agreement (±25%) between predicted and measured EFs for both CO and NO_X (CO_2 was not analysed). A study by Carrera *et al.* (2015) compared MOVES predicted EFs with EFs determined for 10 petrol LDVs under real-world driving conditions in an urban area (Monterrey metropolitan area, the third largest urban centre in Mexico). The limitations of the study were recognised (e.g. MOVES not being designed to predict emissions for individual vehicles), and so performance of MOVES was assessed in terms of tendencies rather than absolute difference, with predicted EFs tending to be underestimated compared to measured EFs.

2.5.9.2 Passenger car and Heavy duty Emissions Model (PHEM)

The PHEM was developed during the ARTEMIS project (Boulter and McCrae 2007), and is a latest generation IEM coordinated by the Technische Universität Graz (TUG). PHEM is used as an example in this thesis because it is relevant to European vehicles. A similar IEM relevant to USA vehicles is the Comprehensive Modal Emissions Model (CMEM) produced by the University of California's College of Engineering – Center for Environmental Research and Technology (CE-CERT).

Using as inputs a vehicle's driving pattern, vehicle characteristics data, and a model of driver gear shift behaviour, PHEM computes instantaneous values of engine power and engine speed (Boulter *et al.* 2012). Engine power demand is calculated from the sum of power to overcome rolling resistance, power to overcome aerodynamic resistance, power for acceleration, power to overcome road gradient, power for auxiliaries, and power losses in the transmission system. Engine speed is calculated from vehicle speed, wheel diameter, transmission ratios of the axle and the gear box, and the gear shift model (Hausberger *et al.* 2009).

Instantaneous engine power and engine speed are then used to determine the associated EF using an instantaneous emissions map consisting of EFs plotted on a matrix of engine power versus engine speed (Figure 2-9). These instantaneous emissions maps are constructed based on data from all available sources of emissions testing; that is emissions test data (typically engine dynamometer for HDVs and chassis dynamometer for LDVs) and data from real-world measurements using PEMS. To account for 'how transient' engine operation is in a particular instant, PHEM applies transient correction functions to EFs, with the functions based on parameters related to derivatives of engine power and engine speed. (Hausberger *et al.* 2009).

Early validation (i.e. when PHEM was new) of predictions for emissions of NO_X from HDVs was conducted by Hausberger *et al.* (2003). Predicted emissions were compared to measured emissions from a road tunnel study, with results showing a "clear and remarkably high conformance". A more recent study by Wyatt *et al.* (2014) compared predictions of CO_2 emissions from PHEM with PEMS measurements for a Euro 4 petrol car. The car was driven around a 4.6km fixed test lap, mainly consisting of single lane urban roads with a 30 mph (48 km/h) speed limit, in Leeds, UK. The test lap was driven by the same driver 48 times, over the course of a week, at various different times of the day, in a variety of weather conditions. The average PHEM prediction of total lap CO_2 emissions was found to be 90% of the PEMS measured value, with a range from 81% to 110%.

EMs that calculate EFs for individual vehicles (i.e. Cycle Variable and Modal EMs) are sometimes used as a tool to derive the EFs used in less detailed EMs (Ligterink *et al.* 2012). An example of this process is the use of PHEM to calculate emissions from simulated emissions tests for the construction of HBEFA (refer to Section 2.5.6.1) (Hausberger *et al.* 2009)

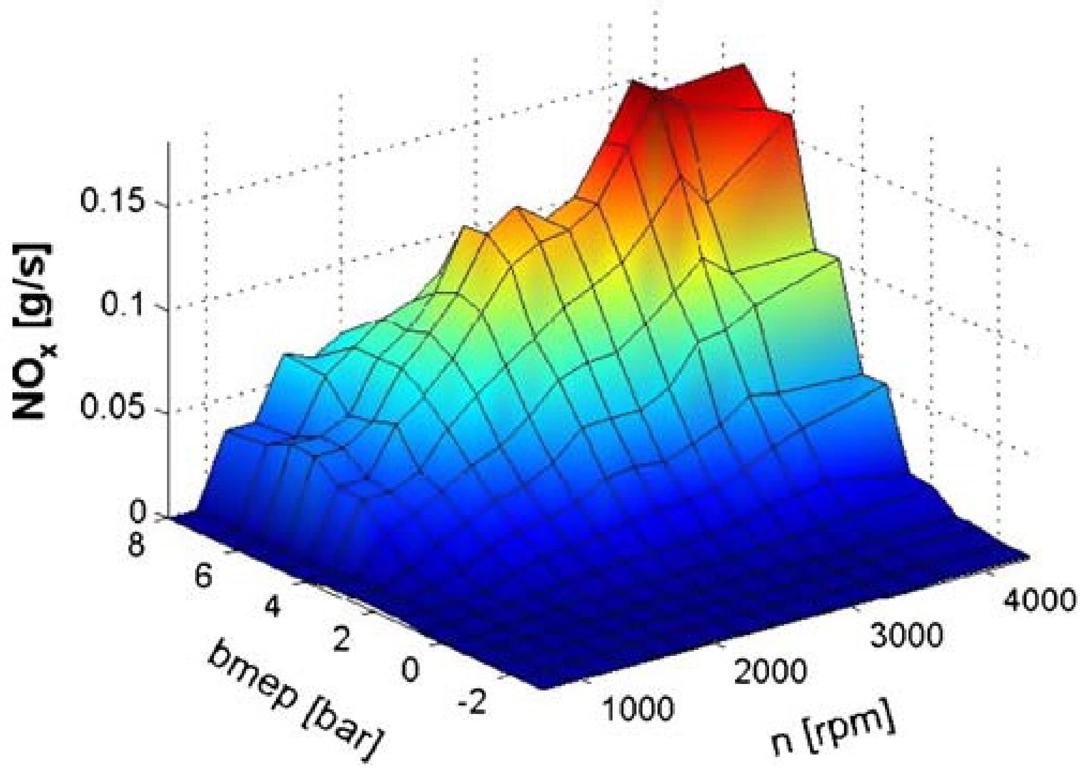

Figure 2-9: Instantaneous emissions map showing NO_X EFs plotted on a matrix of bmep vs. engine speed.

- This emissions map is for NO_X (shown on the vertical axis in g/s), but the principle is the same for CO_2 emissions.
- Brake mean effective pressure (bmep) is the average pressure which, if imposed on the pistons during the power stroke, produces the measured engine power output.
- Source: Ajtay *et al.* (2008).

2.5.9.3 AIMSUN built-in emissions model

The AIMSUN built-in model for fuel consumption (which is directly proportional to CO_2 emissions) is essentially a Modal EM, calculating fuel consumption for each vehicle dependant on time spent idling, accelerating, decelerating, or cruising at constant speed. Four formulae (one for each mode) are used, which require the values of seven parameters to be specified for each vehicle category. These parameters are: idling fuel consumption rate; decelerating fuel consumption rate; two coefficients used in the accelerating fuel consumption rate formula (used in conjunction with instantaneous values of a vehicle's speed and acceleration); fuel consumption at 90km/h; fuel consumption at 120km/h; and the speed at which fuel consumption is minimised. Example values for these parameters are included in the AIMSUN users' manual, but the data are from the 1990s and for a limited number of vehicle categories (Ford Fiesta, Ford Escort and Ferrari Testarossa). New vehicle categories can be defined, but the user must provide values for each parameter for every new category, which would be a sizeable undertaking, particularly for a large number of vehicle categories (TSS 2013).

AIMSUN also has a built-in IEM that can predict CO_2 emissions for each vehicle. This EM is taken from work carried out by Int Panis *et al.* (2006) who developed an IEM based on the results of real-world PEMS measurements (using the VOEM system, refer to Section 2.5.8.1) from vehicles driven in urban traffic. Measurements were analysed for 25 vehicles complying with a range of Euro Standards (Pre-Euro 1 through to Euro 3), consisting of 6 buses, 2 HGVs, 12 petrol cars, and 5 diesel cars. Non-linear multiple regression was used to determine emission functions for each vehicle as a function of instantaneous speed and acceleration. Based on their respective proportions of the vehicle fleet (in which country is not stated), the emission functions for each vehicle were then used to determine an average emission function for the following aggregate vehicle categories: petrol cars, diesel cars, LPG cars (from where the LPG data came is unspecified, all the test vehicles being petrol or diesel fuelled), HGVs, and buses. These are the emission functions used in AIMSUN's built-in IEM. However, the functions are limited to only five highly aggregate vehicle categories, and are based on emissions data for vehicles only up to Euro 3 standard. Assessment of the emission functions was attempted by calculating total emissions for the morning peak period at a study site in Ghent, Belgium, and comparing with estimates from other well-established EMs, including COPERT III and HBEFA – this being model comparison, rather than true validation. The results of this comparison were inconclusive, with large unexplained differences between the results from the well-established models being found.

2.5.9.4 Analysis of Instantaneous Road Emissions (AIRE)

AIRE is an IEM produced by SIAS Limited on behalf of Transport Scotland[71]. It is designed to take a driving pattern input and process instantaneous values of speed, acceleration and road gradient, and then estimate a vehicle's emissions using instantaneous emissions Look-Up Tables (LUTs). AIRE incorporates over 3,000 LUTs, which were derived from PHEM and based

[71] National transport agency for Scotland.

on instantaneous values of engine power and engine speed. PHEM has the facility to alter vehicle specific characteristics and can therefore include real-world effects such as use of auxiliaries or levels of vehicle maintenance. However, no such effects were included in the PHEM runs used in AIRE's development (Barlow 2016).

AIRE is specifically designed to integrate easily with S-PARAMICS[72] micro-RTM, but can be used with driving patterns generated by any micro-RTM or by GPS tracking of vehicles (Transport Scotland 2011; Gastaldi *et al.* 2014; Shaw 2015). Vehicle categories are disaggregated according to Euro Standard at the finest level of detail, and the software contains default values for each category's proportion of the national fleet from 1996 to 2025 based on the NAEI national fleet model. These default proportions can also be adjusted by the user if required (Transport Scotland 2011). However, the latest Euro Standards included in AIRE are Euro 4 for LDVs and Euro V for HDVs.

After the initial software development was completed by SIAS Limited, the outputs from the EM were independently verified by TRL in order to validate AIRE. The user manual also states that emissions estimates from AIRE were compared against estimates from Average Speed EMs using real project examples – but this is model comparison, rather than true validation (Transport Scotland 2011).

2.5.9.5 Integrated routing and CO_2 emissions model for goods vehicles

Palmer (2007) developed an IEM to predict CO_2 emissions from a generic LGV. Initially, link flow (vehicles/h taken from the Surrey County Transportation Model, a macro-RTM) is used as an input to speed-flow formulae (taken from COBA[73]) for specified road types to determine link average speed. Then, a driving cycle is used to account for speed variability, with the driving cycle adjusted so that cycle average speed matches that calculated from the speed-flow formulae. Three LGV driving cycles are available to be used in the EM (a suburban cycle, a congested urban cycle, and an uncongested urban cycle), all provided by TRL. Instantaneous values of speed and acceleration derived from the adjusted driving cycle are used as inputs to an instantaneous fuel consumption formula (the formula also has an input for gradient, but this was assumed to be zero) to calculate fuel consumption (which is directly proportional to

[72] S-Parallel Microscopic Simulation (S-PARAMICS) is produced by SIAS Limited.

[73] Cost Benefit Analysis (COBA) is a software application sponsored by Highways England, and distributed by TRL. It estimates the effects of highway improvements, in terms of time, vehicle operating and accident costs on road network users, and then compares them with construction and maintenance costs over the appraisal period.

CO_2 emissions) for an individual LGV travelling on the link. The coefficients in the fuel consumption formula are representative of a generic LGV (Palmer 2007). Limited, explicit account for congestion is allowed in the choice between a congested or uncongested driving cycle.

The main disadvantage of this IEM is the process used to determine a vehicle's driving pattern. Each step in the process has potential for inaccuracy compared to the real-world situation: initial link flows are generated using an RTM, followed by use of generic speed-flow formulae, and finally a choice between three generic driving cycles. Driving patterns resulting from this process are unlikely to be representative of real-world driving patterns. A further limitation of the EM is that it only has a single vehicle category (i.e. a generic LGV). Also, delays at intersections are not included. In other words, any effect on a vehicle's driving pattern of crossing an intersection is ignored (Palmer 2007). The IEM developed in this study is a sub-model, constituting only one component of an overall model aimed at optimising routings for goods vehicles. Hence, no specific validation of the CO_2 emissions sub-model was included.

2.5.10 Emissions Models Using UTC Data as Inputs

This section does not constitute a separate type of EM. Instead, because of its particular appeal, research into predicting emissions (using various EM types) based on UTC data as inputs was grouped together here for convenient review. UTC data can be considered a by-product of the traffic signal control system, allowing it to be collected with little extra effort or expense on the part of LGAs. Hence, it is easy to see the attraction of being able to accurately predict emissions through the use of these data.

2.5.10.1 SCOOT UTC system built-in emissions model

The SCOOT UTC system predicts emissions using a built-in Average Speed EM, based on emission functions derived from TRL EFs 2009 (refer to Section 2.5.5.1). Traffic average speed for a link is determined using link length and the time taken to travel the link length. Time taken to travel the link length is found from the sum of free-flow cruise time and an estimate of average delay per vehicle. The only data provided by conventional ILDs are whether or not they are currently occupied. Hence, SCOOT does not have any information concerning vehicle categories. To overcome this, SCOOT assumes a distribution of vehicle categories based on the national fleet model, although the user may specify a different distribution if preferred. However, only 7 aggregate vehicle categories are included, which are petrol car, diesel car, petrol LGV, diesel LGV, OGV1[74], OGV2 and buses (Bretherton *et al.* 1998; Bretherton *et al.* 2011).

2.5.10.2 Monitoring and prediction of air pollution from traffic in the urban environment

Research by Reynolds (1996) investigated the use of SCOOT data to predict roadside concentrations of AQ pollutants. In this respect the investigation was attempting to produce a concentration model, but the methodology employed has similarities to the development of EMs. Planned applications for the final model included real-time assessment of air quality without the need for pollution monitoring, and use in UTC systems to allow optimisation for air quality rather than for (the more typical) traffic delay or stops. Roadside pollutant concentration data were collected using electrochemical cells for CO, SO_2 and NO_2, along with the concurrent traffic data from SCOOT. However, the SO_2 and NO_2 sensors were found to be unsatisfactory, so the research focused on developing a model for CO concentrations. Statistical analysis in the form of MLR was performed on the data, which produced a concentration function as shown in Equation 9.

Equation 9

AV_CO = (0.0261 x DELAY) – (0.0018 x FLOW) + 0.9991

Where: AV_CO is the 5 minute average CO concentration (ppm).

DELAY is the 5 minute average delay from SCOOT (1/10 vehicle.h/h).

FLOW is the 5 minute average traffic flow from SCOOT (vehicle/h).

This concentration model is analogous to a Traffic Variable EM because both DELAY and FLOW are traffic variables. However, the R^2 value for Equation 9 was calculated as 0.273, and it was found that DELAY and FLOW were significantly correlated with each other, which violates one of the underlying assumptions of MLR. Eventually, after a series of statistical tests, the MLR analysis was rejected as invalid.

A different approach was then taken based on using SCOOT data to estimate the number of vehicles in each of three operating modes: idling, cruising and accelerating. The analysis attempted to find a relationship between CO concentration and the number of vehicles in each mode as derived from the SCOOT data. Whilst this concentration model does consider

[74] Other Goods Vehicle 1 (OGV1) is rigid vehicles over 3.5 tonnes Gross Vehicle Mass (GVM) with two or three axles; Other Goods Vehicle 2 (OGV2) is rigid vehicles with four or more axles, and all articulated vehicles.

operating modes, it should still be classified as a Traffic Variable model (rather than a Modal model) because it is based on the number of vehicles in each mode for the traffic as a whole, which was, in turn, derived from traffic variables. However, this model was also deemed to be unsuccessful, and a general conclusion of the research was that there is no straightforward relationship between CO concentration and traffic variables.

2.5.10.3 Development of an emissions inventory model for mobile sources

Reynolds and Broderick (2000) describe a methodology for compiling an AQ emissions inventory based on real-time road traffic data acquired from a combination of a UTC system and a closed circuit television (CCTV) system. All vehicles were assumed to be either queueing or moving at a constant velocity. The UTC and CCTV data were analysed to estimate the number of vehicles queueing on a link, and to estimate the number of vehicles moving on a link and the associated traffic average speed. For example, UTC data were used to provide information about traffic flow. CCTV data were analysed to estimate the space-mean-speed of the traffic, and to estimate the proportion of vehicles in each of five aggregate vehicle categories (cars, LGVs, buses, HGVs and motorcycles). However, in general, only limited details are provided on the processes used to analyse the UTC and CCTV data. An advantage of the methodology developed is that it was deliberately designed to have the flexibility to also be applied based on data acquired from Road Traffic Models (RTMs), so as to cater for parts of urban areas where UTC systems are not installed or for predictions of hypothetical scenarios.

To calculate emissions, constant idling EFs (different for each vehicle category) were applied to the queueing traffic, and average speed emission functions for each vehicle category were applied to the moving traffic. The EFs used in the study were taken from a range of sources, including studies of UK urban areas, European initiatives (e.g. COPERT, HBEFA, MODEM), and the EPA in the USA. The methodology was demonstrated by compiling an emissions inventory for a case study survey site in Dublin, Ireland. The survey site was chosen as one of the busiest signalised intersections in the city, characterised by high local congestion and nearly 40,000 vehicle crossings per day. The UTC system installed in Dublin is SCATS[75], which is a widely used system similar to SCOOT.

[75] Sydney Coordinated Adaptive Traffic System (SCATS) was developed by Roads and Maritime Services, a New South Wales Government agency in Australia.

Due to the absence of a practical method for measuring real-world emissions, validation of the case study inventory was conducted through comparison with real-world ambient air quality measurements. Predicted emissions, combined with site geometry and meteorological data, were used as inputs to a pollutant dispersion model to predict pollutant concentrations, which were then compared with measured pollutant concentrations. The results of the validation showed that, in general, there was good agreement between predicted and measured concentrations, with the values being within 25% of each other.

2.5.10.4 Real-time microscopic emissions model

Marsden *et al.* (2001) developed a Modal EM for predicting emissions of CO based on the integration of UTC data with SIGSIM[76] micro-RTM. The UTC system installed was SCOOT. However, this study was not based on parameters generated by SCOOT after processing of the data from ILDs (i.e. SCOOT modelled data). Instead, the 'raw' ILD data were used directly. The integrated system determined vehicle categories from the relationship, at a given constant speed, between the number of occupancy bits registered by an ILD and vehicle length. Based on differing vehicle lengths, three categories were distinguished: car (all cars, three wheelers, and transit vans); LGV (commercial minibuses, two axle goods vehicles, and short, multiple axle goods vehicles); and HGV (single and double deck buses, articulated goods vehicles, long multiple axle goods vehicles). CO emissions from diesel engines were assumed to be negligible, and all LGVs and HGVs were assumed to have diesel engines and disregarded. The car category was assumed to be split in a fixed proportion into the following categories: 14% petrol with properly functioning emission control; 8% petrol with malfunctioning emission control; 25% petrol with naturally deteriorated emission control; 36% petrol non-catalyst; and 17% diesel (assumed to emit negligible CO and disregarded). From a review of the literature, EFs (gCO/mile) for the four different categories of petrol car were derived for five different operating modes: harsh acceleration, acceleration, idle, cruise and deceleration.

ILD count data (i.e. traffic flow) were used as an input to SIGSIM, which estimated the speed of vehicles crossing the ILD, additionally accounting for the influence on speed of the location of the back of any queue on the link. Vehicle speed and ILD occupancy period could then be used to estimate vehicle length, in turn allowing vehicle categorisation. Based on driving pattern outputs from SIGSIM, the distance travelled in each operating mode was calculated for each

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[76] SIGSIM was developed by Newcastle University.

vehicle. Then, having already categorised each vehicle, the appropriate category- and mode-specific EFs were applied to calculate each vehicle's emissions.

Evaluation of the EM was undertaken by directly (i.e. taking no account of emission dispersion) comparing the time-series distribution of predicted traffic CO emissions to the time-series distribution of measured roadside CO concentrations, based on the hypothesis that roadside concentrations would be related to exhaust emissions. The units of predicted emissions and measured concentrations were different, so the distributions had to be standardised prior to comparison. The distribution of standardised predicted emissions was found to be not statistically significantly different from the distribution of standardised measured concentrations. Whilst it was acknowledge that this was not true validation, the result was felt to lend confidence to the approach taken.

2.5.10.5 Emission Specific Characteristics (ESC) model

Nesamani *et al.* (2007) report a study that developed an intermediate model that could provide better estimates of link average speeds (space-mean-speed) based on a set of Emission Specific Characteristics (ESC) for each link. The premise of the investigation was that link average speeds from ILDs could be adjusted to be closer to the link average speeds output from a micro-RTM, based on the assumption that micro-RTM speeds are a more accurate representation of the real-world. Where ILDs were unavailable, it was suggested that macro-RTM link average speeds (i.e. equilibrium link average speeds constant over the period of interest, e.g. a peak hour) could be substituted and adjusted by the ESC model instead. The adjusted link average speeds were then used as an input to an Average Speed EM, which was MOBILE in the case of this study.

Initially a Q-PARAMICS[77] micro-RTM was constructed of the study network (located in California, USA and consisting of a 6-mile section of Freeway I-405, a 3-mile section of Freeway I-5, a 3-mile section of Freeway SR-133, and all major adjacent roads). To construct the ESC model, a MLR process was used, with link average speed from Q-PARAMICS as the outcome variable. Alongside ILD average speed, many other factors were considered as predictor variables, such as ILD flow, link length, number of lanes, link type (curved or straight), time of day (peak or off-peak), presence of a traffic signal or stop sign, speed limit, intersections per

[77] Q-Parallel Microscopic Simulation (Q-PARAMICS) is produced by Quadstone.

mile, and land-use adjacent to the road. The ILD data used in the investigation were generated by simulated ILDs within the Q-PARAMICS model itself. The final form of the ESC model was as shown in Equation 10.

Equation 10

$$S_A = (0.714 \times S_{LD})+(0.51 \times S_{Lim})+(2.46 \times LU_{Mix})-(3.84 \times L_{Type})+(12.83 \times L_{Len})-(1.34 \times AD)-21.62$$

Where: S_A is adjusted link average speed in mph.

S_{LD} is ILD link average speed in mph (range 12-84 mph).

S_{Lim} is speed limit in mph (range 25-65 mph).

LU_{Mix} is mixed land-use (i.e. residential and commercial) (1 for mixed land-use, otherwise 0).

L_{Type} is link type (1 for curved, 0 for straight).

L_{Len} is link length in miles.

AD is access density in intersections per mile (range 0-11 intersections per mile).

No validation of the ESC model by comparison to real-world link average speeds was conducted. Instead, for links not used in the original MLR process, the adjusted link average speeds predicted by Equation 10 were compared to the Q-PARAMICS link average speeds, and the Mean Absolute Percentage Error[78] (MAPE) was found to be 6.1%. Comparison between (un-adjusted) ILD link average speeds and Q-PARAMICS link average speeds gave a MAPE of 8.9%. Therefore, the ESC model provides a closer approximation to micro-RTM speeds than ILD speeds alone.

2.5.10.6 Newcastle University Integrated Database and Assessment Platform (NUIDAP)

The Newcastle University Integrated Database and Assessment Platform (NUIDAP) described by Bell *et al.* (2012) has been developed by Newcastle University in collaboration with Amey plc and Medway Council (an English LGA that is a Unitary Authority and therefore also a LHA, refer to Section 1.5.1). NUIDAP is an on-line system that receives inputs from a SCOOT UTC system, meteorological monitoring stations, Automatic Urban and Rural Network (AURN) precision air quality monitoring stations (maintained by DEFRA) and pervasive environmental sensors (motes). The motes are small, inexpensive sensors designed by Newcastle University to monitor temperature, humidity, noise, CO, NO_2 and NO.

[78] Mean Absolute Percentage Error (MAPE) is the mean of the absolute differences between predicted and real-world (Q-PARAMICS in this case) values expressed as a percentage of real-world values.

The emissions estimator sub-system within NUIDAP is essentially a Traffic Variable EM which estimates link-level emissions based on SCOOT modelled data. The data are collected from SCOOT messages[79] M02 (stops, delay and flow), M08 (queue lengths), M29 (flow and ILD occupancy time) and M37 (traffic signal timings). Determined from the SCOOT data, traffic state/congestion information, along with four traffic flow regimes (quiet, smooth flow, unstable/busy, and congested) defined by threshold values for occupancy and flow, are used as inputs to algorithms that estimate emissions, based on an assumed fleet mix in accordance with the NAEI national fleet model.

NUIDAP allows the network status to be continually monitored in real-time, and network problems and pollution hotspots to be identified. Potential solutions to an identified problem (e.g. traffic signal control, rerouting, dynamic speed limits, bus priority measures) are then assessed using off-line traffic modelling. SCOOT data (e.g. flow, delays and stops) are used to validate a Road Traffic Model (RTM) of the current network state. The RTM then predicts the flow, delays and stops expected when a solution is implemented, which are used to predict the impact on emissions.

Assessment of NUIDAP was achieved for CO_2 and CO. CO_2 predictions were assessed using archived SCOOT data from Leicester, UK. These data were used as inputs to the emissions estimator to predict the CO_2 emissions for an area of the road network in the vicinity of a shopping centre. When these predictions were compared to predictions from an Average Speed EM (which has only limited ability to account for the influence of congestion on emissions, refer to Section 2.5.5), the Average Speed EM was found to underestimate total emissions by 11%. However, this process constituted model comparison rather than true validation. True validation (i.e. comparison with independent real-world observations) was performed for CO. Using the emissions estimator and the pollutant dispersion model, in combination with meteorological data, CO concentrations were predicted by NUIDAP for the locations of the 109 motes (in the Medway region of the UK), which were then compared to the concentrations measured by the motes. The correlation between predicted and measured CO concentrations was found to be good except during peak traffic periods when predicted concentrations had a much sharper peak than concentrations measured by the motes.

[79] Section 5.4.2.1 contains further details of SCOOT messages.

However, this process was not validation of the emissions estimator alone, but instead validation of the combination of the emissions estimator and the pollutant dispersion model.

2.5.10.7 Estimating vehicle emissions using inductive loop detector data

An example of an investigation into emissions predictions based on road traffic data generated by enhanced ILDs is reported in Jeng *et al.* (2013). Similar to the work detailed in Section 2.5.10.4, this study used 'raw' ILD data rather than the outputs from a UTC system. The system of enhanced ILDs was known as the inductive loop signature-based detection system, and went beyond just vehicle category classification (as for typical enhanced ILDs, refer to 2.4.5), working on the principle that the resulting change in inductance (inductive signature) due to the passage of a vehicle over an ILD is (ideally) unique to that vehicle. This enabled the system to track individual vehicles and estimate travel times for known distances, thus allowing traffic space-mean-speeds to be estimated. The mix of vehicle categories can also be estimated based on the data from the enhanced ILDs, with vehicle categories defined according to the US Federal Highway Administration (FHWA) classification[80]. The authors claim that upgrading conventional ILDs to the enhanced version is "straightforward and can be performed easily." No modification of the sensor itself is required, but an advanced detector card is needed along with a processing unit in the field. However, no details are provided regarding the costs of upgrading.

Once vehicle category mix and time-varying traffic average speed have been estimated for each link, these data were then used as inputs to the MOVES EM (refer to Section 2.5.9.1) in order to calculate emissions. The performance of the model was evaluated by application to a case study site spanning 7 ILDs along a 6.2 mile section of the northbound Freeway I-405 in California, USA. A ground-truth estimate for total traffic CO_2 emissions of 30,315.5 kg/h was calculated using speed data from GPS equipped probe vehicles as input to MOVES. Comparison was then made with MOVES estimates using data from different sources. Compared to ground-truth, predicted emissions using speed data from a macro-RTM and MOVES default vehicle mix were 18% lower; using speed data from conventional ILDs and MOVES default vehicle mix were 6% lower; and using speed and vehicle mix data from enhanced ILDs were 1% lower. The better performance of the enhanced ILDs was seen as

[80] The Federal Highway Administration (FHWA) defines 13 vehicle categories: motorcycles, cars, LDVs other than cars, buses, and nine HGV categories. This is a more aggregate classification than (for example) the NAEI national fleet model, which disaggregates according to Euro Standard at the finest level of detail.

demonstrating their advantage in producing more accurate speed and vehicle mix data. However, this was not true validation of the methodology because no comparison was made with real-world emissions.

2.5.11 Emissions Models to Assess Intelligent Transport Systems

This section does not constitute a separate type of EM. Instead, because ITS assessment has generated substantial research into predicting urban network emissions (using various EM types), this work is grouped together here for convenient review, with particular emphasis on European applications. ITS are defined as any application of ICT employed to facilitate more efficient use of transport networks, which includes a broad range of different transport interventions such as average speed enforcement, dynamic speed limit systems, traffic signal control systems, internet-based travel information, road side Variable Message Signs (VMS), on-board navigation systems, route guidance to parking spaces or loading/unloading bays, road pricing, congestion charging, restricted traffic zones (e.g. low emission zones), and provision of driver information to facilitate eco-driving (De Kievit *et al.* 2014a). One of the benefits often sought from implementing ITS schemes is reduction of CO_2 emissions from road vehicles. Hence, assessment of ITS schemes often requires emissions to be predicted.

2.5.11.1 AMITRAN and ECOSTAND

Both AMITRAN (Assessment Methodology for ICT in Transport) and ECOSTAND[81] were research projects concerned with the development of standard methodologies for evaluation of the effects of ITS on CO_2 emissions. The objective of AMITRAN was to develop a standard methodology for emissions from surface transport (including road, rail, inland waterways and short-sea shipping), for application throughout Europe (Jonkers *et al.* 2014). The objective of ECOSTAND was not to develop a standard methodology itself, but to provide support for an agreement between the EU, Japan and the USA on a framework for a common methodology for emissions from road traffic, through formulating a roadmap to enable future development of the methodology (De Kievit *et al.* 2014a).

A conclusion of both projects was that road network geographic scale has a major bearing on the appropriate type of EM for assessment. For localised ITS interventions that affect vehicle dynamics along specific links, a detailed EM is required that predicts emissions for individual vehicles (e.g. Cycle Variable or Modal EMs). However, when assessing ITS interventions on

[81] Both European Commission 7th Framework projects.

larger geographic scales, a less detailed EM is acceptable and may be the only practical option. For example, the ECOSTAND project stated that "on a regional scale, the use of average speed emission models is usually appropriate" (De Kievit *et al.* 2014a; Jonkers *et al.* 2014).

2.5.11.2 CARBOTRAF

The objective of the CARBOTRAF[82] project was to combine real-time traffic monitoring with emissions predictions for different simulated traffic situations to provide recommendations for alternative traffic management options (e.g. traffic signal control, rerouting, dynamic speed limits, VMS) in order to minimise traffic CO_2 emissions. Initially, for two case study cities, a range of traffic situations resulting from implementation of different traffic management options were simulated using a micro-RTM and an IEM (VISSIM/AIRE for Graz, Austria and S-PARAMICS/AIRE for Glasgow, UK). The simulation results were stored in a Look-Up Table (LUT) database that linked the traffic situations with the overall emissions specific to each situation.

The main element of CARBOTRAF is the Decision Support System (DSS), which receives real-time data from sensors monitoring the traffic situation. DSS then predicts the traffic situation at 30-60 minutes into the future using a macro-RTM. For the current and predicted traffic situations, CO_2 emissions are derived by searching the LUT database. Alternative traffic situations that satisfy traffic demand with reduced overall CO_2 emissions are offered to the traffic control centre operator, who decides on the implementation of the associated traffic management options (Litzenberger *et al.* 2012; North and Hu 2012).

The CARBOTRAF system is essentially a Traffic Variable EM predicting network emissions from data that describe the traffic as a whole. As well as using conventional sources such as ILDs, the real-time monitoring of the traffic situation is supplemented by a specialist road side sensor called the smart eye Traffic Data Sensor (TDS)[83] which can determine the proportion of accelerating vehicles in the traffic (Litzenberger *et al.* 2012). Therefore, using CARBOTRAF is reliant on installation of specialist equipment throughout an urban area's road network, which would require an LGA to meet the associated costs.

[82] European Commission 7th Framework project.
[83] A proprietary sensor produced by the Austrian Institute of Technology.

2.5.11.3 ICT-Emissions

The objective of ICT-Emissions[84] was to develop a methodology for evaluation of the effects of ITS on CO_2 emissions from road traffic in urban areas. Similar to AMITRAN and ECOSTAND, road network geographic scale was identified as having a major bearing on the appropriate type of EM for assessment. However, the ICT-Emissions methodology attempted to address the situation where an ITS intervention had an effect on detailed vehicle dynamics (requiring a detailed EM) over a large-scale network (e.g. an entire city, requiring a less detailed EM). In fact, the authors highlighted that a local ITS intervention could well have knock-on consequences across the wider network, so the ability to assess whole network emissions was important (Toffolo *et al.* 2013). ITS interventions considered during the project were: Variable Speed Limits[85]; UTC on or off[86]; green navigation[87]; eco-driving[88]; stop-start engine technology[89]; and adaptive cruise control vehicle technology[90] (Valdés Serrano 2015b).

The ICT-Emissions approach was to model in detail the local effect of an ITS intervention, and then extrapolate the effect across the network. Two methods were proposed to integrate between detailed, local-scale modelling and less detailed, larger-scale modelling. The first method used a micro-RTM (AIMSUN or VISSIM) to model the impact on driving patterns for a local area, allowing new relationships resulting from the ITS intervention to be determined between traffic average speed, traffic flow and traffic density. These new relationships were then used to adjust speed-flow-density relationships in a macro-RTM (AIMSUN or VISUM[91]) of the whole network and an Average Speed EM (COPERT) used to predict network emissions (Toffolo *et al.* 2013; Valdés Serrano 2015a). The method assumes that the impact on emissions of changes to driving patterns can be adequately captured by changes to speed-flow-density relationships and application of an Average Speed EM, which may not be a valid assumption (e.g. it is possible driving patterns altered by an ITS intervention could result in the

[84] European Commission 7th Framework project.

[85] Variable Speed Limits is a speed limit management system that varies limits to smooth traffic flow (also known as dynamic speed limit system).

[86] UTC on or off involves assessing emissions with the UTC system either operational or non-operational.

[87] Green navigation involves drivers being offered route guidance to minimise emissions based on real-time traffic congestion information.

[88] Eco-driving is a set of techniques for drivers to reduce fuel consumption (e.g. early upshifting to avoid high engine rpm, maintaining steady speed, anticipating traffic, avoiding harsh acceleration/deceleration and avoiding long idle times).

[89] Stop-start engine technology reduces fuel consumption by switching off the engine during idle times.

[90] Adaptive cruise control vehicle technology controls vehicle speed based on the gap to the preceding vehicle and the system can be set to reduce fuel consumption by minimising harsh and frequent accelerations.

[91] VISUM was defined as a meso-RTM by Boulter *et al.* (2012), but defined as a macro-RTM in ICT-Emissions, which underlines the point previously made that there is no clearly agreed demarcation between the different scales (refer to Section 2.4.4). AIMSUN can function at micro, meso or macro scales.

same traffic average speed as existed prior to the intervention). A further assumption is that a local change in speed-flow-density relationships is replicated across the whole network.

The second method involved constructing an Extended Average Speed EM. Driving cycles were selected to represent driving patterns under conditions with and without the ITS intervention in place (e.g. in Figure 2-10 these are normal, eco and aggressive driving), and an IEM (CRUISE[92]) used to predict emissions for each vehicle category from each driving cycle. EFs output from the IEM were used to develop a separate average speed emission function for each condition (e.g. separate emission functions for normal, eco and aggressive driving as shown in Figure 2-10). An estimate was then made of the penetration of the ITS intervention (e.g. in Figure 2-10 this would be the percentage of vehicles for normal, eco and aggressive driving). A macro-RTM (AIMSUN or VISUM) was used to determine average speeds for each link in the network, which were used as inputs to the Extended Average Speed EM to predict network emissions (Toffolo *et al.* 2013). The process of constructing an Extended Average Speed EM is resource-intensive, and would need to be repeated to represent different ITS interventions. Additionally, the method assumes that the selected driving cycles are representative of real-world driving patterns, and that the impact of an intervention on driving patterns is replicated across the whole network.

Calibration and validation of the constituent models in ICT-Emissions (particularly the Road Traffic Models) was achieved by comparison to data from cars driven in the real-world in field trials in Madrid, Rome and Turin, with good agreement being found (Valdés Serrano 2015a). However, there was no large-scale validation of emissions predictions from the overall methodologies, presumably due to the inherent difficulties of collecting real-world emissions data from every vehicle in a large geographic area.

[92] IEM software application produced by AVL LIST GmbH.

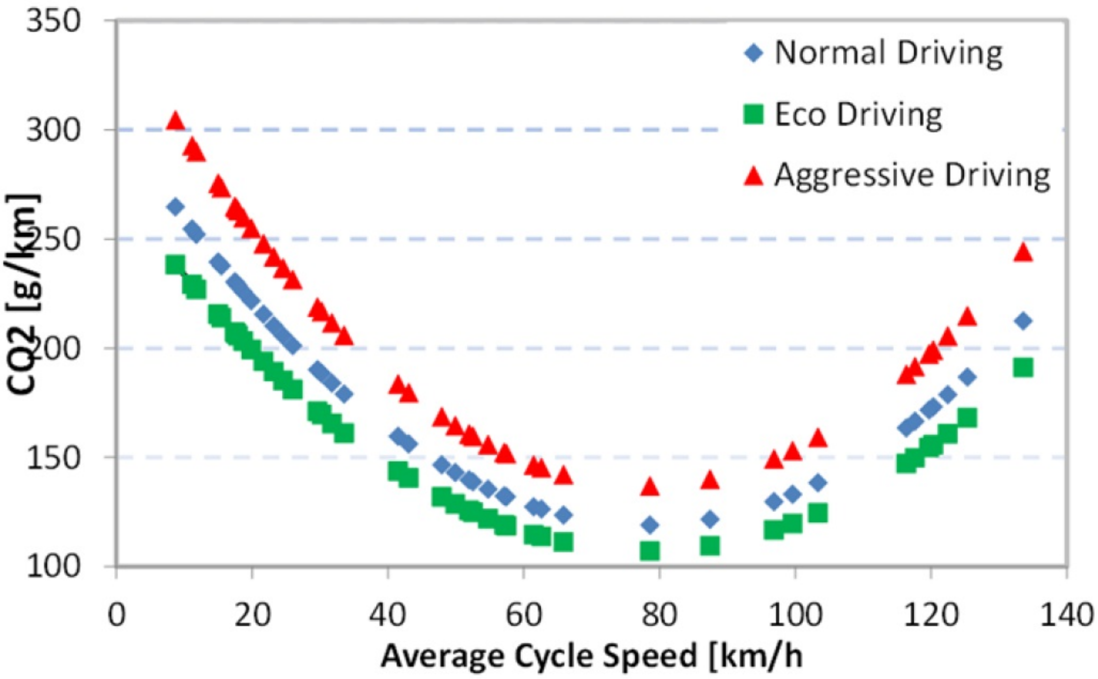

Figure 2-10: Extended Average Speed EM for an ITS intervention encouraging eco-driving.

- Based on a Euro 3 diesel car with engine size 1400-2000cc.
- Chart was provided in the original source material for illustrative purposes, and would be likely to change (slightly) when calibrated with real data.
- Source: Toffolo *et al.* (2013).

2.5.11.4 Stepwise Speed Function (SSF)

The SSF is a Cycle Variable EM developed by Kuwahara *et al.* (2013) for assessing the effect of ITS schemes on CO_2 emissions through reducing stop-and-go driving conditions. Initially, the outputs of a meso-RTM (consisting of whether a vehicle is running or stopped, but no data on its acceleration or deceleration) are used to create a rudimentary driving pattern called a SSF for each vehicle. The overlay of a SSF onto a vehicle's full driving pattern is shown in Figure 2-11. Average speed, running distance and average gradient are the cycle variables used as inputs to the EM for predicting emissions. Additionally, because emissions are calculated for each SSF separately, the number of stops performed by a vehicle is also indirectly used as an input variable. Congestion influence is explicitly accounted for in the dynamics of the different SSFs. The EM has fairly limited disaggregation of vehicle categories, with only 11 different categories defined.

Validation of the EM was conducted by comparing measured and predicted emissions for a 1.7km section (including 10 intersections) of urban road in Tokyo. Probe vehicles (13 vehicles including 1 HGV) were driven along this section of road between 06:30 and 10:00 on a weekday so that congestion in the morning peak period would be observed (Tanaka *et al.*

2011). Predicted CO_2 emissions were compared to CO_2 emissions derived from measured fuel consumption and very good agreement was found with a value of R^2=.99.

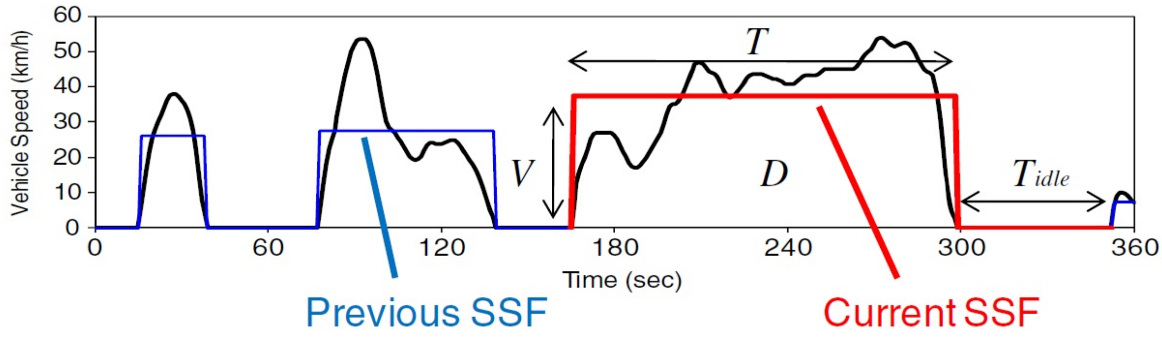

Figure 2-11: Overlay of a Stepwise Speed Function (SSF) on a vehicle's driving pattern.

- V is average speed; T is running duration; D is running distance; and T_{idle} is idling duration.
- Source: Kuwahara *et al.* (2013).

2.5.12 Emissions Model Outputs in LGA Policy Making

There are a number of different ways in which LGAs currently use the outputs generated by EMs to inform their policy making[93]. In some cases, LGAs use EMs to calculate road traffic's contribution to an emissions inventory compiled for their area of administration. For example, the Greater London Authority (GLA)[94] produces the London Atmospheric Emissions Inventory (LAEI) which is an inventory of all atmospheric pollutants emitted during an assessment year (last assessment was LAEI 2013) in the Greater London area. The TRL EFs 2009 Average Speed EM (refer to Section 2.5.5.1) was used to calculate CO_2 emissions from road traffic (GLA 2010a). The purposes of the LAEI are, *inter alia*, to identify emissions sources that could be targeted if emissions reductions are required, to provide an input to policy making on emissions abatement and controls, and to monitor progress against air quality targets (GLA 2010b). For similar reasons, Transport for Greater Manchester (TfGM), the transport arm of the Greater Manchester Combined Authority (GMCA), produces the Emissions Inventory for Greater Manchester (EMIGMA), which is an inventory of all atmospheric pollutants emitted during an assessment year (last assessment was 2010) in the Greater Manchester area. Again, calculation of CO_2 emissions from road traffic is based on the TRL EFs 2009 Average Speed EM (TfGM 2013).

[93] A typical definition of policy making is the formulation of ideas and plans used by government authorities as a basis for making decisions intended to solve problems and improve the quality of life for their citizens.

[94] The Greater London Authority (GLA) and Greater Manchester Combined Authority (GMCA) are regional authorities whose areas of administration encompass several LGAs, with Transport for London (TfL) and Transport for Greater Manchester (TfGM) being their respective transport delivery arms (refer to Section 1.5.1).

In other cases, LGAs use the outputs of EMs for the real-time assessment of emissions. For example, Swansea City and County Council are developing a real-time EM called Nowcaster[95]. A network of enhanced ILDs provides traffic count, vehicle speed and vehicle category data (e.g. two-wheel, car/van, rigid HGV, articulated HGV, or bus) at 1 minute resolution. These data are then combined with EFs (which were obtained from those developed during the ARTEMIS[96] project) to calculate emissions for each link. EFs are fixed at present (i.e. an Aggregate EM with EFs independent of speed), but the introduction of average speed emission functions (i.e. an Average Speed EM) is planned for future development (Swansea City and County Council 2014; Govier 2015). Other inputs to the system are data from dedicated meteorology stations (Swansea Valley macro-conditions and street level micro-conditions), pollutant concentration measurements from air quality monitoring stations in the city, and the geometry for each link that influences pollutant dispersion (e.g. road/pavement widths and building heights). Through combining these inputs, the aim of the system is to make hourly forecasts of AQ conditions for every defined link within the area of operation (mainly the AQMA in the Hafod area of Swansea). Initially, these hourly forecasts will be made up to 3 hours in advance of conditions occurring, but ultimately the forecasts will be made up to 8 hours in advance to allow for mitigation through traffic management interventions (Swansea City and County Council 2014; Govier 2015). Nowcaster outputs will be disseminated through an interface that allows the public to view forecasts, through emails sent to local media stations, and through messages displayed on VMS to encourage traffic to divert away from the area with high congestion and poor air quality (Swansea City and County Council 2014).

LGAs also use EM outputs to inform decision making when considering different pathways to achievement of their emissions reduction targets through forecasting the emissions impact of potential transport interventions. For example, Haringey Council has developed an Average Speed EM which is seen as a management tool to assess what measures are required to achieve a particular CO_2 emissions reduction target (Battershill 2011). The EM is a spreadsheet model based on the WebTAG formulae (refer to Section 2.5.5.3). The necessary EM inputs of traffic average speed and vehicle category data for each link are obtained by modelling the potential intervention in the North London Highway Assignment Model (NoLHAM), which was

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[95] Development of Nowcaster has been hindered by budgetary constraints and delays in software development, but is expected to start operation later this year (2016).

[96] Assessment and Reliability of Transport Emission Models and Inventory Systems (ARTEMIS) – a European Commission 5th Framework project.

developed by Transport for London (TfL) based on the SATURN RTM (Battershill 2011; TfL 2016). Another example of pre-implementation assessment of interventions is the use of emissions models to forecast the potential impact of Low Emission Zones (LEZs). Broadly, LEZs are areas where access is restricted based on vehicle emissions and can involve a total ban or a charge to enter (i.e. higher emitting vehicles are banned from, or charged to enter, LEZs). In Europe, LEZs have been introduced in a number of cities, such as Amsterdam, Berlin, London, Milan, Munich and Stockholm (Holman *et al.* 2015). A policy of LEZs is currently being pursued in the UK to tackle AQ emissions. In addition to the LEZ already in-place in London, national government is legislating for LGAs to implement Clean Air Zones (i.e. LEZs) by 2020 in Birmingham, Leeds, Nottingham, Southampton and Derby, which are the five cities in England (outside London) projected to still be exceeding limit values for NO_2 in 2020 (DEFRA 2015b).

A further way in which LGAs use EM outputs to inform their policy making, is through monitoring the emissions impact of interventions post-implementation (i.e. retrospective assessment of the impact of interventions to inform future policy). For example, a case study on the carbon impacts and congestion relief achieved by interventions implemented under the Local Sustainable Transport Fund (LSTF, refer to Section 1.5.2.1) was recently completed by the University of Southampton. One of the primary aims of the case study was to estimate the impact on CO_2 emissions of any net change in traffic. The method used was based on comparison of five treatment areas (Coalville, Eastleigh, Gosport, Rochdale and Tameside) with three control areas (Fareham, Hinckley and Wigan). To calculate emissions, an Average Speed EM (WebTAG formulae) was used for car travel and an Aggregate EM (DEFRA 2013 GHG Conversion Factors for Company Reporting[97]) used for bus travel[98]. A small reduction was found of approximately 2.5% of the pre-intervention CO_2 emissions in the treatment areas relative to the control areas. Whilst not strictly conducted by an LGA, this assessment was done (it could be argued) on their behalf, and results are likely to inform future LGA policies.

Another situation is where LGAs use the outputs of EMs to demonstrate that their policy making complies with legislation. An example of this is provided from outside the UK. For LGAs in the USA to discharge their responsibilities under the Federal Clean Air Act, they must

[97] National government guidance provided to assist companies in complying with the GHG reporting regulation (a requirement under the Climate Change Act 2008), which constitutes a set of EFs for all emissions sources (not only transport) potentially relevant to companies (DEFRA 2013a).

[98] The LSTF was more concerned with interventions aimed at persuading people to switch from cars to public transport, cycling or walking, rather than the movement of freight; as such, emissions from LGVs and HGVs were not included in the case study.

submit a State Implementation Plan (SIP) to the EPA for approval. A SIP constitutes the regulations and policies developed by state government to allow the state to achieve National Ambient Air Quality Standards (NAAQS) by a certain date (Colburn *et al.* 2012) and relates to emissions from all sources (not just transport). The EM approved for the purposes of calculating road traffic emissions in a SIP is MOVES2014 (refer to Section 2.5.9.1) (EPA 2014a; EPA 2015). MOVES2014 is also the EM mandated[99] for use in Regional Emissions Analysis for Transportation Conformity Determinations (termed Transportation Conformity Analyses) (EPA 2014a; EPA 2015). Transportation Conformity Analyses must be approved by the EPA to ensure highway projects conform to the air quality goals established in a SIP and to secure federal funding. However, these SIP and Transportation Conformity Analyses requirements do not apply to emissions of GHGs (EPA 2014b).

2.6 DISCUSSION

Having reviewed the literature concerning road traffic data and its use as inputs to the different types of road traffic EMs, this section discusses the results of that review. Particular emphasis is placed on the implications for the LGA emissions modelling process.

2.6.1 Readily Available Road Traffic Data

The results of the literature review indicate that the detail level of road traffic data readily available for collection by LGAs within their resource constraints is data aggregated at traffic level rather than data disaggregated at individual vehicle level; i.e. traffic variables rather than driving patterns. In general, driving patterns lack availability because they are difficult to collect, are rarely used in traffic engineering to describe road network performance, and their simulation in micro-RTMs is of questionable accuracy.

Two sources of traffic variables readily available on a link-by-link basis are UTC data and Road Traffic Model (RTM) output data. UTC data are particularly appealing because they are a by-product of the traffic signal control system. RTM data are required for instances when UTC data are not available, such as for assessment of hypothetical situations or for areas of the road network where ILDs are not installed. Reliance on other road traffic data sources to provide EM input data is likely to incur additional costs for collection and processing on a link-by-link basis (i.e. data are not routinely available for each link of a network), and/or involve sources that are not widely used by LGAs.

[99] MOVES2014 was approved for use from October 2014, and mandated for use from October 2016.

UTC data are more appropriate for the assessment of smaller, tactical interventions because their real-world nature means assessment can only be achieved post-intervention through comparing before and after emissions estimates. Examples of smaller interventions include altering traffic signal timings, re-routing particular vehicles (e.g. HGVs or buses), restricting vehicle loading/unloading to certain times, or prohibiting on-street parking at certain locations (Reynolds 1996; Reynolds and Broderick 2000). When assessing these interventions, it should be CO_2 emissions for the whole network (or substantially large parts of the network) that are analysed, rather than local scale emissions, because assumptions about random errors averaging out become less valid for localised assessments (Smit *et al.* 2008b). Whilst acknowledging that UTC data may not be an entirely accurate representation of the real-world traffic situation (refer to Section 5.4.4), their ready availability means their utility as a source of EM inputs that could enhance (in terms of accuracy of predictions) the emissions modelling process is worthy of investigation.

The emissions impact of large, strategic interventions typically requires assessment prior to implementation, when there will be no real-world UTC data available for hypothetical post-intervention scenarios. However, such interventions are likely to be modelled using an RTM to assess the impact on traffic, and the outputs of this RTM can therefore be used as a source of traffic data for emissions modelling. Examples of large interventions include substantial alterations to the road infrastructure, variation of area-wide speed limits, or provision of large car parking facilities or park-and-ride schemes. The use of RTM outputs in the emissions modelling process relies on the assumption that the RTM has been properly validated by comparison to real-world values for traffic variables in the base-case scenario. Another point to note is that RTMs typically have the facility to generate simulated UTC data from simulated ILDs installed in the modelled network. Consequently, an EM that can only accept UTC data as inputs does not preclude its use when an RTM is the data source.

Network characteristics are an additional source of traffic variables readily available to LGAs. Data on these characteristics have the advantage of being fairly easily measured by (or on behalf of) LGAs; and having been measured once, are not subject to change very often. The rise in vehicle telematics (i.e. vehicle tracking data collected from in-vehicle devices) is also a potential source of traffic variables that could come to satisfy LGA traffic data requirements, and investigation of relationships between these data (e.g. TCIs, refer to Section 2.4.3) and CO_2 emissions is a subject worthy of investigation.

2.6.2 Summary of Reviewed Emissions Model Examples

Table 2-4 provides a summary of the EM examples that have been discussed in the literature review showing the positives and negatives associated with their potential use by LGAs (particularly in the UK). Also, where possible, an indication of each EM's prediction accuracy is included; although literature concerning EM validation and quantification of prediction errors is limited (refer to Section 2.6.5).

Table 2-4: Summary of the EM examples used to illustrate the literature review.

Emissions Model	Positives	Negatives	Prediction Accuracy
Aggregate EMs:			
UK Greenhouse Gas Inventory - Refer to Section 2.5.4.1.	- Only inputs required are the fractions of total national VKMs performed by each vehicle category (i.e. fleet mix) on each road type (urban/rural/motorway). - Simplicity means it is practical for an emissions inventory on a national scale.	- Due to fixed EFs (i.e. EFs independent of speed), the effects of transport interventions that vary local traffic average speeds (or any other traffic variable) cannot be analysed. - Account for congestion is implicit.	- No validation details found, but normalisation of results to agree with the total fuel sold in the UK ensures accuracy. - This normalisation approach would have limited applicability at sub-national scales because of cross boundary traffic (i.e. fuel sold in a region is not necessarily used in the same region).
Average Speed EMs:			
TRL Emission Factors 2009 - Refer to Section 2.5.5.1.	- In addition to VKMs performed by each vehicle category, the only inputs required are traffic average speeds. - Officially recognised EM for use in the UK; although a switch to COPERT is imminent (refer to Section 2.5.5.1).	- Limited ability to account for congestion, particularly in urban areas. - Account for congestion is implicit.	- Validation results indicated that the EM probably provides "a reasonably accurate characterisation of total emissions from road transport".
DfT Basic Local Authority Carbon Tool - Refer to Section 2.5.5.2.	- In addition to VKMs performed by each vehicle category, the only inputs required are traffic average speeds. - Based on the officially recognised EM for use in the UK (TRL EFs 2009).	- Limited ability to account for congestion, particularly in urban areas. - Account for congestion is implicit.	- Validation as for TRL EFs 2009.
WebTAG - Refer to Section 2.5.5.3.	- In addition to VKMs performed by each vehicle category, the only inputs required are traffic average speeds. - Based on the officially recognised EM for use in the UK (TRL EFs 2009).	- Limited ability to account for congestion, particularly in urban areas. - Account for congestion is implicit. - Only includes 7 vehicle categories, which are aggregated compared to TRL EFs 2009.	- Validation as for TRL EFs 2009 (subject to the considerable aggregation of the vehicle categories specified in TRL EFs 2009).
COPERT - Refer to Section 2.5.5.4.	- In addition to VKMs performed by each vehicle category, the only inputs required are traffic average speeds. - Regularly updated by its supplier (Emisia).	- Limited ability to account for congestion, particularly in urban areas. - Account for congestion is implicit.	- Validation by comparison to PEMS measurements from 6 cars (3 petrol & 3 diesel) driven in Italy resulted in predictions of between -14% and +33% of real-world values.

Table 2-4 continued.

Emissions Model	Positives	Negatives	Prediction Accuracy
Emissions Factors Toolkit - Refer to Section 2.5.5.5.	- In addition to VKMs performed by each vehicle category, the only inputs required are traffic average speeds. - CO_2 estimates are based on the officially recognised EM for use in the UK (TRL EFs 2009). - AQ estimates are based on COPERT 4.	- Limited ability to account for congestion, particularly in urban areas. - Account for congestion is implicit.	- Validation as for TRL EFs 2009 and for COPERT.
DEEM - Refer to Section 2.5.5.6.	- In addition to VKMs performed by each vehicle category, the only inputs required are traffic average speeds.	- Limited ability to account for congestion, particularly in urban areas. - Account for congestion is implicit. - Only a sub-model of the UK Transport Carbon Model, and not intended for separate use.	- No specific validation details found for the sub-model.
VSP Distribution Model (VDM) - Refer to Section 2.5.5.7.	- Ability to predict VSP distributions based on average speed bins allows SCFs to be calculated without the resource-intensive process of emissions tests. - In addition to VKMs performed by each vehicle category, similar to Average Speed EMs based on emission functions, the only inputs required for Average Speed EMs based on SCFs are traffic average speeds.	- Calculation of SCFs from predicted VSP distributions relies on the availability (for each vehicle category) of a suitable database of ERs associated with VSP bins. - Only developed to predict VSP distributions for LDVs driven on urban, restricted-access roads in Beijing. - Similar to Average Speed EMs based on emission functions, Average Speed EMs based on SCFs have limited ability to account for congestion, particularly in urban areas; and account for congestion is implicit.	- SCFs calculated based on VSP distributions predicted by the VDM were found to be “well-matched” with SCFs calculated based on VSP distributions from real-world GPS driving patterns.
SCOOT UTC System built-in EM - Refer to Section 2.5.10.1. - UTC.	- SCOOT provides both required inputs: VKMs performed by each vehicle category; and traffic average speeds. - Assumes a distribution of vehicle categories based on the national fleet model, although a user-specified distribution can be used instead. - Based on the officially recognised EM for use in the UK (TRL EFs 2009).	- Limited ability to account for congestion, particularly in urban areas. - Account for congestion is implicit. - Only includes 7 vehicle categories, which are aggregated compared to TRL EFs 2009.	- Validation as for TRL EFs 2009 (subject to the considerable aggregation of the vehicle categories specified in TRL EFs 2009).
ICT-Emissions method 1: Micro-RTM relationships to adjust a macro-RTM, followed by an Average Speed EM - Refer to Section 2.5.11.3. - ITS.	- In addition to VKMs performed by each vehicle category, the only inputs required are traffic average speeds. - Improved ability to account for congestion through adjustment of macro-RTM based on micro-RTM outputs.	- To generate traffic average speed inputs, a local area micro-RTM is required to adjust speed-flow-density relationships in a wide area macro-RTM. - More appropriate for blanket interventions that affect all links at once in a similar fashion. - Ability to account for congestion still limited due to reliance on an Average Speed EM.	- Good agreement was found in validation of the constituent models by comparison to data from cars driven in the real-world in field trials in Madrid, Rome and Turin.

Table 2-4 continued.

Emissions Model	Positives	Negatives	Prediction Accuracy
ICT-Emissions method 2: Extended Average Speed EM - Refer to Section 2.5.11.3. - ITS.	- In addition to VKMs performed by each vehicle category, the inputs required are traffic average speeds. - Improved ability to account for congestion through extension of an Average Speed EM.	- Penetration of an ITS intervention also required as input. - New version of an Extended Average Speed EM needs to be calibrated for assessment of each different intervention. - More appropriate for blanket interventions that affect all links at once in a similar fashion. - Ability to account for congestion still limited due to reliance on an Average Speed EM.	- Validation as for ICT-Emissions method 1.
Traffic Situation EMs:			
HBEFA - Refer to Section 2.5.6.1.	- In addition to VKMs performed by each vehicle category, the only inputs required are: road type; and qualitative description of traffic conditions. - Account for congestion is explicit through the qualitative description of traffic conditions.	- Designed specifically to be representative of conditions in Germany, Austria, Switzerland, Sweden, Norway and France. Application in the UK would be questionable.	- Validation concluded that CO_2 emissions can be predicted "quite accurately".
Traffic Variable EMs:			
TEE-KCF - Refer to Section 2.5.7.1.	- Account for congestion is explicit and quantitative through traffic variable inputs.	- Out-of-date vehicle categories (e.g. only up to Euro 1).	- Validation of CO concentrations predicted by a combination of TEE-KCF and ADMS (a dispersion model) against measured concentrations at two sites in a small (0.16 km^2) road network found over-predictions within a factor of 1.5.
SATURN built-in EM - Refer to Section 2.5.7.2.	- Account for congestion is explicit and quantitative through traffic variable inputs. - Traffic variable inputs are generated by SATURN.	- Only one out-of-date vehicle category.	- The user manual states that if the EM "gets to within an order of magnitude of the true answer it will be doing well".
Average Speed Distribution - Refer to Section 2.5.7.3.	- Account for congestion is improved compared to Average Speed EMs through including the variation of vehicle average speeds from the traffic average speed.	- Not been developed into a format useable by LGAs as an EM. - Account for congestion is implicit because the user cannot vary the link-specific average speed distribution.	- Model comparison found that predictions for CO_2 were up to 4% greater than those from the standard application of an Average Speed EM (COPERT 4).
Delay Correction Model (DCM) - Refer to Section 2.5.7.4.	- Account for congestion is explicit and quantitative through traffic variable inputs.	- Only developed to predict emissions for Euro III buses crossing intersections in Beijing.	- Average percentage difference between predicted fuel consumption factors and fuel consumption factors calculated based on VSP distributions from real-world GPS driving patterns was 5.6%.
Monitoring & Prediction of Air Pollution from Traffic in the Urban Environment (Concentration Model) - Refer to Section 2.5.10.2. - UTC.	- Account for congestion is explicit and quantitative through traffic variable inputs. - Traffic variable inputs are generated by SCOOT.	- Model development deemed to be unsuccessful.	- General conclusion of the research was that there is no straightforward relationship between CO concentration and the traffic variables investigated.

Table 2-4 continued.

Emissions Model	Positives	Negatives	Prediction Accuracy
Development of an Emissions Inventory Model for Mobile Sources - Refer to Section 2.5.10.3. - UTC.	- Account for congestion is explicit and quantitative through traffic variable inputs. - Traffic variable inputs are generated by SCATS and CCTV.	- Only included 5 aggregate vehicle categories.	- For validation, predicted emissions (combined with site geometry and meteorological data) were used as inputs to a pollutant dispersion model to predict pollutant concentrations, which were then compared with measured concentrations, with values found to be within 25% of each other.
ESC Model - Refer to Section 2.5.10.5. - UTC.	- Not an EM itself, but a method for better estimating traffic space-mean-speed based on ILD traffic average speed and other traffic variable inputs (e.g. speed limit, access density, etc.). This adjusted traffic average speed was then used as an input to an Average Speed EM (MOBILE). - Account for congestion is explicit and quantitative through traffic variable inputs used to adjust Average Speed EM inputs.	- Investigation was USA-specific. - No validation against real-world traffic average speeds.	- Adjusted traffic average speeds were compared to traffic average speeds in a micro-RTM (assumed to be real-world values), resulting in a MAPE of 6.1%. A similar comparison between unadjusted ILD traffic average speeds and traffic average speeds in a micro-RTM resulted in a MAPE of 8.9%. This meant adjusted speeds were seen as a better estimate of (assumed) real-world values.
NUIDAP - Refer to Section 2.5.10.6. - UTC.	- Account for congestion is explicit and quantitative through traffic variable inputs. - Traffic variable inputs are generated by the SCOOT UTC system.	- Not been developed into a commercially available product. - Details of emissions estimator algorithms are commercially sensitive. - Mote sensors need to be installed throughout a road network.	- Model comparison for CO_2 found that Average Speed EM predicted emissions were 11% less than those of NUIDAP. - Validation of NUIDAP predicted CO concentrations by comparison to mote measured concentrations found a good correlation except during peak traffic periods when predictions had a much sharper peak than measurements.
CARBOTRAF - Refer to Section 2.5.11.2. - ITS.	- Account for congestion is explicit and quantitative through traffic variable inputs. - Traffic variable inputs are generated by ILDs and specialist smart eye Traffic Data Sensors (TDS)	- TDS need to be installed throughout a road network. - CO_2 emissions impact of all possible alternative traffic management options must be pre-calculated (using a micro-RTM and IEM combination) to provide a Look-Up Table database for system operation. - Only applies to assessment of alternative traffic management options.	- No validation details found.
Cycle Variable EMs:			
VERSIT+LD (original version) - Refer to Section 2.5.8.1.	- Account for congestion is explicit and quantitative through cycle variable inputs.	- Requires individual vehicle driving patterns as inputs. - Now been superseded by a newer version which is a Modal EM.	- No validation details found.

Table 2-4 continued.

Emissions Model	Positives	Negatives	Prediction Accuracy
NEMO - Refer to Section 2.5.8.3.	- Account for congestion is explicit and quantitative through cycle variable inputs.	- Requires a driving pattern representative of the traffic as input.	- In model comparison, predictions of NO_X and PM emissions were compared with HBEFA predictions for average driving situations in Austria. For urban driving, NEMO predicted NO_X emissions 10-20% higher and PM emissions 5-30% lower than HBEFA.
Velocity and Payload EM for HGVs - Refer to Section 2.5.8.4.	- Account for congestion is explicit and quantitative through cycle variable inputs (i.e. vehicle average speed is used as a cycle variable input).	- Requires an individual vehicle's driving pattern, gross vehicle mass and percentage of maximum payload as inputs. - Only developed for Euro V HGVs.	- Validation found that predicted emissions corresponded well with measured PEMS data.
Stepwise Speed Function - Refer to Section 2.5.11.4. - ITS.	- Account for congestion is explicit and quantitative through cycle variable inputs.	- Requires a meso-RTM to generate (rudimentary) individual vehicle driving patterns for use as inputs. - Only includes eleven vehicle categories.	Validation compared measured (based on measured fuel consumption for vehicles driven in the real-world) and predicted CO_2 emissions for 13 vehicles on a 1.7km section of urban road in Tokyo. Very good agreement was found (R^2=.99).
Modal EMs:			
VERSIT+LD (modal version) & VERSIT+HD - Refer to Section 2.5.8.1.	- Account for congestion is explicit and quantitative through vehicle mode inputs.	- Requires individual vehicle driving patterns as inputs.	- Validation of VERSIT+LD found the correlation between predicted and measured CO_2 emissions resulted in an average value of R^2=.80. - No validation details found for VERSIT+HD.
EnViVer - Refer to Section 2.5.8.2.	- Account for congestion is explicit and quantitative through vehicle mode inputs.	- Requires VISSIM micro-RTM to generate individual vehicle driving patterns for use as inputs.	- Incorporates a simplified version of VERSIT+, so prediction accuracy is unlikely to exceed that of VERSIT+LD.
MOVES - Refer to Section 2.5.9.1.	- Account for congestion is explicit and quantitative through vehicle mode inputs.	- Requires a driving pattern representative of the traffic as input (but can also automatically select a default driving pattern if traffic average speed and road type are the only available inputs). - USA-specific vehicle categories.	- Validation found reasonable agreement (±25%) between predicted and measured EFs for both CO and NO_X (CO_2 was not analysed).
PHEM - Refer to Section 2.5.9.2.	- Account for congestion is explicit and quantitative through vehicle mode inputs.	- Requires individual vehicle driving patterns as inputs. - Requires detailed vehicle characteristics as inputs (e.g. wheel diameter, transmission ratios). - Requires a driver gear shift behaviour model as input.	- Early validation found predictions showed a "clear and remarkably high conformance" with real-world measurements. - Recent validation found predicted CO_2 emissions were on average 90% of PEMS measured values.

Table 2-4 continued.

Emissions Model	Positives	Negatives	Prediction Accuracy
AIMSUN built-in EM - AIMSUN includes both a fuel consumption model and an EM. - Refer to Section 2.5.9.3.	- Account for congestion is explicit and quantitative through vehicle mode inputs. - Individual vehicle driving pattern inputs are generated by AIMSUN.	- Micro-RTM driving pattern outputs are of uncertain accuracy. - Fuel consumption model only includes default parameters for a very limited number of vehicle categories, and the data (from the 1990s) are now out-of-date. - EM only includes five vehicle categories, and Euro Standards up to Euro 3.	- In model comparison, predictions were compared with predictions from other well-established EMs (COPERT & HBEFA), but results were inconclusive, with large unexplained differences found.
AIRE - Refer to Section 2.5.9.4.	- Account for congestion is explicit and quantitative through vehicle mode inputs. - Distributed free of charge.	- Requires individual vehicle driving patterns as inputs. - Only includes vehicles up to Euro 4/Euro V.	- Validation was achieved through independent verification of outputs by TRL.
Integrated Routing and CO_2 EM for Goods Vehicles - Refer to Section 2.5.9.5.	- User only has to select from three generic driving patterns to use as input (suburban, congested urban, or uncongested urban). - Account for congestion is explicit and quantitative through the choice between the three driving patterns, but this limited choice is unlikely to accurately represent a vehicle's real-world driving pattern.	- Only developed for a generic LGV. - Only a sub-model of a model aimed at optimising routings for goods vehicles, and not intended for separate use.	- No specific validation details found for the sub-model.
Real-Time Microscopic EM - Refer to Section 2.5.10.4. - UTC.	- Account for congestion is explicit and quantitative through vehicle mode inputs. - Individual vehicle driving pattern inputs are generated by SIGSIM.	- Only includes CO emissions. - Vehicle category identification is based on ILD occupancy, vehicle speed and vehicle length, and distinguishes only 3 categories (car, LGV, HGV), of which only cars have their emissions predicted (LGVs and HGVs are assumed to have diesel engines which emit negligible CO).	- The time-series distribution of predicted traffic CO emissions was compared to the time-series distribution of measured roadside CO concentrations (based on the assumption that roadside concentrations would be related to exhaust emissions), with the distributions found to be not statistically significantly different.
Estimating Vehicle Emissions using ILD Data - Refer to Section 2.5.10.7. - UTC.	- Not an EM itself, but a method using enhanced ILDs to estimate traffic space-mean-speed and to identify vehicle category for use as inputs to MOVES.	- Vehicles are categorised according to the US FHWA classification (i.e. USA-specific). - Conventional ILDs need to be upgraded to enhanced ILDs.	- MOVES predictions for CO_2 emissions based on inputs from enhanced ILDs were 1% lower than 'ground-truth' MOVES predictions based on speed data collected from GPS-equipped vehicles.

- For brevity, abbreviated names of some EMs have been used in the table; an EM's full name can be found in the relevant section of the literature review.
- UTC in the Emissions Model column indicates an EM detailed in Section 2.5.10 'Emissions Models Using UTC Data as Inputs'.
- ITS in the Emissions Model column indicates an EM detailed in Section 2.5.11 'Emissions Models to Assess the Impacts of Intelligent Transport Systems'.

2.6.3 Optimal Emissions Model Complexity for LGAs

Resulting from the literature review and based on the ready availability to LGAs of traffic variables, a hypothesis was formed that optimal model complexity for LGAs (i.e. the point beyond which decreasing accuracy of input data begins to offset any accuracy gains through increasing model complexity, refer to Section 2.2.2) is represented by Traffic Variable EMs. This is because using less complex models (i.e. Aggregate, Average Speed or Traffic Situation

EMs) does not fully utilise all traffic variables readily available to LGAs, which offer potential to improve accuracy through explicitly including congestion influence. It has been suggested that including only the influence of vehicle category and speed, and ignoring other influences, could be a simplification that distorts the information supporting policy making (Ligterink *et al.* 2012).

Using more complex models (i.e. Cycle Variable or Modal EMs) requires LGAs to collect and process accurate driving patterns for each vehicle on the network, which is impractical within existing and likely future resource constraints. Even when LGAs invest in micro-RTMs, because they are typically calibrated for aggregate traffic measures (i.e. traffic variables) rather than for individual vehicle driving patterns, there is uncertainty about whether simulated driving pattern outputs are accurately representative of the real-world. A case study by Vieira da Rocha *et al.* (2015) found some evidence that the effect of inaccuracies in simulated driving patterns causing inaccuracies in predicted emissions tends to average-out when lots of driving patterns are used to predict emissions from groups of vehicles. However, even if these findings apply universally, the significant data processing requirements of collecting (accurate or inaccurate) driving patterns for every vehicle in a network, and then inputting them to Cycle Variable or Modal EMs are likely to be off-putting for LGAs.

2.6.4 Emissions Model Options for LGAs

A reason for the prevalence of Average Speed EMs in network emissions modelling is the common availability of traffic average speed data for use as inputs (which should be space-mean-speed, but does not mean attempts aren't made in practice to use time-mean-speed). However, other traffic variables that can be used as indicators of congestion are also readily available to LGAs. Hence, a Traffic Variable EM that includes the influence of congestion is a practical option for LGAs. A further point worthy of reiteration is the advantage of Traffic Variable EMs over Average Speed EMs whereby a Traffic Variable EM can distinguish between different traffic conditions that happen to result in the same average speed. It is also worth noting the possibility that a Traffic Situation EM, which includes the influence of congestion qualitatively, may be able to compete with a Traffic Variable EM in terms of accuracy and resource consumption.

If LGAs want to use Traffic Variable EMs (or Traffic Situation EMs), what options do they have? The examples that have been detailed in this literature review are typical of the options available, and serve to illustrate some of the obstacles that LGAs face. TEE-KCF was a fully developed example of a Traffic Variable EM, but the emissions data on which it is based are now over 10 years out-of-date. In general, out-of-date emissions data are a constant problem for EMs. As vehicle and fuel technologies improve, and emissions regulations become stricter (e.g. the Euro 6 Standard for LDVs came into force on 1st September 2014 for new type approval, and applied to the registration and sale of all new vehicles from 1st January 2015), the emissions profile of the vehicle fleet changes. To address this, the calibration process for EMs must be updated and repeated at regular intervals (e.g. a five year interval between Euro 5 and Euro 6).

The application of average speed distributions by Smit *et al.* (2008b) was a case study investigation, which has not been developed into a format useable by LGAs as an EM. Development of the DCM by Song *et al.* (2015) was accomplished for buses traversing intersections in Beijing, China. Therefore, it would need extension to cover other vehicle categories, traversing links as well as intersections, in other global regions, before it can have wider application. NEMO has not achieved traction as a widely used EM, and has not replaced the wide-spread use across Europe of COPERT and HBEFA.

Both HBEFA (in Europe) and MOVES (in the USA) are fully developed, up-to-date EMs that are currently used by LGAs. However, both would require extension to be useable in other global regions (such as the UK). In general, transferability is an obstacle to be overcome when considering an EM developed in one global region for application in another. This is because vehicle category classifications can be markedly different between regions and there is often no easy way to map between them. Even within a given global region (e.g. Europe) where the system of vehicle category classification is standardised, transferability between sub-regional areas (e.g. European countries) may not be straightforward. The reason for this relates to inter-country differences in factors such as network characteristics, traffic management strategies or vehicle fleet compositions.

Reynolds (1996) attempted to predict roadside CO concentrations based on traffic variables output from SCOOT. Unfortunately, no relationship could be established, and no model was produced. Whilst this work concerned a different pollutant, and concentrations rather than emissions, the results suggest it may prove difficult to develop a Traffic Variable EM for CO_2 based solely on outputs from a UTC system. The development of NUIDAP included an emissions estimator which was a Traffic Variable EM, but has not yet reached the stage of being a commercially available product. Additionally, having been developed in collaboration with Amey plc, the details of the algorithms used to estimate emissions from UTC system outputs (i.e. SCOOT message data) are commercially sensitive (Bell 2016), and therefore unlikely to be freely available for use by LGAs. Rather than UTC system outputs, Jeng *et al.* (2013) investigated the use of 'raw' enhanced ILD data. However, this study was not aimed at developing an EM itself, but was a method to provide more accurate road traffic input data to existing EMs, and additionally requires LGAs to invest in upgrading conventional ILDs to enhanced versions. Similarly, the ESC model developed by Nesamani *et al.* (2007) was designed to provide more accurate estimates of traffic average speeds based on ILD average speed data (and other link characteristics) for use as inputs to existing EMs.

CARBOTRAF is a Traffic Variable EM predicting network CO_2 emissions. However, CARBOTRAF is pre-loaded with a database of network CO_2 emissions for each alternative intervention (in CARBOTRAF these are alternative traffic management options), which have been pre-calculated using driving patterns from a micro-RTM as inputs to an IEM. CARBOTRAF works because the range of alternative traffic management options is limited, allowing their emissions to be pre-calculated. Extending CARBOTRAF to assess an open-ended range of interventions would entail assessing each alternative with a micro-RTM and an IEM, which is just the kind of resource-intensive process likely to be beyond LGA budgets. Also, CARBOTRAF is reliant on the specialist TDS, which would require LGAs to meet associated installation costs.

ICT-emissions proposes two methods for including changes to vehicle dynamics in network-level emissions modelling, both based on Average Speed EMs. However, as both methods rely on the assumption that a micro-scale effect can be extrapolated across a network as a whole, they are more appropriate for blanket interventions that affect all links at once in a similar fashion (e.g. area-wide promotion of eco-driving) rather than for interventions that affect different links in different ways (e.g. altering signal timings on certain links). Additionally, the first method assumes the impact on emissions of changes to driving patterns can be adequately captured by changes to speed-flow-density relationships and an Average Speed EM; and the second method requires the resource-intensive process of constructing an extended Average Speed EM to be repeated for each alternative intervention.

It could be argued that if an LGA has invested in building a Road Traffic Model (RTM), then an efficient way to calculate emissions would be to use the RTM's built-in EM (if it has one). However, built-in EMs come with problems. For example, the distributors of SATURN suggest that the built-in Traffic Variable EM is extremely crude, and that emissions predictions would be best handled using a stand-alone EM (Atkins Limited 2014). The AIMSUN built-in IEM highlights another problem, which is the mismatch in vehicle category disaggregation between RTMs and EMs (Toffolo *et al.* 2013). RTMs are typically only concerned with highly aggregate vehicle categories; whereas, to accurately predict emissions, EMs are typically concerned with highly disaggregate vehicle categories. The AIMSUN IEM provides emission functions for only five aggregate vehicle categories, which is consistent with the vehicle category aggregation one might expect in RTMs (TSS 2013). It is possible to define many more vehicle categories in AIMSUN, each with different emission functions. However, acquiring the data to define all the emissions-related characteristics of each new vehicle category would be a substantial task. Additionally, a large increase in the number of vehicle categories would entail a large increase in complexity of O-D demand matrices in order to accurately represent the proportion of vehicles in each category travelling between each origin-destination pair. A further problem that affects micro-RTMs with built-in Modal EMs is the aforementioned issue of micro-RTM calibration and validation for aggregate traffic variables rather than for accurate driving patterns (refer to Section 2.4.4), leading to uncertainty about the simulated driving patterns used as inputs to the built-in Modal EM.

The examples discussed in this section demonstrate that extant methodologies in the domain of predicting network emissions based on traffic variables typically have (to a greater or lesser extent) limitations. These must be addressed if an EM that explicitly includes congestion, whilst remaining within LGA resource constraints, is to be widely established.

2.6.5 Research Gap Identification

The hypothesis that a Traffic Variable EM is the optimal model complexity for LGAs was based on qualitative literature review results. It was not possible to quantitatively assess this hypothesis through a literature review because there have been only limited attempts at EM validation and quantification of prediction errors (Kousoulidou *et al.* 2013a). A meta-analysis by Smit *et al.* (2010) provided a general review of studies dealing with EM validation and concluded that there was limited literature relating to the subject. In the literature that was reviewed during the meta-analysis (50 studies), five EMs appeared frequently, which was a reflection of their common use. These EMs, which together constituted 65% of the studies reviewed, were MOBILE (18%), COPERT (16%), HBEFA (13%), EMFAC[100] (9%) and EMs from the ARTEMIS project (9%). A common feature of the validation attempts described was that they were often for localised studies, i.e. for specific local traffic conditions during relatively short time periods (hours or days). Consequently, these studies were restricted to partial validation of EMs, and cannot be extended to provide an overall, complete validation. This led the study authors to conclude that “there is inadequate understanding of the uncertainties in traffic emission models and the main factors affecting prediction errors”. Subject to the preceding caveats, for the 50 studies reviewed, the average prediction errors for CO_2 were generally found to be within a factor of 1.3 of the measured values. Another, interesting finding of the meta-analysis was that there was no conclusive evidence for more complex EMs systematically predicting emissions with more accuracy than less complex EMs. Part of the explanation for this could be that more complex EMs are being used with input data at less than ideal accuracy, i.e. accuracy gains from decreasing specification error (e_s) are offset by increasing measurement error (e_m).

In general, research is required into the comparative accuracy of Average Speed, Traffic Situation and Traffic Variable EMs (EMs likely to be useable within LGA resource constraints) before the hypothesis can be assessed quantitatively, and this was the research gap identified for this project. More specifically, because of its focus on UK LGAs, the scope of this project was defined as developing a new CO_2 Traffic Variable EM, and then comparing the accuracy of its emissions predictions with that of the existing Average Speed EM recommended for use by LGAs in the UK (i.e. TRL EFs 2009 as the basis of the DfT Basic Local Authority Carbon Tool). In other words, investigation into whether the new Traffic Variable EM represented optimal complexity for LGAs, improving on the ability of the existing Average Speed EM to capture the influence of congestion, whilst remaining within resource constraints. During this investigation, it was possible that the existing Average Speed EM would prove equivalent to the new Traffic Variable EM, but evidence from the USA where the EPA felt that MOBILE (Average Speed EM) needed replacing with the more detailed MOVES suggested the research was worth pursuing.

As a final point, the examples detailed in Section 2.5.12 provided insight into the various ways in which LGAs use the outputs of EMs to inform policy making. However, the examples also

[100] EMission FACtors (EMFAC) is an Average Speed EM and is the tool used by the California Air Resources Board's for estimating emissions from road vehicles.

demonstrated that use of EMs tends to vary from LGA to LGA. Overall, from the literature review it was difficult to gain a full appreciation of the general situation regarding current attitudes and practices of LGAs concerning the road traffic emissions modelling process. Therefore, a survey was considered necessary to investigate which methods for predicting CO_2 emissions were considered practical by all (or the majority of) LGAs. This survey is described in Chapter 4.

The following research questions were formulated based on the identified research gap:

1. What data and models are currently used by LGAs for road traffic CO_2 emissions modelling, and what are their attitudes to the issues of resource use and prediction accuracy?
2. Is it possible to identify traffic variables as indicators of congestion that have a consistent relationship with CO_2 emissions from road traffic, and that are readily available to LGAs?
3. By virtue of being readily available, is it possible to use such traffic variables, in addition to traffic average speed, to explicitly include congestion influence and improve the accuracy of urban network CO_2 emissions predictions compared to predictions from EMs based solely on average speeds, whilst avoiding a substantial increase in model complexity and remaining a tractable tool for use by LGAs in transport intervention assessments?

2.7 CONCLUSIONS

The principal conclusion of the literature review was that the qualitative evidence indicated that LGAs do not necessarily have the right options to accurately include the effects of congestion on emissions of CO_2 (or other pollutants) from traffic on urban road networks. Based on readily available road traffic data, the hypothesis was put forward that the optimal model complexity for LGAs is a Traffic Variable EM. More complex models, that calculate emissions for individual vehicles, were discounted as an option because they require driving patterns as inputs, which are difficult to collect, rarely used in traffic engineering to describe road network performance, and simulated with questionable accuracy in micro-RTMs.

In contrast, traffic variables are used to describe network performance and are more readily available to LGAs. Average Speed and Traffic Situation EMs were both viable options for LGAs because they use traffic variables as inputs, are well established, and are less complex than Traffic Variable EMs. However, they may not fully realise the explanatory power of all traffic variables available to LGAs, which could be used to explicitly include congestion influence and improve emissions prediction accuracy. Unlike Average Speed EMs which are well established in the UK (e.g. TRL EFs 2009), the main example of a Traffic Situation EM (HBEFA) is well established only in certain other European countries and was discounted (from the perspective of this project's scope) as an option.

Whilst the superiority of Traffic Variable EMs over Average Speed EMs in terms of accuracy has not been established quantitatively, there was enough qualitative evidence in the literature to conclude that this subject warranted further research. Therefore, this project investigated the prediction of network CO_2 emissions by a Traffic Variable EM, and compared this quantitatively with predictions based on the DfT's recommended Average Speed EM, in order to determine whether (or not) the traffic variable approach was justified.

Chapter 3 OVERALL PROJECT METHODOLOGY

3.1 INTRODUCTION

The purpose of Chapter 3 (this chapter) is to provide an overview of the entire project methodology in order to assist the reader in navigating this thesis. In general, a brief introduction has been provided to the various constituents of the overall project methodology, along with references to other sections of the thesis where more detailed explanations can be found. This short chapter has been divided into two main sections. An outline of the overall project methodology is presented in Section 3.2 and conclusions provided in Section 3.3.

3.2 OUTLINE OF THE OVERALL PROJECT METHODOLOGY

3.2.1 Project Methodology Flow Chart Series

An outline of the overall project methodology has been provided to describe (in brief, with reference to fuller explanations elsewhere in the thesis) the processes that were accomplished to move from the initial project objectives through to the final project results and outcomes. Also provided are four figures that depict the overall project methodology as a series of increasingly detailed flow charts. The first flow chart in the series (Figure 3-1) depicts the macro-process of the overall project methodology. For the three subsequent flow charts the reader is directed to Chapter 5 (because the more detailed flow charts were better placed later in the thesis in closer proximity to the more detailed accompanying explanatory text). The second flow chart in the series (Figure 5-1) depicts a more detailed expansion of the PEMLA development methodology meso-process (shown by the dot-dashed line in Figure 3-1). The third and fourth flow charts (Figure 5-2 and Figure 5-3, respectively) depict even more detailed expansions of the two parallel data collection micro-processes (micro-processes A and B shown by the dashed lines in Figure 3-1).

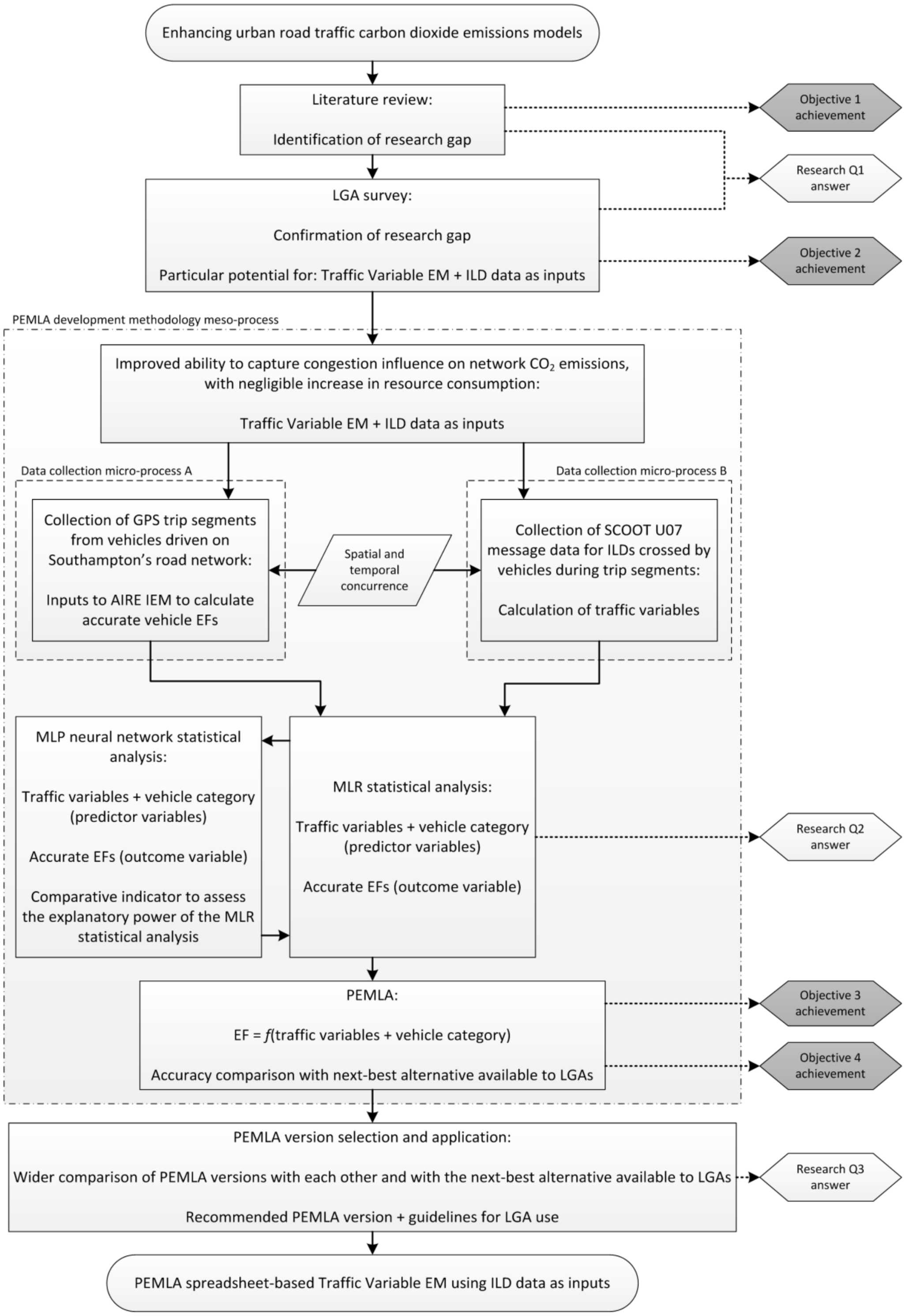

Figure 3-1: Flow chart of the overall project methodology macro-process.

- ILD is Inductive Loop Detector.
- The SCOOT U07 message contains data returned by each ILD in the UTC system (refer to Section 5.4.2.1).
- Analysis of Instantaneous Road Emissions (AIRE) is an Instantaneous Emissions Model (IEM) (refer to Section 2.5.9.4).
- MLR is Multiple Linear Regression (refer to Section 5.5.1.1).
- MLP is Multilayer Perceptron (refer to Section 5.5.1.3).
- Practical Emissions Model for Local Authorities (PEMLA) is the new EM developed during this project.

3.2.2 Literature Review and LGA Survey

The aim of this project was to provide a more accurate representation of road traffic CO_2 emissions in urban areas, whilst remaining within limited LGA resource budgets (refer to Section 1.1). Initially, an extensive review was conducted of the literature concerning the factors that influence road traffic CO_2 emissions, the potential sources of road traffic data for use in the emissions modelling process, and the practicalities of the use of such data by LGAs in EMs. This literature review is detailed in Chapter 2.

As a result of the literature review a research gap was identified (refer to Section 2.6.5) which can be formally stated as follows:

> *An investigation into whether a Traffic Variable EM represented optimal complexity for LGAs, improving on the ability of well-established Average Speed EMs to capture the influence of congestion on emissions, whilst remaining within resource constraints.*

As explained in Section 2.2.2, in the research gap statement the phrase 'optimal model complexity for LGAs' is defined as the point beyond which decreasing accuracy of input data (i.e. increasing measurement error) begins to offset any accuracy gains through increasing model complexity (i.e. decreasing specification error). The three research questions that constituted the framework for this project (refer to Section 2.6.5) were formulated based on the identified research gap. Completion of the literature review allowed Project Objective 1 to be achieved (refer to Section 1.1).

Overall, from the literature review alone it was difficult to gain a full appreciation of the general situation regarding current attitudes and practices of LGAs concerning the road traffic emissions modelling process (refer to Section 2.6.5). Therefore, a survey was considered necessary to investigate which methods for predicting CO_2 emissions were considered practical by all (or the majority of) LGAs. This case study survey of British LGAs is described in Chapter 4.

The results from the survey were consistent with the research gap identified during the literature review, in that Traffic Variable EMs were recognised as having the potential to improve the accuracy of emissions predictions, based on inputs obtained from readily available road traffic data sources. In particular, two sources of traffic variables rated highly for convenience by survey participants were UTC systems (i.e. ILD data) and Road Traffic Models (RTMs) (refer to Section 4.4). Completion of the survey allowed Project Objective 2 to be achieved (refer to Section 1.1) and Research Question 1 to be answered (refer to Section 2.6.5).

3.2.3 PEMLA Development Methodology

Two key findings from the combined results of the literature review and the LGA survey were: (1) Traffic Variable EMs were identified as potentially offering an improved ability to capture congestion impacts compared to the widely used alternative of Average Speed EMs, through including other traffic variables (in addition to traffic average speed) as quantifiable measures of congestion, with little associated increase in complexity; and (2) ILDs were identified as a readily available source of these traffic variables, where collection does not entail additional expenditure of resources by or on behalf of LGAs.

Based on these two findings, project investigations sought to develop a new CO_2 Traffic Variable EM (termed the Practical Emissions Model for Local Authorities, PEMLA) based on ILD inputs, and then to compare the accuracy of its emissions predictions with those of the existing Average Speed EM recommended for use by LGAs in the UK (TRL EFs 2009 Average Speed EM[101] as the basis of the DfT Basic Local Authority Carbon Tool, refer to Section 2.5.5.1 and Section 2.5.5.2, respectively).

The first step in the PEMLA development methodology was to create a manageable number of vehicle categories for PEMLA, with the target being to reduce by approximately an order of magnitude the number of categories found in the (highly disaggregated) NAEI national fleet model (over 200 categories, refer to Figure 2-5). This was done for practicality reasons, both in the analyses conducted within the resources of this project and in the future use by LGAs of PEMLA, and resulted in 24 PEMLA vehicle categories (refer to Section 5.2.2 and Table 5-1).

3.2.3.1 Data collection

Southampton's road network was used as a test bed for collection of the data used to calibrate PEMLA. Two parallel (and matched) data collection and manipulation processes were employed: (1) calculation of accurate vehicle EFs from GPS driving patterns (micro-process A in Figure 3-1); and (2) calculation of traffic variables from ILD data (micro-process B in Figure 3-1).

GPS loggers were sent out with volunteers (refer to Section 5.3.4.1) to record the traces of their journeys as they drove their different types of vehicles around Southampton. The

[101] From Chapter 5 onwards in this thesis reference is often made to TRL/NAEI EM rather than TRL EFs 2009 Average Speed EM. As explained in Section 5.2.2, TRL/NAEI EM denotes the TRL average speed emission functions for each vehicle category (i.e. TRL EFs 2009 Average Speed EM), weighted by the NAEI national fleet model predictions for each category's fraction of total national VKMs on urban roads in England outside London in 2016. Therefore, any comparison with TRL/NAEI EM constitutes comparison with TRL EFs 2009 Average Speed EM.

different types of vehicles defined for GPS data collection were LDVs, HDVs (except buses), buses, and two-wheel vehicles (refer to Section 5.3.3).

A trip segment was adopted as the unit of observation and defined as follows (refer to Section 5.3.2.1):

> *Any segment of the GPS trace collected from a test vehicle's trip that runs continuously between two intersections along the course of at least two links, and crosses at least one operational ILD*.

Trip segments were extracted from the GPS traces of vehicles in accordance with this definition (refer to Section 5.3.4.4). A map depicting examples of GPS trip segments and the ILD(s) that they crossed has been provided, with the map divided into two parts (for clarity): Figure 3-2 shows northern and central Southampton and Figure 3-3 shows eastern Southampton.

For calculation of accurate vehicle EFs (micro-process A in Figure 3-1), a driving pattern (1Hz speed-time profile) was collected from the GPS data for each trip segment (refer to Section 5.3.4.4). After some manipulation (refer to Section 5.3.5.2), these GPS trip segment driving patterns were used as input files to AIRE (a detailed Instantaneous EM, refer to Section 2.5.9.4) to calculate accurate total CO_2 emitted for each trip segment, which was then converted to an EF (gCO_2/VKM) by dividing total emissions (gCO_2) by trip segment length (km) (refer to Section 5.3.5.3). Accurate EFs for two-wheel vehicle GPS trip segment driving patterns were calculated using an alternative method because AIRE does not include any two-wheel vehicle categories (refer to Section 5.3.5.4).

GPS trip segment driving patterns collected from LDVs were used to calculate accurate EFs for all PEMLA LDV vehicle categories (categories 01 to 19 in Table 5-1); those collected from HDVs were used for all PEMLA HDV vehicle categories except buses (categories 20, 21 and 23 in Table 5-1); those collected from buses were used for the PEMLA bus vehicle category (category 22 in Table 5-1); and those collected from two-wheel vehicles were used for the PEMLA two-wheel vehicle category (category 24 in Table 5-1) (refer to Section 5.3.3).

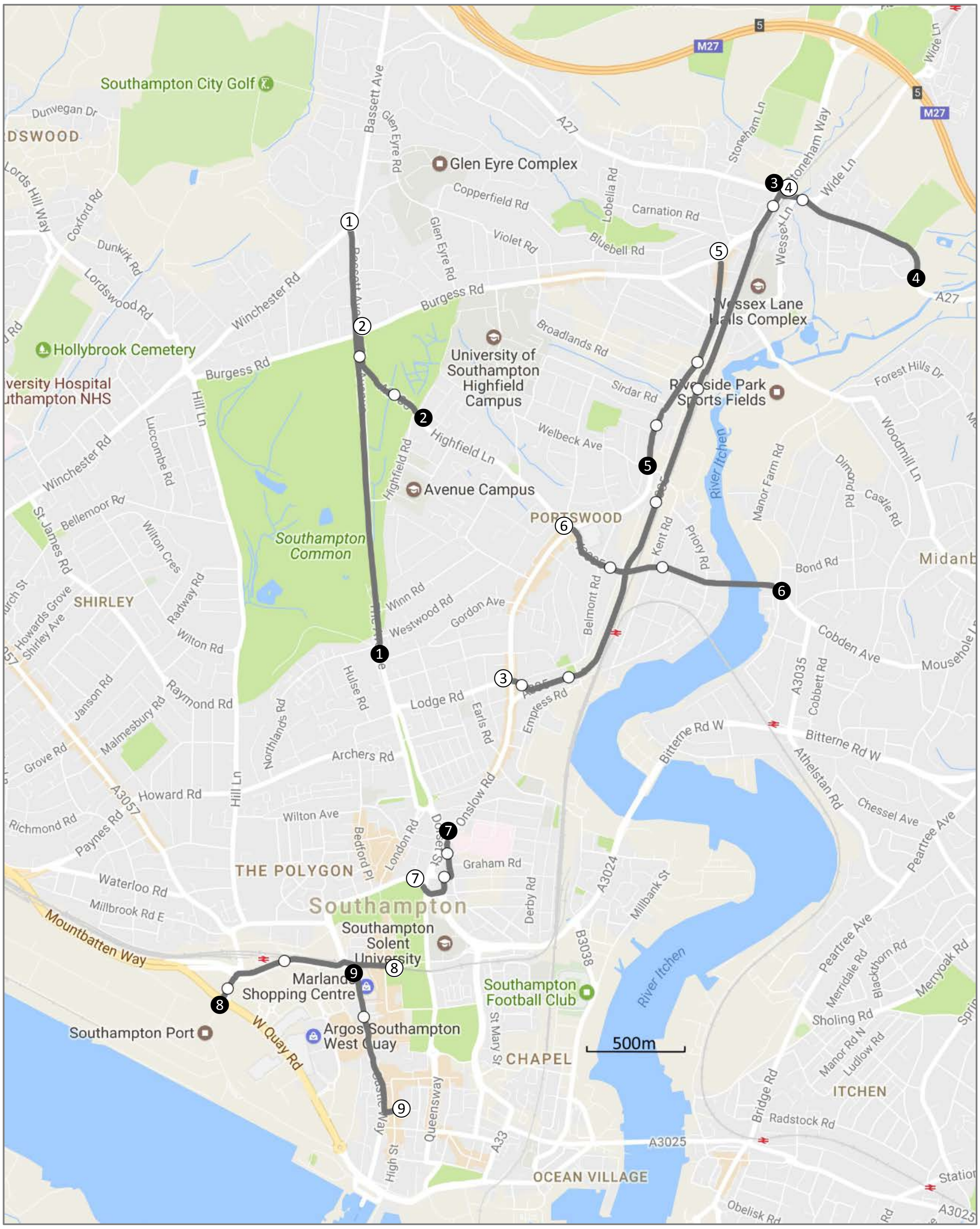

Figure 3-2: Map of example trip segments collected in the northern and central regions of Southampton.

- GPS traces of trip segments performed by vehicles are shown by thick grey lines.
- Plain white circles show the positions of Inductive Loop Detectors (ILDs) crossed by vehicles during trip segments.
- Numbered black circles indicate the start of trip segments, and numbered white circles indicate the end of trip segments.
- Scale bar indicates a distance of 500 metres.
- Source: Base map obtained from Google Maps.

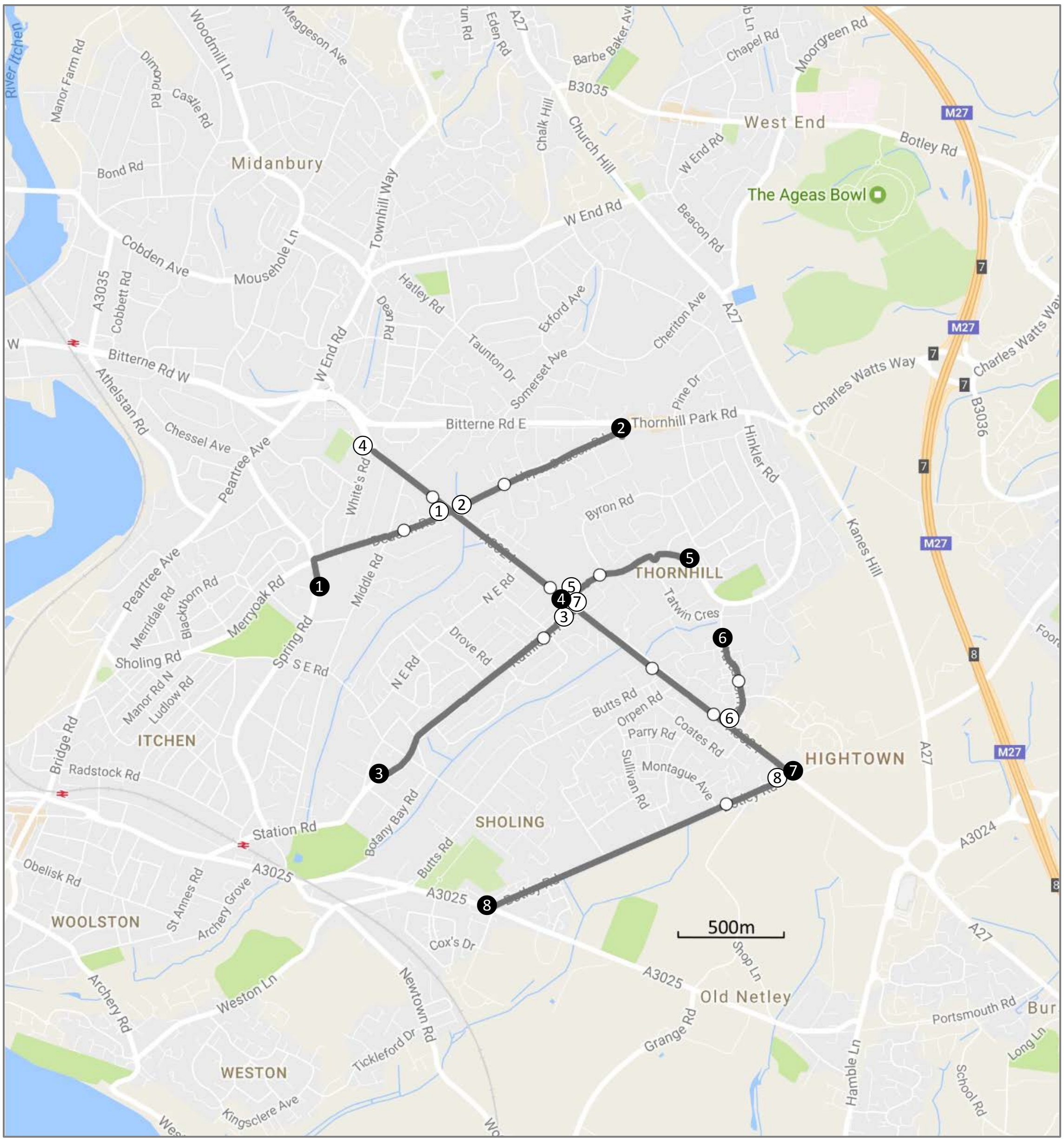

Figure 3-3: Map of example trip segments collected in the eastern region of Southampton.

- GPS traces of trip segments performed by vehicles are shown by thick grey lines.
- Plain white circles show the positions of Inductive Loop Detectors (ILDs) crossed by vehicles during trip segments.
- Numbered black circles indicate the start of trip segments, and numbered white circles indicate the end of trip segments.
- Scale bar indicates a distance of 500 metres.
- Source: Base map obtained from Google Maps.

For calculation of traffic variables (micro-process B in Figure 3-1), the initial step was to select the set of traffic variables that were investigated with regard to their ability to predict EFs. Five traffic variables were selected which characterised the traffic conditions at the time each trip segment was performed. They were traffic average speed (km/h), traffic average speed squared $(km/h)^2$, traffic density (vehicles/km), traffic average delay rate (s/vehicle.km) and access density (intersections/km) (refer to Section 5.4.1).

The source of ILD data, from which values for the five traffic variables were calculated, was the SCOOT UTC system U07 message (refer to Section 5.4.2.1). An audit of the U07 message revealed that there were many non-operational ILDs (i.e. not returning any data) in Southampton's SCOOT system, which therefore restricted locations where suitable trip segments that crossed operational ILDs (i.e. in accordance with the trip segment definition) could be collected (refer to Section 5.4.2.2).

The daily U07 message contains, *inter alia*, an estimate of traffic average speed (time-mean-speed) and vehicle count for every five minute period (from midnight to midnight) for each ILD in the network (except non-operational ILDs) (refer to Section 5.4.2.1 and Section 5.4.2.2). These two pieces of information, ILD traffic average speed (km/h) and ILD traffic flow (vehicles/5 minutes), were used to calculate values for the five traffic variables (except access density which was calculated by map inspection) (refer to Section 5.4.3).

The GPS trip segments were matched to the ILD data using the spatial location and time of day of a trip segment (taken from the GPS data) to extract from the U07 message the required data from the ILD(s) crossed during the trip segment at the relevant time. A weighted average of the traffic variable values calculated from the data from the ILD(s) crossed over the length of a trip segment was then used to calculate a single value for each traffic variable for each trip segment (refer to Section 5.4.5).

At the end of the two parallel data collection and manipulation processes, the collected dataset constituted: for each of the 24 PEMLA vehicle categories, a set of at least 110 trip segment samples (approximate minimum sample size required for the statistical analysis, refer to Section 5.5.1.2), each associated with an accurate vehicle EF (calculated from AIRE using a GPS driving pattern) and a value for each of the five traffic variables (calculated from the matched U07 ILD data).

3.2.3.2 Statistical analysis

The two parallel data collection processes were brought together through statistical analysis, which was used to explore relationships between the traffic variables (predictor variables) and accurate EFs (outcome variable), ultimately leading to the calibration of PEMLA. The primary method selected for the analysis was Multiple Linear Regression (MLR) because it is a widely used method for exploring relationships between a set of predictor variables and an outcome variable, it is very well understood mathematically, its results are easily interpreted (e.g. it is easy to see how a change in a predictor variable affects the outcome variable), and it has been widely used in the calibration of different EMs (refer to Section 5.6).

An initial appreciation of the ability of the traffic variables to predict EFs was gained during the preliminary statistical analysis, where four representative PEMLA vehicle categories (category 22 representing buses; category 20 representing HDVs except buses; category 01 representing LDVs; and category 24 representing two-wheel vehicles) were analysed individually (refer to Section 5.5.2). In general, the results of the preliminary analysis suggested that the five traffic variables measured during the project possessed only moderate performance as predictors of EFs. Therefore, during the principal statistical analysis, it was decided to incorporate vehicle category as an additional predictor variable, and to perform MLR analysis on a single dataset constituting the combined data for all 24 PEMLA vehicle categories (refer to Section 6.4.1).

The principal statistical analysis produced six versions of PEMLA, all calibrated using MLR analysis. The first three versions (v.1 to v.3) investigated three different methods of incorporating vehicle category as an additional predictor variable (refer to Section 5.5.3.1). Following comparison of the three methods (refer to Section 7.2.2), PEMLA v.3 was identified as having the greatest potential. Therefore, three further versions of PEMLA (v.4, v.5 and v.7) were subsequently developed based on the PEMLA v.3 calibration method. These further PEMLA versions sought to investigate solutions to the violation of certain assumptions that underpin MLR (refer to Section 5.5.3.3) evident in the calibration of PEMLA v.3 (PEMLA v.4 and v.5 both investigated violation of the assumption of homoscedasticity, refer to Section 6.4.3.1 and Section 6.4.3.2, respectively; and PEMLA v.7 investigated (the less serious) violation of the assumption of normally distributed residuals, refer to Section 6.4.3.3). Completion of the MLR statistical analysis allowed Research Question 2 to be answered (refer to Section 2.6.5).

For each PEMLA version calibrated by MLR analysis, a parallel Multilayer Perceptron (MLP) neural network statistical analysis was also performed as a comparative indicator to assess the explanatory power of the associated MLR analysis through comparison of the respective values for the coefficient of determination (R^2) for the MLR and MLP analyses (refer to Section 5.5.1.3). This was because it is possible for complex data relationships to go undetected when analysis is performed using standard conventional statistical methods such as MLR. In contrast, MLP can represent relationships between predictor and outcome variables that are unconstrained by assumptions such as those that underpin MLR analysis (refer to Section 5.5.3.3). Therefore, comparison of R^2 values allowed the extent to which any explanatory power was being lost due to the more restrictive constraints of MLR assumptions to be assessed (refer to Section 5.5.1.3). Despite its more restrictive assumptions, MLR was preferred as the primary statistical analysis method. MLP served only as a comparative indicator because it is more of a 'black box' method in that it is not as easy to interpret results or see the significance and effect of predictor variables (refer to Section 5.6).

3.2.3.3 Accuracy Comparison

The final part of the PEMLA development methodology was to compare the prediction accuracy of each PEMLA version to that of the next-best alternative EM available to UK LGAs (refer to Section 5.5.5), i.e. comparison to TRL EFs 2009 Average Speed EM as the officially recognised EM recommended for use in the UK and the basis of the DfT Basic Local Authority Carbon Tool (refer to Section 2.5.5.1 and Section 2.5.5.2, respectively). Results showed that PEMLA v.7 mean predictions (the PEMLA version ultimately recommended for LGA use, refer to Section 7.2.4) were 2% greater than observed values, while TRL EFs 2009 Average Speed EM predictions were 12% less (refer to Table 6-20). Completion of the accuracy comparison allowed Project Objectives 3 and 4 to be achieved (refer to Section 1.1).

3.2.4 PEMLA Version Selection and Application

In addition to the quantitative assessment of the prediction accuracies of the PEMLA versions in comparison to TRL EFs 2009 Average Speed EM conducted during the PEMLA development methodology (refer to Table 6-20), an extensive, wider discussion of the advantages, disadvantages and limitations associated with the application of the PEMLA versions in comparison to each other and in comparison to TRL EFs 2009 Average Speed EM was completed. This wider discussion is detailed in Chapter 7. During the discussion, PEMLA v.7 was identified as the version recommended for LGA use and its performance therefore examined in detail (refer to Section 7.2.4).

Conclusions drawn from the wider discussion, and from the project as an overall whole, are detailed in Chapter 8. One of the most important conclusions was that PEMLA v.7 represented an EM closer to optimal complexity for LGAs than TRL EFs 2009 (refer to Section 7.3.1 and Section 8.2). This conclusion was based on a combination of two factors: (1) PEMLA v.7 out-performed TRL EFs 2009 in accuracy comparison (refer to Table 6-20) through using as inputs other traffic variable congestion indicators (in addition to traffic average speed), which provided an improved ability to capture the influence of congestion on emissions; and (2) traffic variable inputs to PEMLA v.7 (except access density) are calculated from ILD data that are considered a by-product of UTC systems, meaning they are readily available to LGAs and their re-purposing as EM inputs is an efficient use of resources, and operation of PEMLA therefore will be within LGAs' limited resources and no more expensive than TRL EFs 2009 Average Speed EM. In short, PEMLA v.7 provides improved accuracy without increased resource consumption. Completion of the wider discussion and the recommendation of PEMLA v.7 as suitable for LGA use in predicting network level CO_2 emissions allowed Research Question 3 to be answered (refer to Section 2.6.5).

3.3 CONCLUSIONS

The purpose of Chapter 3 (this short chapter) was to provide the reader with an overview of the entire project in order to facilitate navigation and understanding of this thesis. The various processes within the overall project methodology have been introduced and briefly explained, alongside references directing the reader to other thesis sections containing more detailed explanations. Also provided was an indication of how completion of the various project processes enabled the initial aim and objectives of the project (refer to Section 1.1) to be achieved and answers to the research questions that formed the framework for this project (refer to Section 2.6.5) to be realised.

Chapter 4 LGA ROAD TRAFFIC EMISSIONS MODELLING SURVEY

4.1 INTRODUCTION

The initial step in investigating the hypothesis that a Traffic Variable EM represents optimal model complexity for LGAs (i.e. the point beyond which decreasing accuracy of input data begins to offset any accuracy gains through increasing model complexity, refer to Section 2.2.2) was to establish LGAs' current practices and attitudes concerning the emissions modelling process, i.e. to answer Research Question 1. As the literature review has demonstrated, existing EM methodologies range from less detailed, aggregate approaches based on traffic as a whole (i.e. traffic variable inputs) to highly detailed, disaggregate approaches based on individual vehicles (i.e. driving pattern inputs), with more detail normally entailing higher resource consumption for data collection and processing. However, an absence of research specifically investigating the practicalities of LGAs engaging in emissions modelling has been found (Grote *et al.* 2016a), and it was not clear which of the available approaches they can afford to utilise and which they ignore. Therefore, a survey was designed to discover the level of detail considered practical by British LGAs (n=34) within their limited resources. Strategies for mitigating climate change must tackle the problem of road traffic GHG emissions, with LGAs in all countries having an important role, and understanding their requirements is essential if practical options for estimating emissions are to be developed and gain traction.

It was not possible within the constraints of this project to provide a full analysis of the transferability of the results from the case study survey of Britain. However, previous research into the governance of transport and climate change by Marsden and Rye (2010) concluded that, although decision-making structures may be different in other countries, issues concerning delivery of strategies to tackle climate change were not solely dependent on the formal institutional structures in a country and so "the cases of England and Scotland will have some parallels to other locations"[102].

[102] Whilst Wales is not included in this quote, the comparison has merits because England and Scotland together comprise 184 out of the total for Britain of 206 LHAs.

Details of the survey have been divided into four main sections. Section 4.2 explains the survey method. Survey results are presented in Section 4.3, and those results are discussed in Section 4.4. Section 4.5 details the conclusions of the survey. (An abridged version of the research detailed in this chapter can be found in the published journal article by Grote *et al.* (2016b), which is included as Appendix B).

4.2 METHOD

4.2.1 Participants and Survey Design

LGA personnel constitute a combination of councillors who are elected to decide policy on behalf of the electorate, and officers who have the expertise to translate policy into practice (Meek *et al.* 2010). Prerequisites for meaningful survey responses were that participants had expertise, experience and detailed familiarity with road traffic data and emissions modelling. As elected councillors were unlikely to meet such requirements, a decision was made to survey only officers. After consultation with the Local Government Association, a UK public sector database specialist (Oscar Research Ltd) was employed to provide at least one named, senior highways officer contact for each of the 206 LHAs in Britain, giving a total of 376 potential participants. An online questionnaire survey compiled in the iSurvey format (a University of Southampton research tool for distributing online questionnaires) was selected as the most effective method to reach this number of potential participants in the time available, with a cross-sectional survey design being appropriate for gathering data on current LGA attitudes to CO_2 emissions modelling. A paper copy of the questionnaire survey is included as Appendix C. The data gathered by the questionnaire were intended to be statistically analysed and reported. Therefore, closed rather than open questions were used (i.e. including response choices, which produced either categorical or ordinal variables). However, a free-text 'Further Details' box was offered at the end of some questions (Oppenheim 1992; Fink 2003a; Fink 2003b). It is accepted that this survey design was unlikely to capture the full nuanced picture of LGAs' attitudes. However, in line with the objectives of this project to investigate methods for predicting CO_2 emissions useable by all (or the majority of) LGAs (refer to Section 1.1), an indication of the general situation was sought, rather than the nuances which are likely to vary from LGA to LGA. To fully capture nuances, a more in-depth (and more time-consuming) survey design would have been necessary (e.g. a telephone or Skype interview survey). The automated iSurvey reminder email facility, followed by 3 further reminder emails sent manually, were used to maximise rates of response. Finally, those that had shown any interest (by opening the URL link to the survey) but not completed the questionnaire were contacted by telephone in an attempt to encourage participation.

4.2.2 Survey Questions

The relative importance of factors affecting allocation of resources to emissions modelling was established by asking participants to indicate the extent of their agreement with nine different statements, each asserting that a particular factor was important. An ordinal five-point Likert scale was used for responses (Strongly disagree, Disagree, Neither agree nor disagree, Agree, Strongly agree). Scores were assigned from Strongly disagree=0, through to Strongly agree=4.

EMs require road traffic data as inputs, and resources must be expended on collection of these data. In general, using convenient sources of such data minimises expenditure. Details of the numerous different sources of road traffic data about which participants were questioned can be found in Section 2.4. Three questions in the survey were concerned with road traffic data sources. The first established the perceived convenience of data sources by asking participants to select one categorical response that best described their opinion of the availability of data from each source. In the second, participants were asked to indicate all time periods when (if ever) data from each source had been routinely collected by (or on behalf) of their organisation. An additional time period response category was added to this question of 'Planned for future collection' because road traffic data to which LGAs have access 'going forward' are the most convenient for use in future emissions modelling. The third question examined in more detail LGAs' use of Road Traffic Models (RTMs). This was for three reasons: (1) where LGAs have invested in RTMs, the outputs are likely to be a convenient source of EM input data; (2) the type of RTM used (macro/meso/micro) affects the detail of data available as EM inputs; and (3) some RTMs incorporate their own built-in EM. Participants were asked whether or not they had used different RTM software applications. If an RTM had been used, participants were asked to select from categorical responses to indicate when it was last used by (or on behalf) of their organisation.

LGAs' use of EMs was examined by asking participants whether or not they had used different EM software applications, with EM types classified as in Section 2.5 (i.e. in accordance with the system set out by Smit *et al.* (2010)). Where an EM had been used, participants were asked to indicate when it had last been used by (or on behalf) of their organisation.

Two questions were developed to investigate LGAs' willingness to commit resources to the emissions modelling process. To permit the extent of resource commitment to be quantifiably evaluated, the questions were designed so that results could be expressed as an implied monetary value placed on CO_2 emissions reductions (£/tonne), which would then allow comparison with official UK national government CO_2 valuations. Two questions were used, each with a different transport intervention scenario, to assess whether (or not) CO_2 valuations remained consistent.

In the scenarios for both questions it was assumed that there was a true amount of CO_2 emissions reduction resulting from an intervention. Participants were asked to compare the use of two different EMs (EM1 and EM2) for predicting this reduction. The less expensive, less complex and less accurate model (EM1) under-estimates the reduction. The more expensive, more complex and more accurate model (EM2) gets closer to the true reduction, and ultimately (in the series of response options offered to participants) replicates the true reduction exactly without ever over-shooting. In essence EM2 is assumed to have (near) optimal complexity. The difference between the predictions leads to EM2 predicting a greater emissions reduction than EM1. For both scenarios, this difference ranged from 100 tonnes up to 1000 tonnes (Table 4-1), with the latter occurring when the prediction from EM2 exactly matched the true reduction.

Of course, both EM1 and EM2 could over-estimate the true emissions reduction. However, if this was the case, EM1 would appear to predict a greater reduction than EM2. A less expensive EM predicting a greater emissions reduction would be appealing to LGAs (regardless of the true emission reduction which would be unknowable in the real-world), and would have undermined the purpose of the two questions. This is why in this hypothetical experiment EM2 needed to be posited as an optimal model and EM1 as a sub-optimal model in a particular direction (i.e. under-estimation). Additionally, for simplicity, any issues about precision or statistical variability in model predictions were deliberately omitted.

Information presented to the participants in the two scenarios (pre- and post-intervention annual road traffic CO_2 emissions, intervention cost, EM cost and population size) was based on real-world data from an abstraction of a Southampton case study (SCC 2011d) and a personal communication to the author from Genis (2014). This is why the measurements used in the questions are absolute (£s and tonnes of CO_2) rather than percentages.

Participants were asked, for a given cost increase, what improvement in accuracy from EM2 would justify its extra cost. For both questions, this sub-question was repeated five times, with the cost of EM2 increasing in £10,000 steps from £60,000 to £100,000. For example, participants were asked '*If EM1 costs £50,000 and EM2 costs £60,000, moving from left to right, select the button that best indicates the point at which the improvement in accuracy offered by EM2 becomes large enough to justify the extra cost of using EM2*' and offered response categories as shown in Table 4-1. Considering only the extra cost of using EM2, and the associated extra predicted CO_2 saving, the choices available to participants in both questions placed valuations on CO_2 as shown in Table 4-2.

Table 4-1: Response categories for both survey questions investigating LGAs' willingness to commit resources to emissions modelling.

Increased CO_2 reduction predicted by EM2 compared to EM1 (tonnes)	100	200	300	400	500	600	700	800	900	1,000	No switch to EM2
	○	○	○	○	○	○	○	○	○	○	○

Table 4-2: CO_2 valuations associated with response categories for both survey questions investigating LGAs' willingness to commit resources to emissions modelling.

Increased CO_2 reduction predicted by EM2 compared to EM1 (tonnes)	100	200	300	400	500	600	700	800	900	1,000	No switch to EM2
£10,000 extra cost for EM2	100	50	33	25	20	17	14	13	11	10	0
£20,000 extra cost for EM2	200	100	67	50	40	33	29	25	22	20	0
£30,000 extra cost for EM2	300	150	100	75	60	50	43	38	33	30	0
£40,000 extra cost for EM2	400	200	133	100	80	67	57	50	44	40	0
£50,000 extra cost for EM2	500	250	167	125	100	83	71	63	56	50	0

- Figures in the body of the table are resultant CO_2 valuations (£/tonne).

4.3 RESULTS

4.3.1 Non-Response Bias Analysis

Thirty four surveys were returned with at least one question completed, and rates of response to individual questions ranged from a maximum of 9% (n=34) to a minimum of 6% (n=23). It is acknowledged that these sample sizes are relatively small, but other surveys of a similar type exist with sample sizes of a comparable order of magnitude. For example, Xenias and Whitmarsh (2013) report research into expert and public attitudes to sustainable transport policies and technologies where sample sizes were 53 and 40 for the transport experts sample and the public sample, respectively. Best efforts were made to maximise the number of participants, and low response rates may be symptomatic of pressure on LGAs' resources leading to a lack of available time/manpower to complete the survey.

Whilst low response rates are not necessarily indicative of non-response bias (Lineback and Thompson 2010), they do increase the need for a non-response bias analysis to provide confidence in the data quality. Of the 206 LHAs in Britain, responses were received from at least 27 (13%) different authorities (7 of the 34 participants elected to remain anonymous). The group of known respondents was compared to the group of non-respondents (which also included the 7 anonymous respondents) to identify any statistically significant differences. Variables for comparison were selected based on availability of data for both groups and likely relation to LGA attitudes to emissions modelling, and were population size (all usual residents in a LGA area according to 2011 census data), geographical size (LGA area in hectares), an indicator of urbanisation (population density in residents/hectare), and an indicator of spending (LGA net[103] revenue expenditure per capita in £s for 2013/14). Analysis was performed using IBM SPSS 22 software. All the variables were found to be non-normally distributed for both groups. Therefore, non-parametric Mann-Whitney tests[104] were conducted (Mann and Whitney 1947; Field 2009). The tests showed that levels of the four variables in the sample of respondents (medians = 252,973 residents; 29,736 Ha; 5.21 residents/Ha; and £780 per capita) did not differ significantly from those found in the non-respondents (medians = 226,578 residents; 19,184 Ha; 8.63 residents/Ha; and £845 per capita). Additionally, the distribution of regional response rates was as follows (i.e. the number of LHAs that responded as a percentage of LHAs in each region): Scotland 16%; Wales 14%; SE England 11%; SW England 25%; London 3%; East of England 9%; East Midlands 22%; West Midlands 29%; Yorkshire and the Humber 13%; NE England 17%; and NW England 4%.

4.3.2 Question Responses

Results from statistical analysis of response scores from the question asking participants their opinion on the importance of factors affecting allocation of resources are shown in Table 4-3, with a higher mean importance score (range 0 to 4) indicating a factor was perceived as more important. A score of 2 corresponds to the neutral statement: Neither agree nor disagree. Mean importance scores are all greater than 2, indicating that, on average, every factor was regarded as important to some extent. To determine if the observed differences in responses to the different factors were statistically significant a non-parametric Friedman test[105] (Friedman 1937) was appropriate because response scores are ordinal data and were found to be non-normally distributed for each factor (Field 2009). Results showed there was a

[103] Net revenue expenditure is gross expenditure less fees and charges for LGA services and specific grants, where specific grants are grants ring-fenced for dedicated purposes.

[104] A Mann-Whitney test is based on testing for a statistically significant difference between the sum of ranked positions for values of a particular variable taken from different groups (i.e. testing for differences between the groups).

[105] A Friedman test is based on testing for a statistically significant difference between the sum of ranked positions given to a set of different factors by a group of participants (i.e. testing for differences between the factors).

statistically significant difference ($p<0.05$). However, this result only confirmed that a statistically significant difference existed somewhere, but did not pinpoint which factors in particular differed from each other. Post-hoc Dunn tests[106] (Dunn 1964) were applied to each possible pairwise comparison of factors to determine which pairs had a statistically significant difference from each other, with a Bonferroni correction[107] used to compensate for multiple pairwise comparisons ($p<0.05/36=0.0014$). The four pairwise comparisons having statistically significant differences were: 'Ability to re-use model in future projects' and 'Avoiding staff training'; 'Ability to re-use model in future projects' and 'Quick completion'; 'Ability to re-use model in future projects' and 'Avoiding employing external consultants'; and 'Easy availability of input data' and 'Avoiding employing external consultants'. In general, the Dunn test results indicated that statistically significant differences only existed between responses to factors at the extremes of the rankings (i.e. between the top two and bottom three factors). Friedman test mean rankings are shown in Table 4-3, with a higher ranking (range 1 to 9) indicating a more important factor.

Table 4-3: Mean importance scores and Friedman test mean rankings for factors affecting emissions modelling resource allocation.

Factor	Friedman Mean Rank	Mean Importance Score
Ability to re-use model in future projects	6.77	3.27
Easy availability of input data	5.93	2.93
Project significant to local political agenda	5.32	2.77
Avoiding high manpower resources	5.28	2.77
High accuracy	4.92	2.57
Inexpensive	4.80	2.60
Avoiding staff training	4.43	2.33
Quick completion	3.93	2.20
Avoiding employing external consultants	3.62	2.07

- n=30.
- Factors are ordered according to Friedman mean ranking (range 1 to 9), which is (slightly) different to the order of mean importance scores.
- Mean importance score (range 0 to 4).

[106] A Dunn test is based on testing for a statistically significant difference between the sum of ranked positions given to two factors (from a set of different factors) by a group of participants (i.e. testing for differences between pairs of factors).

[107] To compensate for multiple pairwise comparisons, the significance level of the original Friedman test ($p<0.05$) was divided by the total number of pairwise Dunn tests carried out (9 factors = 36 pairwise comparisons). In other words, the significance level of $p<0.0014$ for the individual pairwise comparisons (as in the Dunn tests) is calculated so as to maintain the original significance level of $p<0.05$ when all pairwise comparisons are considered together (as in the Friedman test).

Participant perceptions of the availability of road traffic data sources are shown in Figure 4-1. Time periods when data were collected from these sources are shown in Figure 4-2 and are displayed in descending order of the percentage of participants selecting 'Planned for future collection' in response to a particular data source. LGAs' use of different RTM software applications is shown in Figure 4-3. LGAs' use of different EM software applications is shown in Figure 4-4. It should be noted that WebTAG is not a software application. Instead, it is the DfT's guidance on conducting transport studies, and includes methods for calculating road traffic emissions. This is also the case for the DMRB, which is the DfT's guidance on the design, assessment and operation of trunk roads and motorways (although a software application based on the DMRB is available). Figure 4-5 shows participant responses when aggregated according to EM type.

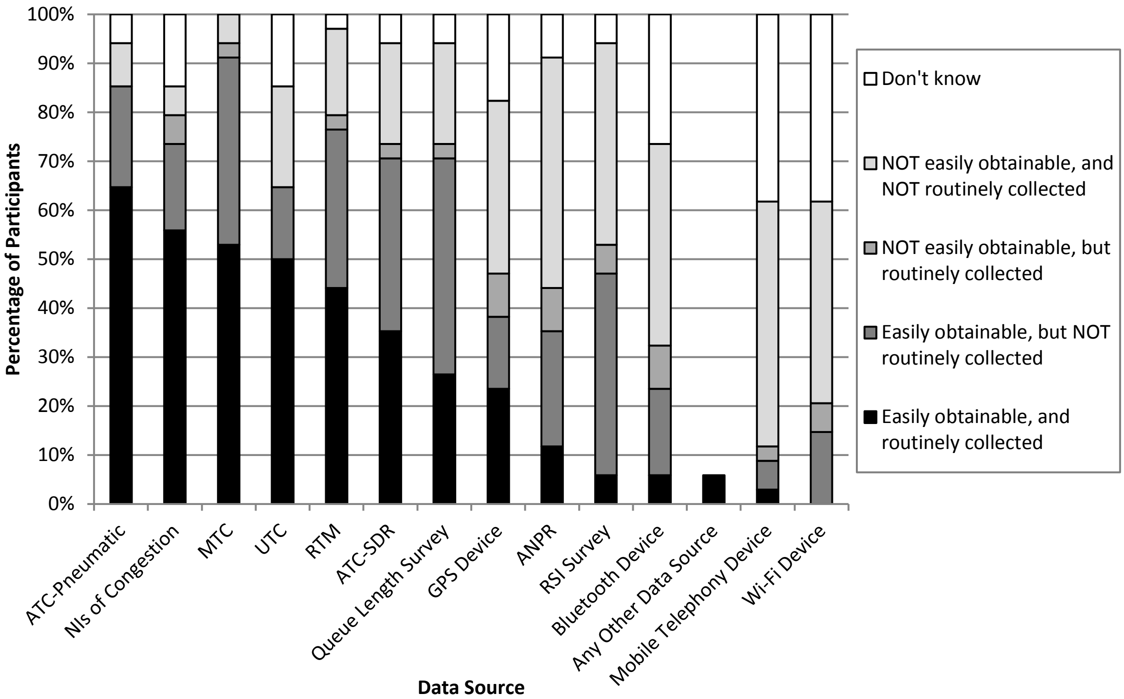

Figure 4-1: Participant perception of the availability of road traffic data sources.

- n=34.
- ANPR is Automatic Number Plate Recognition; ATC is Automatic Traffic Count; MTC is Manual Traffic Count; NIs is National Indicators; Pneumatic is pneumatic tube; RSI is Roadside Interview; RTM is Road Traffic Model; SDR is Speed Detection Radar; and UTC is Urban Traffic Control.
- Two participants specified an 'Any Other Data Source', which were TRICS (UK national database for trip generation analysis) and UK road traffic collision data.

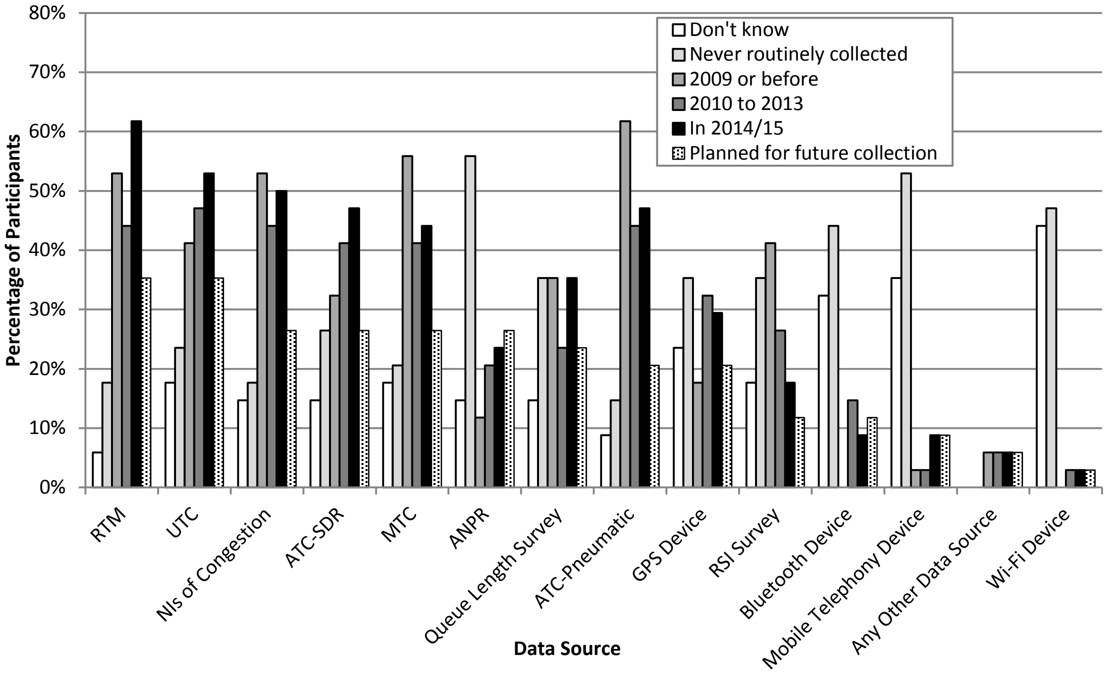

Figure 4-2: Time periods when data were (or are planned to be) collected by (or on behalf of) LGAs from road traffic data sources.

- n=34.
- Abbreviations are as detailed in the notes for Figure 4-1.
- Two participants specified an 'Any Other Data Source', which were TRICS (UK national database for trip generation analysis) and UK road traffic collision data.

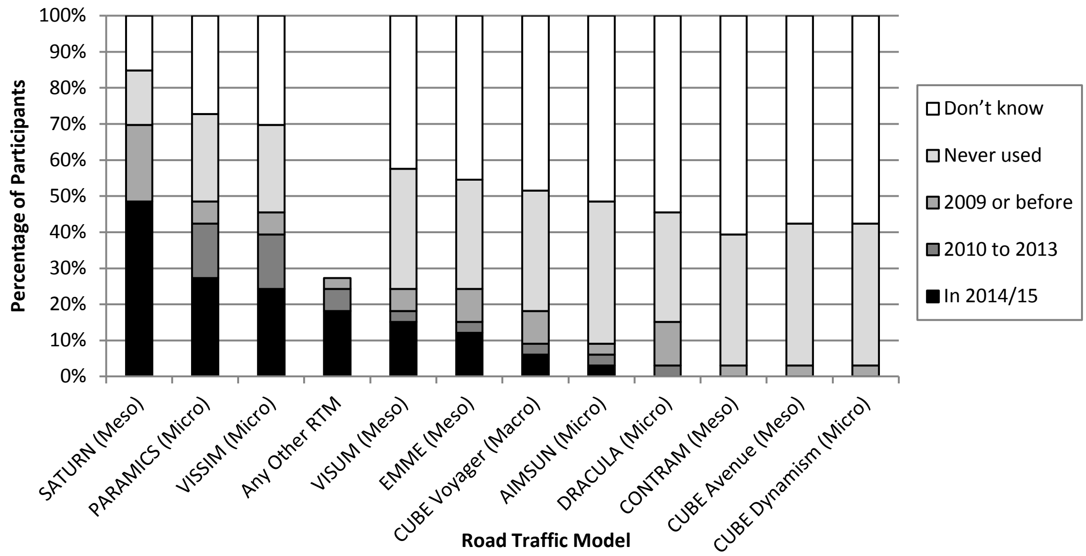

Figure 4-3: Time periods when Road Traffic Model software applications were last used by (or on behalf of) LGAs.

- n=33.
- RTM types are Macro, Meso or Micro.
- Nine participants specified an 'Any Other RTM', which were ARCADY, DELTA, LINSIG, PICADY, QUADRO, TRANSYT and TRIPS.
- Further details of RTM software applications are provided in the Definitions and Abbreviations section at the beginning of this thesis.

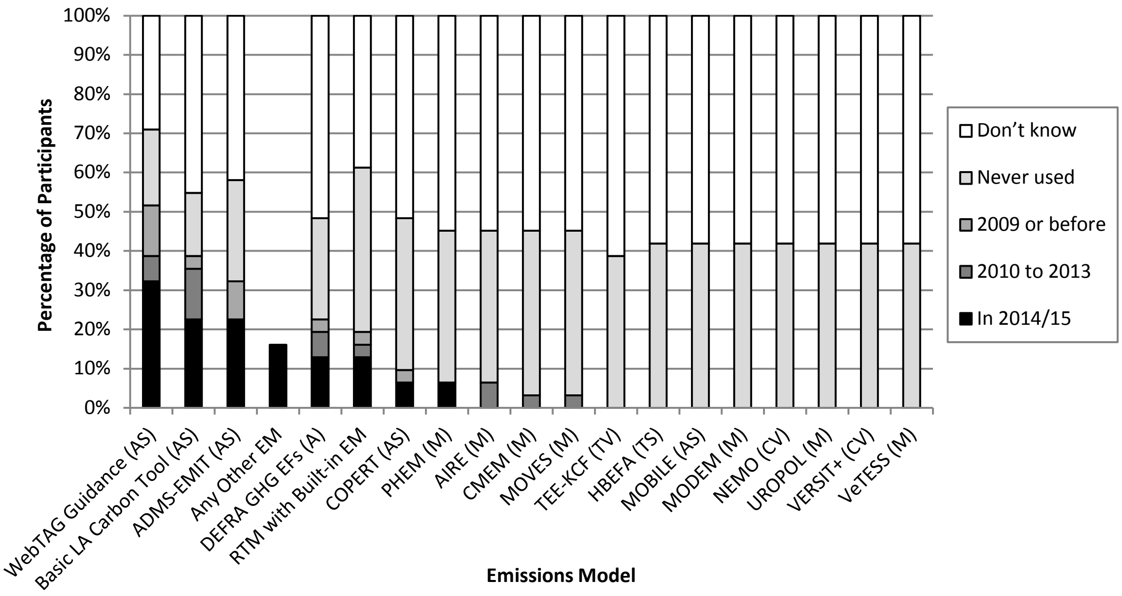

Figure 4-4: Time periods when Emissions Model software applications were last used by (or on behalf of) LGAs.

- n=31.
- EM types: Aggregate (A), Average Speed (AS), Traffic Situation (TS), Traffic Variable (TV), Cycle Variable (CV) and Modal (M).
- Six participants specified a ‘RTM with Built-in EM’, which were VISUM (AS), SATURN (TV), PARAMICS (M) and VISSIM (M).
- Five participants specified an ‘Any Other EM’, which were DMRB guidance (AS), Greater Manchester EM (AS), TUBA (AS) and PITHEM (AS).
- Further details of EM software applications are provided in the Definitions and Abbreviations section at the beginning of this thesis.

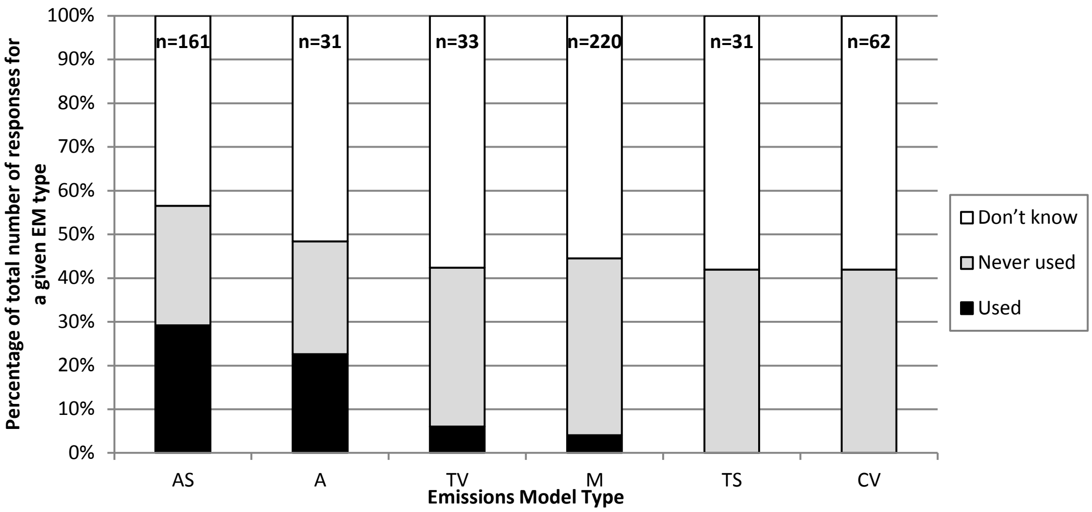

Figure 4-5: Types of Emissions Model software applications used by (or on behalf of) LGAs.

- Some EM types appeared more frequently than others in the list of EM software applications presented to participants. Hence, number of responses (n) varies from type to type.
- EM types: Aggregate (A), Average Speed (AS), Traffic Situation (TS), Traffic Variable (TV), Cycle Variable (CV) and Modal (M).

For the two questions quantifying LGAs' willingness to commit resources to the emissions modelling process, the mean valuation of CO_2 emissions from responses to the first question (n=24) was £11.51/tonne (Standard Deviation, SD £18.56) and from responses to the second question (n=23) was £14.08/tonne (SD £27.50), with an overall mean valuation of £12.77/tonne (SD £23.35). For comparison, for 2015 the UK national government values CO_2 emissions from the untraded sector (i.e. emissions not included in the EU Emissions Trading System, which is the case for petrol and diesel used in road vehicles) at £62.78/tonne (SD £31.39), based on a valuation of £57.40/tonne (SD £28.70) in 2010£s corrected for inflation (DfT 2014d). Therefore, LGAs' mean valuations determined here are less than a quarter of national government values but the standard deviations are of a similar order of magnitude. This indicates the limitations of this comparison in that it is not an ideal like-for-like comparison (i.e. the value of EM accuracy is not the same as the value of emissions). However, the comparison serves the purpose of providing a context against which a general sense can be gained of whether the LGA values are plausible, and the fact that they are less than national government values of actual emissions was consistent with expected results.

4.4 DISCUSSION

An objective of the research was to investigate the emissions modelling process that is the best-fit for (ideally) all LGAs, rather than considering the situation where different EMs are developed to suit different LGAs characterised by urbanisation, population size, location, etc. Hence, in the analysis of survey results LGAs were not disaggregated according to these characteristics. Benefits of a single approach to CO_2 emissions modelling are that it allows comparability of results from transport intervention assessments across different LGAs, and that research and development can be focused on one particular methodology; although it is acknowledged that these benefits would have to be weighed against the benefits of using EMs tailored to specific circumstances. A potential procedure for establishing a consensus on LGA requirements would be a regular survey of LGAs across the globe; although it is acknowledged that the interval between such surveys is likely to be measured in decades due to the size of the undertaking, and that there are considerable difficulties (impossibilities?) inherent in securing such international agreements on mitigation of CO_2 emissions.

Generally, LGAs indicated concern for all the factors affecting allocation of resources to road traffic emissions modelling (mean importance scores all >2), highlighting an overall opinion that resource scarcity is an important issue. Whilst statistically significant differences only existed between factors at the extremes of the Friedman test mean rankings, inspection of

Table 4-3 suggests that survey participants considered model reusability to be the most important factor, i.e. a preference for EMs that have the flexibility to be used in assessment of future, yet to be determined, interventions. From the LGA viewpoint, EMs tailored to the one-off assessment of a particular intervention are best avoided. Reusable EMs bring many additional benefits which may explain the importance attached to this factor, such as: staff familiarity; goodness of fit with existing skills; shorter timescales required to use familiar software applications; avoidance of regular staff retraining; reliability of operation; trust in validity of results; comparability of results across different intervention assessments; and goodness of fit with road traffic data routinely collected.

Easily available input data was also considered an important factor, being ranked second by participants (Table 4-3). Of all the road traffic data sources, the options that appear to be most convenient for LGAs are RTMs and UTC systems. This is for three reasons: (1) they are ranked highly by participants as easily obtainable and routinely collected (Figure 4-1); (2) they are ranked highest and second-highest, respectively, as planned for future collection (Figure 4-2) which is an important indicator of the data LGAs expect to be available for future emissions modelling; and (3) they are available on a link-by-link basis enabling emissions calculations for all (or mostly all) links in a network to be performed. Other data sources considered easily available by LGAs typically do not provide link-by-link data. For example, availability of traffic counts (manual or automatic), surveys and ANPR data are restricted to only a few locations (spatially and also sometimes temporally) within a network, and National Indicators of congestion are normally only available for certain key routes. Where sufficient penetration is achieved (i.e. number of vehicles from which data can be gathered compared to total number of vehicles), vehicle tracking data from GPS, Bluetooth, mobile telephony and Wi-Fi devices are available on a link-by-link basis. However, these technologies are not considered easily available by LGAs and have not been widely collected, indicating a lack of familiarity and experience in their use.

By inspection of Figure 4-2 a general trend appears of a move away from manual, labour-intensive data collection towards automatic, less labour-intensive sources. MTCs and RSI surveys are both decreasing (although queue length surveys are fairly constant), whilst RTMs, UTC, ATC-SDR and ANPR are all increasing (although ATC-pneumatic are decreasing). Explanations for this trend could be the increasing pressure on LGA resource budgets, and/or an expectation that the rise in telematics and ‘big’ data will satisfy LGA traffic data requirements, although the technologies underpinning telematics have low ranks as data planned for future collection.

Due to being rated highly for convenience, LGAs are likely to view RTMs and UTC systems as readily available sources for EM input data. Data available from UTC systems are generated by the Inductive Loop Detectors (ILDs) installed as system sensors (refer to Section 2.4.5), and are typically traffic variables, i.e. describing traffic as an aggregate whole rather than describing individual vehicles. However, using traffic data generated by ILDs leads to certain problems. For example, where traffic average speed is a required EM input this is typically space-mean-speed, whereas ILDs can only provide estimates of time-mean-speed (refer to Section 2.4.5), which in themselves may be of questionable accuracy (refer to Section 5.4.4). Nonetheless, results of the survey indicate use of this convenient data source (with its associated inherent inaccuracies) to provide EM inputs is a subject worthy of further research.

Data output from RTMs depend on RTM type. The RTM most widely used by LGAs is SATURN (Figure 4-3), which is a meso-RTM that outputs traffic variables rather than individual vehicle driving patterns. PARAMICS and VISSIM are the second and third most used RTMs, respectively, and are both micro-RTMs that can output individual vehicle driving patterns. However, collecting and processing driving patterns for every vehicle in a network is a resource-intensive task. Additionally, micro-RTMs are typically validated for aggregate traffic measures (i.e. traffic variables) rather than for driving patterns (refer to Section 2.4.4). Therefore, driving pattern outputs are not necessarily accurate, whereas traffic variable outputs are more likely to be accurate.

A preference for calculating emissions from traffic variables was demonstrated by the common use of Average Speed EMs by LGAs (Figure 4-5), with the three most used EMs all being of the Average Speed type (Figure 4-4). This result agrees with the literature review (refer to Section 2.5.5), which found that most EMs are currently based on average speed, with a suggested reason for this prevalence being that readily available input data are often restricted to estimates of traffic average speed for each link. However, traffic average speed is not the only traffic variable readily available from sources such as RTMs and UTC systems, and inclusion of the explanatory power of other traffic variables may present an opportunity to improve the accuracy of emissions calculations. Consistent with the research gap identified during the literature review (refer to Section 2.6.5), taking advantage of this opportunity involves investigating the development and accuracy of Traffic Situation or Traffic Variable EMs, which are both currently not widely used by LGAs (Figure 4-5). Development of a Traffic Situation EM has already been discounted as an option for this project (refer to Section 2.7), with development of a Traffic Variable EM selected as the scope for investigations instead.

Cycle Variable EMs and Modal EMs are also both currently not widely used by LGAs. Likely reasons for this are that these types of EMs are resource-intensive to use, and that they require accurate driving patterns as inputs which cannot be obtained from the data sources regarded as easily available to LGAs, a situation unlikely to change in the near future based on LGA future data collection plans.

A surprising result was that no participant mentioned using the Emissions Factors Toolkit (EFT) EM (refer to Section 2.5.5.5), which is an Average Speed EM developed by DEFRA specifically to assist LGAs in carrying out their statutory duty to assess local air quality. Given that approximately 60% of UK LGAs have designated areas where AQ objectives are not being met (DEFRA 2014a) and that road traffic emissions are the reason for such designations in 90% of cases (Bell *et al.* 2013), it seems likely the EFT will have been widely used. A possible reason for omission by participants is its specific design for AQ emissions (although it can also calculate CO_2 emissions), whereas the survey was focused on CO_2 emissions.

Comparison of results with national government CO_2 valuations indicates LGAs are willing to commit far fewer resources to the emissions modelling process than might be expected. The majority of LGAs appear to accept the accuracy provided by EMs currently used (mostly Average Speed EMs) and are reluctant to commit extra resources for increased accuracy, even if that increased accuracy indicates interventions are producing greater emissions reduction outcomes than originally calculated. This highlights that, in order to be tractable, any improvements to CO_2 EM accuracy must be at minimal additional cost to LGAs. Both questions produced similarly low mean valuations even though scenarios were worded in different ways.

An important issue with the survey results was the impossibility of being completely certain what was in participants' minds when answering, and hence uncertainty about whether responses were reflective of organisational-level attitudes or individual-level attitudes. As the title of the survey implies, it was organisation-level attitudes that were sought because LGAs engage in the emissions modelling process as a result of organisational decisions, rather than decisions made by a single individual employee. Particularly susceptible to this issue were the two questions designed to quantify LGAs' willingness to commit resources to emissions modelling. Rather than a simple statement of fact (as in most other questions, e.g. whether particular EMs have been used or not), these questions involved complex, hypothetical scenarios and subjective judgements, but are unlikely to have been discussed at organisational-level prior to response. Hence, comparison with organisational-level national government valuations of CO_2 should be treated with caution, although the tendency to under-valuation shown by participants was substantial.

British LGAs do not have a statutory obligation to reduce GHG emissions (refer to Section 1.5.2.1). Therefore, non-compliance with any GHG emissions reduction targets LGAs may set voluntarily incurs little penalty, and low CO_2 valuations perhaps should not come as a surprise. An interesting contrast is the situation for emissions of oxides of nitrogen (NO_X) (of which road traffic is a major source), where the UK is facing potential fines imposed by the European Commission for breach of nitrogen dioxide (NO_2) concentration limit values under the EU Air Quality Directive. This financial sanction has been estimated at up to £300m (Kidney and Price 2012), and UK national government is threatening to pass on (full or partial) payment of any fines to LGAs in whose regions these exceedances are occurring[108] (DEFRA 2014b). These potential fines are particularly relevant in Southampton because the city has been identified as one of the five cities in England (outside London) that are projected to still be exceeding limits for NO_2 by 2020 (DEFRA 2015b). In this situation, LGAs may be willing to commit extra resources to emissions modelling, if that modelling could contribute to a process that demonstrated they were no longer breaching NO_2 limits (a pollutant dispersion model and concentration monitoring would be required to complete this process) and fines be avoided. If the threat of financial penalties does lead to NO_2 emissions reductions, other pollutant emissions (including CO_2) may also be reduced because of potential co-benefits from integrated reduction strategies (DEFRA 2009b; EEA 2009; King *et al.* 2010; Tiwary *et al.* 2013); although this is not always the case, and a reduction in emissions of one pollutant can sometimes cause increases in another. From a cost-benefit perspective, at a time of scarce resources, there is an increasing need for LGAs to include all possible emissions reduction benefits (i.e. for all pollutants, rather than just NO_2) if an argument for implementation of a proposed intervention is to be successful (Tiwary *et al.* 2013).

[108] At the time of writing (September 2016), the UK has just voted to leave the EU and the threat of this fine will recede, which means resources for emissions modelling could start to slip down in priority.

Results show that if a transport intervention has high significance to the local political agenda then this was regarded as an important factor in allocation of resources for emissions modelling (third highest factor in Table 4-3). This finding was reinforced by one participant's free-text supplementary response which stated that if a *"political decision has been made that a problem needs to be addressed, as a rule of thumb, we will do whatever it takes (within reason) to make this happen, such as (for example) spend more on a more accurate/detailed modelling package to make sure the case is made and investment is secured"*. Breaching NO_2 limits provides a case in point, where the threat of fines has pushed this issue up the local political agenda, with more resources likely to be available for any mitigation actions (including modelling the impact of transport interventions). For example, the DfT recently (November 2015) invited proposals to be submitted for novel solutions to the local transport and air quality problem, with grants available for successful submissions from a total fund of £250,000 (DfT 2015a). In general, placing increasing responsibility on LGAs to be accountable for achieving their environmental targets should result in the impact of transport interventions on emissions (including CO_2) being increasingly pushed up the local political agenda. In turn, this should lead to an increasing willingness on the part of LGAs to commit more resources to the emissions modelling process.

4.5 CONCLUSIONS

A central message of the survey results was that scarcity of resources is an important issue for LGAs when conducting road traffic emissions modelling. Participants placed particular importance on EMs having the flexibility to be reusable for assessment of future transport interventions, and on a requirement for input data to be easily available. Of the road traffic data sources that can provide EM inputs, RTMs and UTC systems represent the most convenient options for LGAs for three reasons: (1) they are ranked highly as easily obtainable and routinely collected; (2) they are ranked highest and second-highest, respectively, as planned for future collection; and (3) they can provide traffic variables on a link-by-link basis for all (or mostly all) links in a network. Micro-RTMs can additionally generate individual vehicle driving pattern outputs (required as inputs to more detailed EMs, i.e. Cycle Variable and Modal EMs), but doubts exist concerning their accuracy and their collection and processing is resource-intensive. Therefore, an EM based on traffic variable outputs from RTMs and UTC systems appears to be the most appropriate option for LGAs. An ability to use data from either source is important to overcome situations where UTC data are not available (i.e. links with no ILD installed or hypothetical scenarios).

A trend was identified of a move away from road traffic data sources involving manual, labour-intensive data collection processes, and a move towards sources involving automatic, less labour-intensive collection processes. Explanations for this trend could be increasing pressure on LGA resource budgets, and/or an expectation that the rise in telematics and 'big' data will satisfy LGA traffic data requirements.

The large majority of LGA emissions modelling is currently achieved using Average Speed EMs, with more detailed EM types being used rarely (if at all). However, other traffic variables (in addition to traffic average speed) are easily available for incorporation and could offer opportunities to improve the accuracy of EMs for LGAs. In general, the survey results provided evidence in support of the research gap identified through the literature review (refer to Section 2.6.5), i.e. the ability of a Traffic Variable EM to improve upon the accuracy of network CO_2 emissions predictions based solely on traffic average speed, through explicitly including the influence of congestion, is a subject worthy of investigation. However, any accuracy improvements must come at minimal cost to LGAs because they have indicated a reluctance to commit extra resources for improved accuracy; although this barrier is likely to be less consequential where a transport intervention is of high significance to the local political agenda.

Chapter 5 PEMLA DEVELOPMENT METHODOLOGY

5.1 INTRODUCTION

Two key findings from the combination of literature review and LGA survey results were: (1) Traffic Variable EMs were identified as potentially offering an improved ability to capture congestion impacts compared to the widely used alternative of Average Speed EMs, through including other traffic variables (in addition to traffic average speed) as quantifiable measures of congestion, with little associated increase in complexity; and (2) ILDs installed as part of UTC systems were identified as a readily available source of these traffic variables, where collection does not entail additional expenditure of resources by or on behalf of LGAs. The remainder of this project was built on these two key findings, and constituted investigations aimed at developing a new CO_2 Traffic Variable EM based on ILD inputs, and then comparing the accuracy of its emissions predictions with those of the existing Average Speed EM recommended for use by LGAs in the UK (TRL EFs 2009 as the basis of the DfT Basic Local Authority Carbon Tool), i.e. to answer Research Questions 2 and 3.

The method selected was to investigate the prediction of network-level CO_2 emissions based on traffic variables derived from ILD data. Southampton's road network was used as a test bed. Real-world GPS driving patterns (1Hz speed-time profiles) were collected from vehicles and used as inputs to an IEM in order to provide an accurate estimate of each vehicle's CO_2 emissions.

In parallel, concurrent data were collected from ILDs crossed by a vehicle during its journey. The ILD data were used to calculate values for selected traffic variables that characterised the traffic conditions at the time each driving pattern was performed. A comprehensive list of numerous traffic variables can be found in Smit (2006). However, it was beyond project resources to investigate all possible traffic variables and a combination of the following four key criteria were used to make a selection: (1) successful previous use in predicting emissions; (2) ready availability to LGAs from ILD data; (3) familiar to LGAs; and (4) indicators of congestion. The five traffic variables selected for investigation as predictors of CO_2 emissions were: traffic average speed (km/h); traffic average speed squared $(km/h)^2$; traffic density (vehicles/km); traffic average delay rate (seconds/vehicle.km); and access density (intersections/km) (for full details of the selection of the traffic variables investigated and their calculation from ILD data, refer to Section 5.4.1 and Section 5.4.3, respectively).

These two parallel data collection processes were then blended together through statistical analysis that explored relationships between the set of traffic variables and vehicle emissions, which led to the development of a new Traffic Variable EM. This new EM was termed the Practical Emissions Model for Local Authorities (PEMLA). Performance of PEMLA was assessed against the next-best alternative EM available to LGAs (TRL EFs 2009 Average Speed EM) through accuracy comparisons. (An abridged version of the research detailed in this chapter, and in Chapter 6, Chapter 7 and Chapter 8, was accepted for a poster presentation at the Transportation Research Board (TRB) 96th Annual Meeting, 8-12 January 2017, Washington D.C., USA. The supporting manuscript from the meeting Compendium of Papers is included as Appendix D).

Explanation of the PEMLA development methodology has been divided into five main sections. Section 5.2 details the method used to determine a practical number of vehicle categories for use in PEMLA. Section 5.3 and Section 5.4 concern the methods used for the two parallel data collection processes. Section 5.5 explains the methods used for calibration and assessment of PEMLA through statistical analysis of the collected data. Finally, conclusions are presented in Section 5.6. Figure 5-1 depicts the meso-process of the PEMLA development methodology as a flow chart (second in the series of increasingly detailed flow charts that began with Figure 3-1 in Chapter 3 depicting the macro-process of the overall project methodology). Figure 5-2 and Figure 5-3 (third and fourth in the flow chart series) depict more detailed expansions of the two parallel data collection micro-processes (micro-processes A and B shown by the dashed lines in Figure 5-1).

As a final point (and perhaps most importantly from the perspective of a doctoral thesis), investigation of the feasibility of predicting CO_2 emissions based on traffic variables through the methodology developed in this project was a novel endeavour. No examples to date could be found in the existing literature of EMs based on the same methodology as that detailed in this chapter.

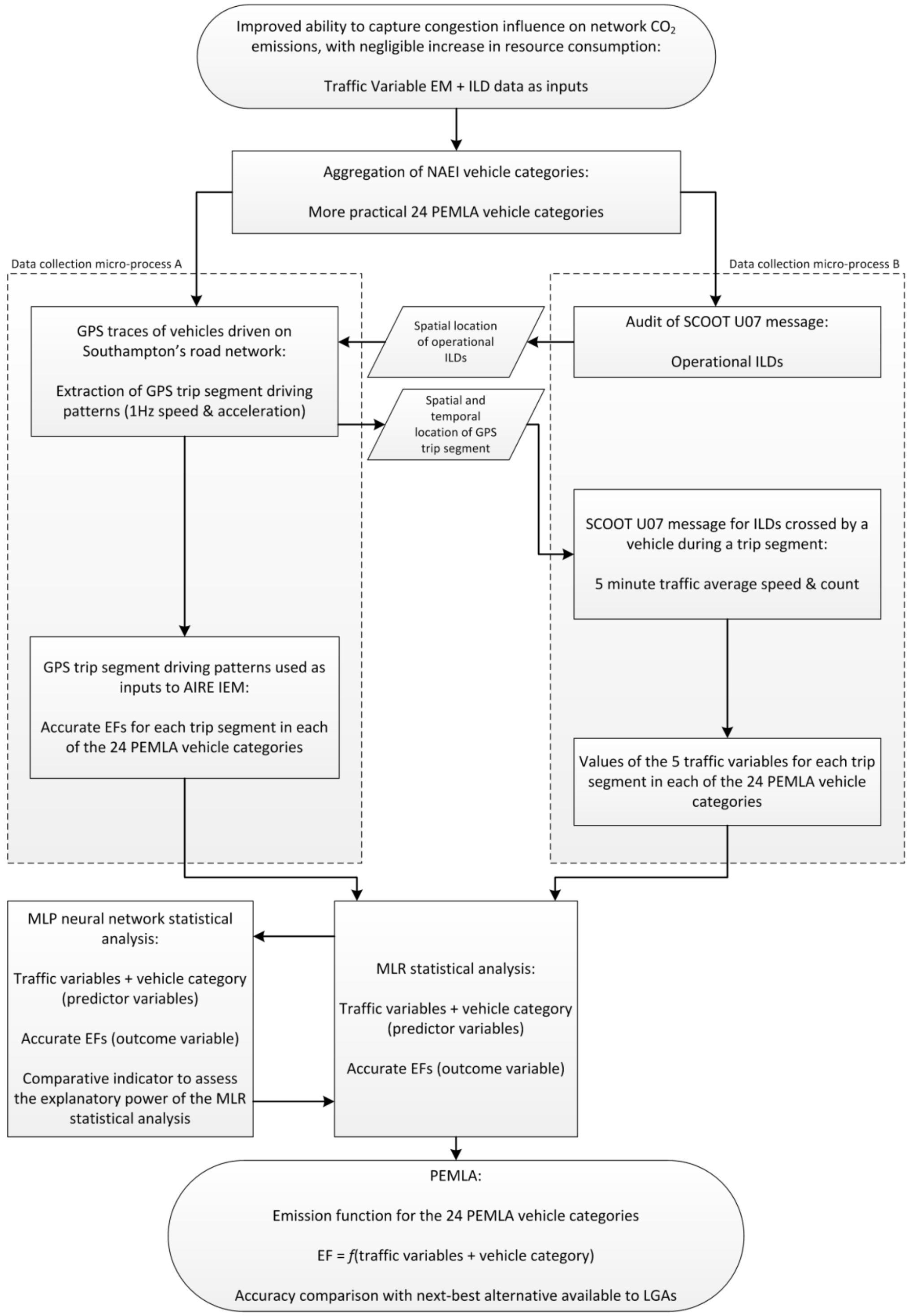

Figure 5-1: Flow chart of the PEMLA development methodology meso-process.

- ILD is Inductive Loop Detector.
- The SCOOT U07 message contains data returned by each ILD in the UTC system (refer to Section 5.4.2.1).
- Analysis of Instantaneous Road Emissions (AIRE) is an Instantaneous Emissions Model (IEM) (refer to Section 2.5.9.4).
- MLR is Multiple Linear Regression (refer to Section 5.5.1.1).
- MLP is Multilayer Perceptron (refer to Section 5.5.1.3).

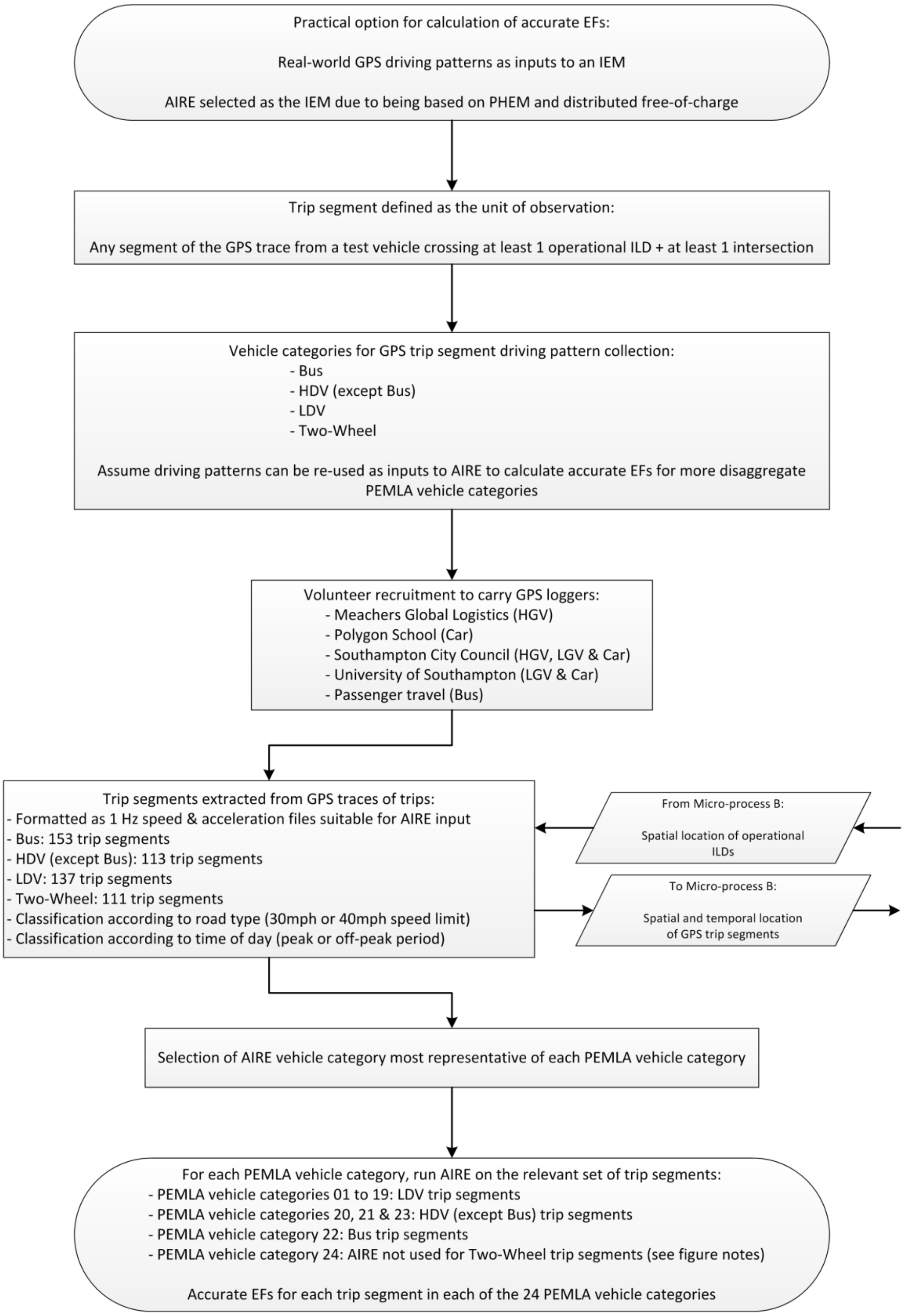

Figure 5-2: Flow chart of the micro-process for calculation of accurate EFs (micro-process A in Figure 5-1).

- Analysis of Instantaneous Road Emissions (AIRE) is an Instantaneous Emissions Model (IEM) (refer to Section 2.5.9.4).
- Passenger car and Heavy duty Emissions Model (PHEM) is an IEM (refer to Section 2.5.9.2).
- LDV is Light Duty Vehicle; HDV is Heavy Duty Vehicle; LGV is Light Goods Vehicle; HGV is Heavy Goods Vehicle.
- For PEMLA vehicle categories, refer to Table 5-1.
- AIRE does not include any two-wheel vehicle categories. Therefore, an alternative method was used to calculate accurate EFs for this category (refer to Section 5.3.5.4).

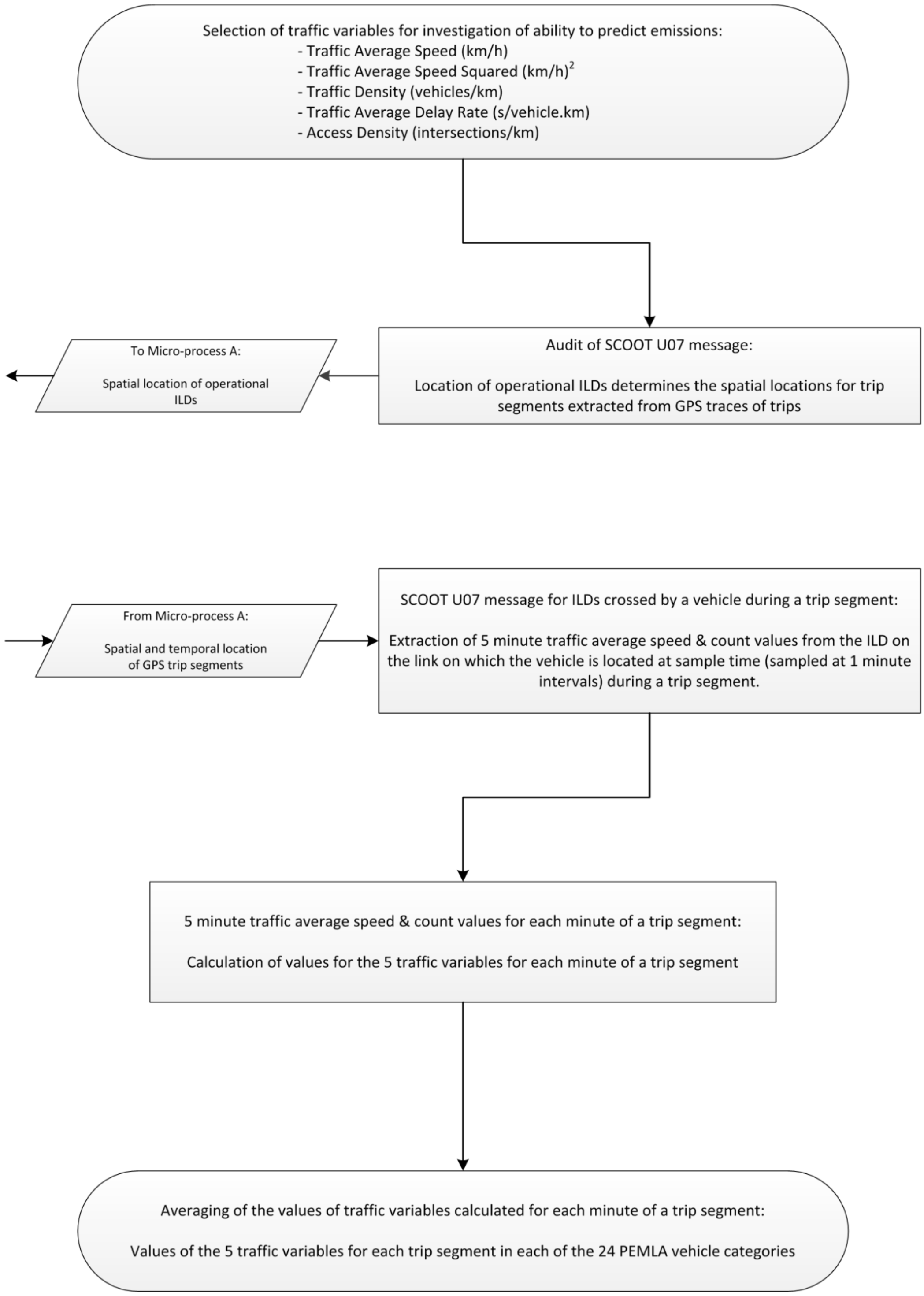

Figure 5-3: Flow chart of the micro-process for calculation of traffic variables (micro-process B in Figure 5-1).

- ILD is Inductive Loop Detector.
- The SCOOT U07 message contains data returned by each ILD in the UTC system (refer to Section 5.4.2.1).
- For simplicity, traffic average speed squared was actually calculated as the square of the average value for a trip segment of traffic average speed, rather than the average of the squares of traffic average speed values for each minute, which would give a slightly different result.

5.2 VEHICLE CATEGORIES IN PEMLA

5.2.1 Target Number of Vehicle Categories

EMs in common use across Europe typically have highly disaggregated vehicle categories that, at the finest detail level, distinguish between compliance with different European Emission Standards (e.g. TRL EFs 2009 Average Speed EM has emission functions for each of the 231 vehicle categories[109] defined in the NAEI national fleet model). For reasons of practicality, both in the analyses conducted within the resources of this study (Multiple Linear Regression (MLR) analysis[110] required at least 110 samples per vehicle category) and in the future use by LGAs of PEMLA, a reduced number of vehicle categories was sought. The target was to reduce the number of vehicle categories closer to that found in EMs such as the MOVES EM, which has 13 different vehicle types, combined with 2 different fuel types (if alternatives to conventional diesel or gasoline are ignored) (i.e. 26 vehicle categories) (EPA 2015).

5.2.2 Vehicle Category Reduction Analysis

The primary factor used in reducing the number of vehicle categories was an analysis of the contribution to a composite EF for the traffic as a whole (EF_T in gCO_2/VKM_T) made by each of the 231 NAEI categories at various traffic average speeds. The analysis was conducted using the TRL average speed emission functions for each vehicle category (i.e. TRL EFs 2009 Average Speed EM), weighted by the NAEI national fleet model predictions (NAEI 2014) for each category's fraction of total national VKMs on urban roads in England outside London in 2016 (hereafter TRL/NAEI EM). The target number of vehicle categories was achieved by aggregating NAEI categories into PEMLA categories whilst applying the criterion that no PEMLA category contributed more than 10% to the EF_T at any speed[111], which resulted in the more manageable 24 vehicle categories shown in Table 5-1, where categories involving aggregation are highlighted by a grey background.

In TRL/NAEI EM, EFs have a non-linear relationship with average speed. Therefore, calculations were repeated over a range of speeds, which encompassed the national average peak period speeds on urban roads in England. The minimum speed boundary condition was

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[109] Introduction of the Euro 4 Standard for two-wheel vehicles in 2016/17 (refer to Footnote 20 in Section 2.3.2) has created an extra seven categories, giving a current total of 238 vehicle categories.

[110] MLR was selected as the statistical analysis technique for this project (refer to Section 5.5.1.1), and a suggested minimum sample size for this technique was 110 samples (refer to Section 5.5.1.2). This sample size coupled with 231 vehicle categories would have required analysis of approximately 23,000 samples (231 x 110), which was beyond project resources.

[111] In fact, inspection of Table 5-1 reveals that the 'LGV, Diesel, All Weights, Euro 5' category contributes 10.2% at 80 km/h, but this small exceedance for only one vehicle category at only the highest speed condition was considered to be acceptable.

selected as 6 km/h because all HDV emission functions have this value as the lower limit of their validity range (all other vehicle categories have a lower limit of 5 km/h). The maximum speed boundary condition was selected as 80 km/h (50 mph) because this is the maximum speed limit to be found on most urban roads in England. Where 80 km/h was above the maximum valid speed for a vehicle category's emission function, it was assumed that vehicles in that category continued at the maximum speed in their validity range, even though the traffic average speed was faster (only two categories were affected: mopeds <50cc with a maximum of 50 km/h; and buses with a maximum of 75 km/h).

For two-wheel vehicles in the NAEI fleet model, a small fraction (less than 8%) of total two-wheel VKMs are predicted to be Euro 4 vehicles in 2016 (refer to Footnote 20 in Section 2.3.2 for application of the two-wheel Euro 4 standard), but there are no TRL emission functions for this category. Therefore, the Euro 4 fraction was included within the Euro 3 fraction. This would not have changed the results of the analysis (where two-wheel vehicles form a single aggregate category) because the highest emission scenario has been considered, i.e. Euro 4 two-wheel vehicles are likely to have lower emissions than Euro 3 two-wheel vehicles.

Three secondary factors were also considered: (1) the vehicle categories available within AIRE because this was the Modal EM selected to calculate accurate EFs from vehicles' GPS driving patterns for each of the PEMLA categories (refer to Section 5.3.5.1). Some NAEI categories are aggregated within AIRE. For example, the NAEI fleet model disaggregates LGVs according to mass, whereas AIRE does not; (2) where possible, earlier Euro Standard categories were aggregated because their fraction of national VKMs will reduce over time, which means their contribution to EF_T will also reduce over time; and (3) where possible, consistent grouping was sought in aggregating the NAEI categories to provide simplicity of use for PEMLA.

Table 5-1: Percentage contributions of PEMLA vehicle categories to the composite traffic EF in urban areas at varying traffic average speeds.

Count	Traffic average speed (km/h)		6	10	20	30	40	50	60	70	80
	Composite traffic EF_T (gCO_2/VKM_T)		529	363	235	190	167	156	150	150	154
	PEMLA vehicle category	Percent of VKMs	Percent contribution to traffic composite EF_T								
01	Car, Petrol, <1400cc, Pre-Euro 5	8.0%	6.7%	6.5%	6.3%	6.4%	6.6%	6.8%	6.9%	7.0%	7.0%
02	Car, Petrol, <1400cc, Euro 5	6.5%	5.2%	4.9%	4.6%	4.5%	4.6%	4.7%	4.8%	4.8%	4.9%
03	Car, Petrol, <1400cc, Euro 6	3.6%	2.8%	2.6%	2.3%	2.2%	2.3%	2.3%	2.3%	2.4%	2.4%
04	Car, Petrol, 1400-2000cc, Pre-Euro 5	8.5%	8.5%	8.4%	8.3%	8.4%	8.4%	8.5%	8.5%	8.4%	8.3%
05	Car, Petrol, 1400-2000cc, Euro 5	6.9%	6.6%	6.3%	6.0%	5.9%	5.8%	5.8%	5.7%	5.7%	5.6%
06	Car, Petrol, 1400-2000cc, Euro 6	3.8%	3.5%	3.3%	3.1%	2.9%	2.9%	2.8%	2.8%	2.7%	2.7%
07	Car, Petrol, >2000cc, Pre-Euro 5	2.4%	3.5%	3.4%	3.4%	3.4%	3.3%	3.3%	3.3%	3.2%	3.2%
08	Car, Petrol, >2000cc, Euro 5	1.9%	2.7%	2.6%	2.5%	2.4%	2.3%	2.3%	2.3%	2.2%	2.2%
09	Car, Petrol, >2000cc, Euro 6	1.1%	1.5%	1.4%	1.3%	1.2%	1.1%	1.1%	1.1%	1.1%	1.0%
10	Car, Diesel, <2000cc, Pre-Euro 5	8.8%	5.9%	6.3%	6.9%	7.1%	7.1%	7.0%	6.9%	6.7%	6.6%
11	Car, Diesel, <2000cc, Euro 5	12.1%	7.7%	8.1%	8.6%	8.6%	8.5%	8.3%	8.0%	7.8%	7.7%
12	Car, Diesel, <2000cc, Euro 6	6.8%	4.2%	4.3%	4.4%	4.4%	4.2%	4.1%	3.9%	3.8%	3.7%
13	Car, Diesel, >2000cc, Pre-Euro 5	3.7%	2.9%	3.3%	3.9%	4.2%	4.4%	4.4%	4.4%	4.3%	4.3%
14	Car, Diesel, >2000cc, Euro 5	5.1%	3.8%	4.2%	4.8%	5.1%	5.2%	5.2%	5.2%	5.1%	5.0%
15	Car, Diesel, >2000cc, Euro 6	2.9%	2.0%	2.2%	2.5%	2.6%	2.6%	2.6%	2.6%	2.5%	2.5%
16	LGV, Petrol, All	0.3%	0.4%	0.4%	0.4%	0.4%	0.4%	0.4%	0.4%	0.4%	0.4%
17	LGV, Diesel, All Weights, Pre-Euro 5	3.3%	4.3%	4.0%	3.7%	3.6%	3.7%	3.8%	4.0%	4.2%	4.5%
18	LGV, Diesel, All Weights, Euro 5	7.4%	9.8%	9.2%	8.3%	8.2%	8.3%	8.7%	9.2%	9.6%	10.2%
19	LGV, Diesel, All Weights, Euro 6	2.3%	2.9%	2.7%	2.5%	2.5%	2.5%	2.6%	2.7%	2.9%	3.0%
20	HGV, Rigid, All	1.7%	5.2%	5.7%	6.5%	6.6%	6.5%	6.3%	6.3%	6.3%	6.4%
21	HGV, Artic, All	0.4%	2.0%	2.2%	2.6%	2.7%	2.6%	2.5%	2.4%	2.4%	2.4%
22	Bus, All	1.0%	5.1%	4.8%	4.3%	4.1%	4.0%	3.9%	3.9%	3.9%	3.8%
23	Coach, All	0.4%	2.4%	2.4%	2.4%	2.2%	2.1%	1.9%	1.8%	1.8%	1.7%
24	Two-Wheel, All	1.2%	0.5%	0.6%	0.7%	0.7%	0.7%	0.7%	0.7%	0.7%	0.7%
	Totals	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%

- EF_T is a composite EF for the traffic as an aggregate whole.
- VKM_T is vehicle-kilometre for the traffic as an aggregate whole.
- Percent of VKMs is the percentage of total urban VKMs for England outside London in 2016 (NAEI 2014).
- Engine capacity is shown in cubic centimetres (cc).
- LGV is Light Goods Vehicle, HGV is Heavy Goods Vehicle and Artic is articulated.
- For reference, average speeds on urban roads in the South-East region of England during peak period are as follows: LDVs on major roads = 47.2 km/h; HDVs on major roads = 46.5 km/h; LDVs on minor roads = 32.6 km/h; and HDVs on minor roads = 32.5 km/h (DfT 2011a).

5.3 ACCURATE EMISSIONS

5.3.1 Method Selection

A hierarchical approach was adopted when assessing the feasibility of different methods for collecting accurate EF data, i.e. commence by assessing the feasibility of the most accurate method; then, if that method is not feasible, move on to the next most accurate; and so on, until a feasible method is found. Arguably, the most accurate method for calculating EFs is to collect real-world emissions measurements using PEMS. However, installing PEMS equipment on vehicles from each of the 24 vehicle categories in PEMLA was deemed impractical.

The next-best option in terms of accuracy was considered to be calculation of accurate EFs using one of the latest generation of Modal EMs (i.e. an IEM) based on collection of real-world GPS driving patterns (1Hz speed-time profiles) for use as inputs, and this was the method selected (for selection of the particular Modal EM used, refer to Section 5.3.5.1). This method is similar to that used in (for example) the construction of HBEFA (Traffic Situation EM) where emissions were calculated from driving pattern inputs to PHEM (Modal EM), rather than being measured during emissions tests or using PEMS (refer to Section 2.5.6.1).

5.3.2 Trip Segment Definition

5.3.2.1 Distance snippets

The urban area used as a test bed for this project was the city of Southampton, and the unit of observation was termed a trip segment. A driving pattern for each trip segment was obtained by equipping vehicles with GPS devices that recorded their progress along the city's roads. Trip segments were extracted from the GPS trace of a vehicle's trip on a distance snippet basis, i.e. trip segment ends were co-located with intersections rather than being defined by a particular time interval (for an explanation of why a time snippet basis was rejected refer to 5.3.2.2). A decision was necessary regarding the appropriate length of a trip segment (in terms of number of links). The minimum trip segment length to be consistent with traffic variable outputs from UTC systems and RTMs was a single link because outputs from these sources are typically available as an average value for each link. However, to ensure the effects of intersections on driving patterns were captured, the minimum segment length was extended to include a series of at least two links. If a single link had been used as a segment, the intersections at either end would be excluded; whereas because all segments constituted at least two links, an intersection was always included. Longer segments also have the advantage of increasing the validity of an assumption of zero gradient (as used in this project) because longer segments are more likely to cover a distribution of positive and negative gradients, allowing gradient effects to be offset (i.e. for EFs calculated assuming 0% gradient, longer segments are likely to give results closer to real-world EFs than shorter segments). A further advantage of longer segments was that, for a given magnitude of error in the measured GPS position, the error is a smaller proportion of total trip segment length, and so causes a proportionally smaller error in the EF calculated from the associated GPS driving pattern.

An additional constraint on what constituted a useable trip segment was imposed by the need to collect associated concurrent traffic variables from ILD data. Therefore, a trip segment was required to also cross at least one operational ILD. The result of the factors outlined in this section was the following formal definition of a trip segment as a unit of observation adopted by this project:

> *Any segment of the GPS trace collected from a test vehicle's trip that runs continuously between two intersections along the course of at least two links, and crosses at least one operational ILD.*

In the event, due to the practicalities of collecting data in the field, the criterion of crossing an operational ILD had to be relaxed to ensure sufficient trip segment samples for statistical analysis could be collected within the resources of this project. Therefore, in some cases, an assumption was made that an ILD from a link adjacent to (but not forming part of) a trip segment could provide the data for calculating the traffic variables associated with that trip segment. Refer to Section 5.4.4 for an assessment of the validity of this assumption. In general, trip segments were extracted from a test vehicle's trip so as to be as long as possible (in terms of distance), with maximum length being constrained by where a test vehicle entered and exited a series of links with an operational ILD (or adjacent link with an operational ILD).

5.3.2.2 Time snippets

An alternative method for extracting trip segments from GPS traces would have been on a time snippet basis, i.e. a trip segment definition based on a time interval rather than a minimum number of links. This method was rejected for three reasons: (1) distance snippets were a more practical method to ensure trip segments crossed at least one intersection, i.e. it was easier to capture the influence of intersections. Time snippets would have made it more difficult to guarantee an intersection was crossed within the duration of a trip segment; (2) distance snippets were a more practical method to ensure trip segments crossed operational

ILDs. For example, during a time snippet trip segment a vehicle may turn-off a link covered by an ILD onto a link without an ILD, whereas a distance snippet would allow the trip segment to be terminated at the intersection where the vehicle turned onto the uncovered link; and (3) GPS trip traces were examined on a background map display which lent itself to distance snippet trip segment extraction based on spatial locations (i.e. intersections) rather than temporal locations.

5.3.3 Reuse of GPS Driving Patterns

Even with PEMLA vehicle categories reduced to 24, finding sufficient volunteer drivers in each of the 24 categories willing to carry GPS devices, and then collecting at least 110 samples (necessary for MLR analysis) from those drivers for each category, would have made both volunteer driver recruitment and trip segment collection (110 x 24 = 2,640 samples) impractical. Instead, an assumption was made concerning the reusability of GPS driving patterns.

Vehicle power-to-mass ratio has a large effect on a vehicle's ability to accelerate, and consequently (alongside other factors such as congestion, driver behaviour, or network characteristics) is likely to have a substantial influence on a vehicle's driving pattern. Power-to-mass ratios for LDVs typically range from 45-60 kW/tonne, whereas for HDVs they range from 8-25 kW/tonne (Ligterink *et al.* 2012), and for two-wheel vehicles they range from 50-375 kW/tonne (Alvarez *et al.* 2009). Considering these differences, a practical assumption for the purposes of driving pattern collection was that HDVs, LDVs and two-wheel vehicles each constituted a single aggregate vehicle category. These vehicle categories were broadly consistent with those typically found in RTMs, where the primary concern is to model vehicle motions rather than emissions. It is only when calculation of emissions becomes desirable that further category disaggregation is necessary.

A caveat to this assumption was where any category-specific vehicle operations had an effect on driving patterns. For example, particularly in urban environments, buses make numerous stops for passengers to board or exit the vehicle, which are not replicated by other HDVs. Therefore, it could be argued buses should be treated as a separate category from other HDVs. Similarly, a proportion of LGVs operating in urban areas will be operating as multi-drop delivery vehicles and are likely to make a number of delivery stops, generating an argument for LGVs to be treated as a separate category from other LDVs (i.e. cars). However, category-specific operations are less likely to be an issue for LGVs than for buses because not all LGVs are operated as multi-drop delivery vehicles; and for those that are, the frequency of stops is likely to be lower than for buses.

Therefore, for trip segment collection, vehicles were aggregated into four categories: bus; HDV (except bus); LDV; and two-wheel vehicle. This meant only 440 trip segments needed to be collected to satisfy MLR analysis minimum sample size requirements (110 x 4 = 440). From each trip segment, a GPS driving pattern was produced. These driving patterns (except two-wheel vehicles, refer to Section 5.3.5.4) were then used as inputs to an IEM to calculate an accurate EF (gCO_2/VKM) for each trip segment in each of the 24 PEMLA vehicle categories, with HDV (except bus) and LDV driving patterns being reused as IEM inputs for all relevant PEMLA categories (HDV (except bus) for categories 20, 21 and 23; and LDV for categories 01-19 in Table 5-1). In other words, a GPS driving pattern collected from any LDV (for example) was assumed to represent the motion of all PEMLA vehicle categories classified as LDV (categories 01-19), and used repeatedly as an IEM input to calculate accurate EFs for all 19 of these categories.

5.3.4 GPS Driving Pattern Collection

5.3.4.1 Volunteer recruitment

For the majority of vehicle categories (HDV (except bus), LDV and two-wheel vehicle), to collect trip segment driving patterns it was first necessary to recruit a sample of volunteers who drove vehicles from those categories, and who were willing to carry GPS devices as they travelled around Southampton's road network. The method used to recruit volunteers was a direct approach by email to contacts at various institutions in Southampton, such as Meachers Global Logistics (HGV fleet), the Polygon School (school car), Southampton City Council (HGV fleet, LGV fleet and employees' cars) and the University of Southampton (LGV fleet and employees' cars). For the bus vehicle category, driving patterns were collected by the author carrying a GPS device and travelling as a passenger on different buses driven by different drivers, on various bus routes within Southampton. Table 5-2 summarises the main characteristics of the collected trip segment driving patterns, including the number of different drivers recruited in each category.

Table 5-2: Summary of the characteristics of the collected GPS trip segment driving patterns.

Characteristic		Driving Pattern Collection Vehicle Category			
		Bus	HDV (except Bus)	LDV	Two-Wheel
Number of trip segments collected		153	113	137	111
Driving pattern IDs assigned to trip segments		BDP001 to BDP165	HDP001 to HDP115	LDP001 to LDP156	TDP001 to TDP120
Dates between which trip segments were collected		03-Jul-15 to 09-Feb-16	19-Oct-15 to 20-Jan-16	17-Sep-15 to 14-Dec-15	14-Oct-15 to 07-Dec-15
Percent of trip segments occurring in the peak period		51%	43%	39%	93%
Number of different drivers		30	6	11	2
Average trip segment length (km)	Mean	0.725	1.480	1.350	0.925
	Median	0.602	1.214	1.012	0.865
Average trip segment duration (s)	Mean	183	211	189	129
	Median	164	191	157	123

- Occasionally trip segments initially extracted from a GPS trip trace turned-out to be unusable for various reasons (e.g. no ILD data available to calculate concurrent values for traffic variables), and were discarded. Therefore, driving pattern IDs were not always consecutively numbered.
- Trip segments in peak periods were defined as any occurring between the hours of 07:00 to 10:00 or 16:00 to 19:00.
- The number of different drivers for bus assumes there was a different driver each time a change of bus was made, which may not always have been the case. Therefore, this characteristic is likely to be an over-estimation.

5.3.4.2 Time of day

Regarding the amount of traffic on road networks, the DfT define the following times of day: weekday (Monday to Friday) peak periods from 07:00 to 10:00 and from 16:00 to 19:00; weekday inter-peak period from 10:00 to 16:00; weekend daytimes from 09:00 to 20:00 on Saturday and from 10:00 to 20:00 on Sunday; and off-peak period at all other times (DfT 2015b). The concern of this project was capturing the impact of congestion on CO_2 emissions. Therefore, the times of day of most interest were the weekday peak periods, which generally have the highest levels of congestion. In practice, times of day for driving pattern collection were dictated by when volunteer drivers made their journeys, with the result that all driving patterns (apart from the occasional journey made before 07:00 or after 19:00) were collected either in the weekday peak period or weekday inter-peak period. For simplicity, the only distinction used in PEMLA was between peak period and off-peak period (refer to Table 5-2). Hence, off-peak period described any time outside weekday peak periods; and driving patterns collected in weekday inter-peak periods were assumed to represent the range of traffic conditions that exist in this off-peak period.

Particularly in the peak period, weight of traffic is likely to vary by direction of travel depending on the road in question (e.g. the majority of traffic heading in one direction in the AM peak period and in the opposite direction in the PM peak period). Again for simplicity in the use of PEMLA this variation was not included, and driving patterns collected in peak periods and in off-peak periods were assumed to represent the range of traffic conditions that exist in those periods.

5.3.4.3 GPS loggers

The GPS devices used for recording vehicle movement were BT-Q1000X GPS Travel Recorders (hereafter GPS loggers) manufactured by Qstarz (shown in Figure 5-4), which have specified accuracies of 3 m for position data and 0.1 m/s (0.36 km/h) for speed data. These loggers have been used previously as a method for recording travel data (e.g. in both the Atlanta Regional Travel Survey and the California Household Travel Survey (NuStats 2011; NuStats 2013)). The loggers are hand-held devices, small enough (approximately half the size of a computer mouse) to be easily carried on the person or stowed conveniently within a vehicle's passenger compartment. They are simple to use, with the only control on the device being a mode switch (OFF/NAV/LOG) that must be selected to 'LOG' prior to beginning a test trip to enable the data log function. An orange LED indicates the status of the device, with a continuous light indicating GPS satellites are being detected, and a flashing light indicating GPS position is fixed and the unit is ready for use.

Figure 5-4: BT-Q1000X GPS Travel Recorders manufactured by Qstarz.

- Source: Qstarz (2009).

5.3.4.4 Trip segment extraction

Once a volunteer had completed a trip (or series of trips) the logged data were imported to the Q-Travel software application (Qstarz proprietorial software) for processing by connecting the GPS logger to a computer via a USB port. During import, the software automatically corrected for errors in GPS position due to drift. The problem of drift typically occurred when a vehicle was stationary but the GPS logger continued to detect a small amount of movement due to environmental factors (e.g. tall buildings, dense tree cover or steep hillsides) causing satellite signals to be disrupted or reflected. Any waypoints[112] suspected of being erroneous due to drift were automatically filtered out by the software.

As a further quality control process, imported trip traces were visually inspected for any obviously erroneous waypoints (i.e. not aligned with the road as shown on the background map display), which were then avoided during the trip segment extraction process. Consideration was also given to the application of map matching to the GPS trip traces (i.e. the process of moving recorded GPS waypoints so that vehicle routings follow the known positions of the road network). However, map matching was not applied for three reasons: (1) vehicle speed at 1 second intervals was the variable of interest, meaning that the positional accuracy of the geographic location of each waypoint was less important; (2) no map matching software was conveniently available to the project; and (3) the Q-Travel automatic error correction facility and visual inspection of trip traces were considered to be sufficient in avoiding any sections of a trip trace with poor GPS accuracy.

Once imported into Q-Travel, test trips were manually divided into trip segments in accordance with the trip segment definition, i.e. segments of a test trip that run continuously between two intersections along the course of at least two links, and cross at least one operational ILD. Each trip segment was then exported from Q-Travel as a .csv file with columns of data providing the following for each one second interval: the validity (or not) of the GPS position fix; UTC date and time[113]; latitude (degrees); longitude (degrees); altitude (metres above sea level); speed (km/h); and heading (degrees). In essence, this file constituted a 1Hz speed-time profile (i.e. driving pattern) for the trip segment being processed.

5.3.5 Emissions Factor Calculation

5.3.5.1 Modal EM selection

A hierarchical approach was again adopted for selection of a suitable Modal EM. Arguably, the foremost examples of the latest generation of Modal EMs are MOVES, VERSIT+ (latest version rather than earlier incarnations) and PHEM (Wyatt *et al.* 2014). However, none of these EMs were feasible for use in this project. Vehicle categories in MOVES were too USA-specific for use in the UK. The price quoted for using PHEM was too expensive. In personal

[112] The GPS loggers were set to record vehicle data at 1 second intervals, and waypoints are plotted at these intervals.
[113] UTC in this context refers to Coordinated Universal Time, often also known as Greenwich Mean Time (GMT), and should not be confused with UTC in the context of Urban Traffic Control.

communications with an expert at TNO it was established that VERSIT+ was viewed more as an in-house development tool rather than a commercial software application and concerns were raised that the traffic conditions under which VERSIT+ was developed were too Netherlands-specific for the EM to be used with confidence in the UK (Eijk 2014a; Eijk 2014b). Even if these concerns could have been overcome, similar to PHEM, the price quoted for using VERSIT+ was too expensive.

The next-best option was considered to be AIRE (refer to Section 2.5.9.4) because it was developed based on PHEM specifically for use on UK roads, is an IEM featuring vehicle categories disaggregated according to Euro Standard (i.e. similar to the detail level in the PEMLA vehicle categories), and (importantly from a project resource perspective) is distributed freely by the manufacturers (SIAS Limited). Therefore, in the absence of a practical method to measure real-world emissions (refer to Section 5.3.1), for the purposes of calculating accurate vehicle EFs, AIRE outputs were assumed to be 'real-world' emissions. This assumption was reasonable because AIRE was independently verified by TRL during its original validation (Transport Scotland 2011).

Whilst primarily being designed to calculate emissions from driving pattern files generated by S-PARAMICS micro-RTM, following discussions with an expert at SIAS Limited, the ability of AIRE to calculate emissions from driving pattern files generated by other sources was confirmed (Shaw 2015). To accomplish this, an appropriately formatted AIRE input file had to be synthesised from each of the trip segment driving pattern .csv files exported from Q-Travel.

5.3.5.2 Synthesising AIRE input files

The first step in synthesising an AIRE input file was to inspect the exported .csv file for any time intervals (i.e. waypoints) that had been automatically deleted by Q-Travel due to drift being detected when a logger was stationary. These deleted intervals had to be replaced, along with an associated value in the speed data column of 0 km/h. Speed then had to be converted to miles per hour (mph), which are the units used by AIRE. In addition to vehicle speed, an AIRE input file also requires vehicle acceleration in metres per second squared (m/s^2). This was calculated using the second-to-second change in speed (m/s). The data columns containing speed (mph) and acceleration (m/s^2) were then copied from the driving pattern file into the appropriate positions in an AIRE input file (known as a carpositions.csv file regardless of vehicle category) obtained from the expert at SIAS Limited. This process was repeated until each trip segment driving pattern file exported from Q-Travel had an associated carpositions.csv AIRE input file.

5.3.5.3 Calculating EFs using AIRE

To calculate emissions from a carpositions.csv file using AIRE, a vehicle category must first be specified (encoded in the carpositions.csv file itself and selected in the fleet model contained within the AIRE software). Therefore, it was necessary to select the AIRE vehicle category that best represented each of the 24 PEMLA vehicle categories (except two-wheel whose EFs were not calculated using AIRE because AIRE does not include any two-wheel vehicle categories, refer to Section 5.3.5.4). However, AIRE vehicle categories did not correspond that closely to PEMLA vehicle categories. Instead, AIRE categories corresponded more closely to TRL/NAEI EM categories. Analysis was therefore conducted to determine the TRL/NAEI EM category within the (more aggregate) PEMLA category that made the greatest contribution to EF_T. The resulting TRL/NAEI EM category was then matched to the closest corresponding AIRE category, with results shown in Table 5-3.

AIRE only includes vehicle categories compliant with Euro Standards up to Euro 4 for LDVs and Euro V for HDVs. Therefore, for PEMLA categories represented by Euro 5/6 or Euro VI vehicles, a TRL Speed-specific Adjustment Factor (TSAF) was calculated for each trip segment as the ratio between emissions from a vehicle of the relevant newer Euro Standard and emissions from a vehicle of Euro 4/Euro V Standard using the TRL/NAEI EM, with vehicle average speed (as calculated from its GPS driving pattern) as input. Vehicle categories to which TSAFs were applied are indicated in Table 5-3.

A further selection had to be made concerning vehicle load, with AIRE offering three choices – un-laden, half-laden or fully-laden. For consistency with the method used in the TRL EFs 2009 Average Speed EM (refer to Section 2.5.5.1), half-laden was chosen as the option for all vehicles. Consistency with TRL EFs 2009 allowed direct comparisons to be made between emissions predicted by PEMLA and emissions predicted by TRL/NAEI EM.

Additionally, an assumption of a zero road gradient was used as an input to AIRE. PEMLA is designed for estimation of emissions at network-level (or substantially large parts of a network, e.g. >1km^2). Therefore, the validity of this assumption is strengthened because random errors introduced by not fully accounting for vehicle-specific values should (to a certain extent) average-out (Smit *et al.* 2008b), i.e. negative gradients will offset positive gradients.

Table 5-3: AIRE vehicle categories that best represent each of the 24 PEMLA vehicle categories.

Count	PEMLA vehicle category	NAEI vehicle category within the PEMLA vehicle category making greatest contribution to EF_T	Closest corresponding AIRE category (x TSAF where applicable)
01	Car, Petrol, <1400cc, Pre-Euro 5	Car, Petrol, <1400cc, Euro 4	Car, Petrol, <1400cc, Euro 4
02	Car, Petrol, <1400cc, Euro 5	Car, Petrol, <1400cc, Euro 5	(Car, Petrol, <1400cc, Euro 4) x Euro 5 TSAF
03	Car, Petrol, <1400cc, Euro 6	Car, Petrol, <1400cc, Euro 6	(Car, Petrol, <1400cc, Euro 4) x Euro 6 TSAF
04	Car, Petrol, 1400-2000cc, Pre-Euro 5	Car, Petrol, 1400-2000cc, Euro 4	Car, Petrol, 1400-2000cc, Euro 4
05	Car, Petrol, 1400-2000cc, Euro 5	Car, Petrol, 1400-2000cc, Euro 5	(Car, Petrol, 1400-2000cc, Euro 4) x Euro 5 TSAF
06	Car, Petrol, 1400-2000cc, Euro 6	Car, Petrol, 1400-2000cc, Euro 6	(Car, Petrol, 1400-2000cc, Euro 4) x Euro 6 TSAF
07	Car, Petrol, >2000cc, Pre-Euro 5	Car, Petrol, >2000cc, Euro 4	Car, Petrol, >2000cc, Euro 4
08	Car, Petrol, >2000cc, Euro 5	Car, Petrol, >2000cc, Euro 5	(Car, Petrol, >2000cc, Euro 4) x Euro 5 TSAF
09	Car, Petrol, >2000cc, Euro 6	Car, Petrol, >2000cc, Euro 6	(Car, Petrol, >2000cc, Euro 4) x Euro 6 TSAF
10	Car, Diesel, <2000cc, Pre-Euro 5	Car, Diesel, 1400-2000cc, Euro 4	Car, Diesel, 1400-2000cc, Euro 4
11	Car, Diesel, <2000cc, Euro 5	Car, Diesel, 1400-2000cc, Euro 5	(Car, Diesel, 1400-2000cc, Euro 4) x Euro 5 TSAF
12	Car, Diesel, <2000cc, Euro 6	Car, Diesel, 1400-2000cc, Euro 6	(Car, Diesel, 1400-2000cc, Euro 4) x Euro 6 TSAF
13	Car, Diesel, >2000cc, Pre-Euro 5	Car, Diesel, >2000cc, Euro 4	Car, Diesel, >2000cc, Euro 4
14	Car, Diesel, >2000cc, Euro 5	Car, Diesel, >2000cc, Euro 5	(Car, Diesel, >2000cc, Euro 4) x Euro 5 TSAF
15	Car, Diesel, >2000cc, Euro 6	Car, Diesel, >2000cc, Euro 6	(Car, Diesel, >2000cc, Euro 4) x Euro 6 TSAF
16	LGV, Petrol, All	LGV, Petrol, All Weights, Euro 4	LGV, Petrol, All Weights, Euro 4
17	LGV, Diesel, All Weights, Pre-Euro 5	LGV, Diesel, All Weights, Euro 4	LGV, Diesel, All Weights, Euro 4
18	LGV, Diesel, All Weights, Euro 5	LGV, Diesel, All Weights, Euro 5	(LGV, Diesel, All Weights, Euro 4) x Euro 5 TSAF
19	LGV, Diesel, All Weights, Euro 6	LGV, Diesel, All Weights, Euro 6	(LGV, Diesel, All Weights, Euro 4) x Euro 6 TSAF
20	HGV, Rigid, All	HGV, Rigid, 28-32t, Euro VI	(HGV, Rigid, 28-32t, Euro V) x Euro VI TSAF
21	HGV, Artic, All	HGV, Artic, 40-50t, Euro VI	(HGV, Artic, 40-50t, Euro V) x Euro VI TSAF
22	Bus, All	Bus, Standard, 15-18t, Euro V	Bus, Single Deck, Euro V
23	Coach, All	Coach, Euro V	Coach, Euro V
24	Two-Wheel, All	N/A	N/A

- EF_T is a composite EF for the traffic as an aggregate whole (gCO_2/VKM_T), where VKM_T is VKM for the traffic as an aggregate whole.
- The analysis was performed at 45 km/h because this is approximately the average speed for vehicles on major urban roads in the South-East region of England (DfT 2011a).
- TSAF is TRL Speed-specific Adjustment Factor.

To enable AIRE to accept the input files, they first had to be stored in an appropriate folder structure. This consisted of 11 separate AIRE model folders, one for each of the PEMLA vehicle categories 01, 04, 07, 10, 13, 16, 17, 20, 21, 22 and 23. The other PEMLA vehicle categories had emissions calculated by application of TSAFs to these 11 categories. The LDV carpositions.csv files were copied into the AIRE model folders for each of the LDV vehicle categories (01, 04, 07, 10, 13, 16 and 17); the HDV carpositions.csv files were copied into the AIRE model folders for each of the HDV (except bus) vehicle categories (20, 21 and 23); and the bus carpositions.csv files were copied into the AIRE model folder for the bus vehicle category (22).

As each input file was processed, AIRE calculates the mass of CO_2 emitted[114] during each time interval using the vehicle speed and acceleration for an interval and relating these values to an ER (gCO_2/s) in a Look-Up Table (LUT) for the specified vehicle category. AIRE then divides this ER according to the duration of the time interval used in the input file to give emissions for an interval. For example, for a time interval duration of 0.5 seconds, the ER would be divided by two. Total emissions for a driving pattern are then the sum of the emissions for each interval. However, the maximum interval duration that AIRE will accept as input is 0.5 seconds, whereas the collected trip segment driving patterns were at 1 second intervals. The solution to this mismatch was that GPS data (at 1 second intervals) were copied into the AIRE input carpositions.csv file (which had a time index advancing in 0.5 second intervals), then the emissions for each interval calculated by AIRE and written to the AIRE output file were doubled (because AIRE would have halved the ER for a given interval based on the 0.5 second interval duration of the input file; whereas, in reality the speed and acceleration values applied to a whole second of the GPS data).

The final part of the EF calculation process was to take the total CO_2 emissions (g) for a trip segment driving pattern output from AIRE, and calculate an EF (gCO_2/VKM) for that trip segment through dividing by the trip segment length (km). For the 11 PEMLA vehicle categories not requiring TSAFs (categories 01, 04, 07, 10, 13, 16, 17, 20, 21, 22 and 23 in Table 5-3), this was the end of the process. For the other vehicle categories, the calculated EF for each trip segment was multiplied by the associated TSAF to arrive at the final EF.

[114] AIRE actually calculates the total carbon mass emitted (mg), which was then converted to CO_2 mass (mg) through multiplying by 44/12 (the ratio of the molecular mass of CO_2 to carbon). In this way, ultimate CO_2 emissions (refer to Section 2.3.10) were calculated for each trip segment.

5.3.5.4 Calculating EFs for two-wheel vehicles

AIRE does not include any two-wheel vehicle categories. Therefore, an alternative method had to be found to calculate EFs from the collected two-wheel trip segments. The method adopted was based on the study by Smit *et al.* (2008b) detailed in Section 2.5.7.3. In summary, the study considered improving the accuracy of emissions predictions from an Average Speed EM through using an average speed distribution as input, rather than a single traffic average speed. In other words, allowing for vehicles travelling at different average speeds, rather than using a single average speed for the traffic as a whole. The study authors considered that application of an average speed distribution was likely to be a closer approximation to reality, and therefore likely to yield more accurate emissions predictions.

In this project, rather than using a statistical model (variance of vehicle average speeds from the traffic average speed) to predict individual vehicle average speeds (as in the study), real-world vehicle average speeds (as calculated from their GPS driving patterns) were used as inputs to the TRL/NAEI EM to calculate two-wheel vehicle EFs (gCO_2/VKM). These EFs were considered to be more accurate than EFs calculated based on traffic average speed. However, this method still falls short of directly accounting for a vehicle's instantaneous motion, and EFs calculated in this way are likely to be less accurate than those calculated using AIRE.

5.4 TRAFFIC VARIABLES

5.4.1 Traffic Variable Selection

Numerous measures of traffic performance (i.e. traffic variables) could potentially have been selected for investigation with regard to their ability to predict EFs (i.e. their ability to act as predictor variables in predicting EFs as the outcome variable). A comprehensive study detailing the many different possible traffic variables can be found in Smit (2006) (refer to Section 2.4.6). Additionally, network characteristics are a further source of traffic variables (as defined in this project, refer to Section 2.4.1) that were considered for selection because they are easily measured by LGAs and generally subject to very little variation over time.

However, it was beyond project resources to investigate all possible traffic variables, and a number of key criteria were used to make a selection. When conducting statistical analysis such as MLR it has been suggested that it is not good practice to measure many predictor variables and then use them all in the regression model. Instead, as a general rule, the fewer predictor variables the better, and those chosen should be selected based on the criterion of successful use in previous research (Field 2009), i.e. a key criterion of previous use in emissions predictions.

Based on the findings of the literature review and LGA survey, two further key criteria for traffic variable selection were that they are familiar to LGAs (i.e. widely used in traffic engineering to describe traffic performance), and easily available for routine collection by LGAs from UTC systems and Road Traffic Models (RTMs). Obviously, as this project was concerned with including congestion influence, a fourth key criterion was that the selected traffic variables also had to be indicators of congestion. Using the four identified key criteria in combination, the following five traffic variables were selected for investigation (for details of how values for the selected traffic variables were calculated from ILD data, refer to Section 5.4.3):

1. Traffic average speed (km/h).

Traffic average speed was selected because emissions are strongly dependent on average speed (Smit *et al.* 2008b), and it has previously seen widespread use as a predictor of emissions (e.g. TRL EFs 2009, COPERT, MOBILE, refer to Section 2.5.5). It also readily complies with the other criteria, being a familiar indicator of congestion widely used in traffic engineering and easily available from UTC systems and RTMs.

2. Traffic average speed squared $(km/h)^2$.

The square of traffic average speed was selected because it has been found to be closely related to emissions (Ligterink *et al.* 2012) and, given that traffic average speed had already been selected, was an easily available supplementary traffic variable. It also has previously been used to predict emissions (e.g. WebTAG, refer to Section 2.5.5.3; and Velocity and Payload Emissions Model for HGVs, refer to Section 2.5.8.4).

3. Traffic density (vehicles/km).

Traffic flow (vehicles/h) is widely used in traffic engineering, is related to congestion, and is readily available from UTC systems and RTMs. However, traffic flow suffers from ambiguity (refer to Section 2.4.6) in that flow can be zero either when traffic is in a motionless queue (high congestion) or when there is no traffic (low congestion). Therefore, traffic density was selected as a less ambiguous alternative to traffic flow. Traffic density is the average number of vehicles on a road section (in a given time period) divided by the length of the road section.

Similar to traffic flow it is widely used in traffic engineering, and can be calculated from traffic flow with Equation 11. Additionally, traffic density has previously been used to predict emissions (e.g. TEE-KCF, refer to Section 2.5.7.1).

Equation 11

Traffic density (vehicles/km) = Traffic flow (vehicles/h)/Traffic average speed (km/h)

4. Traffic average delay rate (seconds/vehicle.km).

Traffic average delay rate is the average delay per vehicle (in a given time period) normalised for distance, where vehicle delay is the difference between achieved travel time and expected free-flow travel time over a given distance. Traffic average delay rate was selected because it is closely related to congestion and readily available from UTC systems and RTMs. It is also a metric that is widely used in traffic engineering, and should be familiar to LGAs because of its similarity to LGA reported congestion indicators. For example, average total vehicle delay for a link (a typical LGA congestion indicator) is readily converted to traffic average delay rate using link length and number of vehicles. Finally, vehicle delay has previously been used to predict emissions (e.g. DCM, refer to Section 2.5.7.4).

5. Access Density (intersections/km).

Access density was selected because both stop signals and vehicle interactions at intersections can disrupt free-flowing traffic conditions and contribute to congestion. It is a metric that can be easily measured by (or on behalf of) LGAs, and, once measured, will be subject to very little change over time. It also has previously been used to predict emissions (e.g. ESC, refer to Section 2.5.10.5).

5.4.2 ILD Data Collection

To complement the method adopted for calculating accurate EFs based on real-world GPS driving patterns, the best available source for concurrent traffic variables (except access density) was to calculate values from real-world data generated by ILDs installed as part of Southampton's UTC system. These have an advantage over traffic variable outputs from RTMs, in that they represent the situation 'on the ground' rather than a modelled representation of reality. In any case, having selected real-world GPS driving patterns as the basis for EF calculation, obtaining concurrent traffic variable values from RTMs was ruled out as a feasible option. Consequently, PEMLA was developed to accept ILD-generated data (plus access density) as inputs. In situations where ILD data are not available and an RTM is used as an alternative source (e.g. a hypothetical intervention scenario modelled in an RTM), PEMLA input data would need to be generated by simulated ILDs installed across the modelled network.

5.4.2.1 SCOOT UTC system U07 message

The UTC system installed in Southampton is SCOOT. The University of Southampton has a data sharing agreement in place with Southampton City Council (SCC) and Balfour Beatty Living Places Limited (the operator of Southampton's City Depot traffic control centre) that allows certain data from the UTC system to be collected by the University. The UTC system database is accessed via numerous different messages, and the University downloads and stores on a daily basis the data returned by the M02, M08, M37, P02, and U07 messages (Table 5-4). The U07 message was selected as the UTC data source for this project for five reasons: (1) the message content provides all the data necessary to estimate values for the chosen traffic variables; (2) the message contains 'raw' ILD data, which (it could be argued) are closer to ground-truth than SCOOT modelled data (i.e. 'raw' ILD data that have been processed by the SCOOT system); (3) it was SCOOT modelled data that were used in the unsuccessful attempt by Reynolds (1996) to develop a concentration model for CO (refer to Section 2.5.10.2); (4) during development of NUIDAP (refer to Section 2.5.10.6), the prediction of emissions based on data in the M02, M08 and M37 messages has been previously investigated (an important reason from the perspective of novelty in a doctoral thesis); and (5) the U07 message provides more comprehensive data coverage, being available for far more of the ILDs in Southampton than the other messages (for example, the M02 message is available for approximately half the number of ILDs for which the U07 message is available, the M08 message is available for only 18 ILDs related to 3 intersections, and the P02 message for only 10 ILDs related to 2 intersections).

The U07 message is a bespoke SCOOT message developed by the University of Southampton. Although this message is specialist in nature, it is available from any SCOOT system, i.e. it is not unique to Southampton and would be available for any urban area in which SCOOT is installed. The message was originally developed to provide estimates of Average Loop Occupancy Time Per Vehicle (ALOTPV) and Average Time Gap Between Vehicles (ATGBV). ALOTPV is calculated for an ILD over a 30 second period, and is obtained by dividing the occupied time (number of occupied intervals reported by the ILD) by the number of vehicles crossing the ILD. ILDs report occupied or unoccupied at 250 millisecond intervals. Therefore, ALOTPV was engineered to return a value between 1 and 120 (30s/0.25s = 120); with the former indicating free-flow conditions and the latter indicating stationary traffic. ATGBV is calculated in a similar way, but is obtained by dividing the unoccupied time (number of vacant intervals reported by the ILD) by the number of vehicles crossing the ILD. ATGBV was also engineered to return a value between 1 and 120; with the former indicating stationary traffic and the latter indicating free-flow conditions (Cherrett *et al.* 2002). The U07 message reports values for ALOTPV and ATGBV averaged over 5 minute time intervals. The U07 message also includes an estimate of traffic average speed (averaged over a 5 minute time interval in both mph and km/h), which is derived from a relationship between ALOTPV and vehicle speed. Development of the relationship between ALOTPV and the measured speeds of vehicles (determined through video surveillance) is described in Cherrett *et al.* (2001), which demonstrated that ALOTPV was a successful parameter for estimating speed over ILDs (Cherrett *et al.* 2002). Two other values reported in the U07 message are flow (vehicle count in a 5 minute time interval) and the percentage of a 5 minute time interval for which an ILD was occupied (Cherrett 2001).

Table 5-4: SCOOT UTC system messages collected by the University of Southampton.

Message	Message Type	Message Data
M02	SCOOT model message	Five minute averages of SCOOT modelled approximations for each link of: vehicle stops (stops/h); delay (vehicle.h/h); and flow (vehicles/h).
M08	SCOOT model message	SCOOT modelled approximations for each link of queue length at times related to traffic signal timings.
M37	SCOOT model message	Traffic signal timings for each intersection.
P02	SCOOT emissions modelling message	Five minute averages of SCOOT built-in Average Speed EM approximations of emissions for each link of: CO_2 (kg/h); CO (g/h); NO_X (g/h); VOC (g/h); and PM (g/h).
U07	Bespoke University of Southampton message	Five minute averages of 'raw' ILD data for each link of: traffic average speed (mph); traffic average speed (km/h); flow (vehicles/5 minutes); percent of 5 minutes ILD was occupied; ALOTPV; and ATGBV.

- ALOTPV is Average Loop Occupancy Time Per Vehicle.
- ATGBV is Average Time Gap Between Vehicles.
- The units of measurement for ALOTPV and ATGBV are not in seconds, but instead relate to the number of times an ILD is sampled for occupancy/vacancy during a 30 second time interval (refer to Section 5.4.2.1).
- Sources: Siemens (2012); Cherrett (2001).

5.4.2.2 Audit of Southampton's ILD data

For Southampton's network of ILDs, the U07 message contains data for each day (from midnight to midnight in local time) divided into 5 minute periods. For example, data with the time stamp 01:10:00 relate to the 5 minute period from 01:05:01 to 01:10:00. Individual ILDs are identified in the data by a unique reference number (loop identifier). These loop identifiers correspond to a set of wiring diagrams for the city that indicate where in the road network each ILD is located (included as Appendix E). However, the wiring diagrams are somewhat out-of-date, and following alterations to the UTC system and works to the road network over the intervening years, some doubts existed concerning which ILDs were working and producing reliable data[115]. Therefore, an audit was performed by reviewing the contents of the U07 message, cross-referenced against ILD locations as depicted in the wiring diagrams, to ascertain which ILDs were generating data and check whether the data being generated were as one would expect. The most recent audit was conducted using data from 8th December 2015 (two other audits were completed, one for 21st July 2015 prior to commencement of data collection, and one on the 19th October 2015 during the data collection period, with very minor variations in working ILDs between the three audit dates, e.g. due to road works). Results showed that, of the 323 ILDs identified in the U07 message, 169 (52%) were generating data that appeared sensible. Figure 5-5 shows the regions of the city within which these operational ILDs are located. As Figure 5-5 demonstrates, the number of non-operational ILDs led to areas of the city that lacked ILD coverage. This increased the time taken for collection of GPS trip segment driving patterns because the restrictions on the locations where concurrent ILD data were available limited the number of useable trip segments that could be extracted from the GPS trace of a particular vehicle's trip.

[115] In personal communications it was established that even the operator (Balfour Beatty Living Places) of Southampton's SCOOT system was lacking a systematic record of this information.

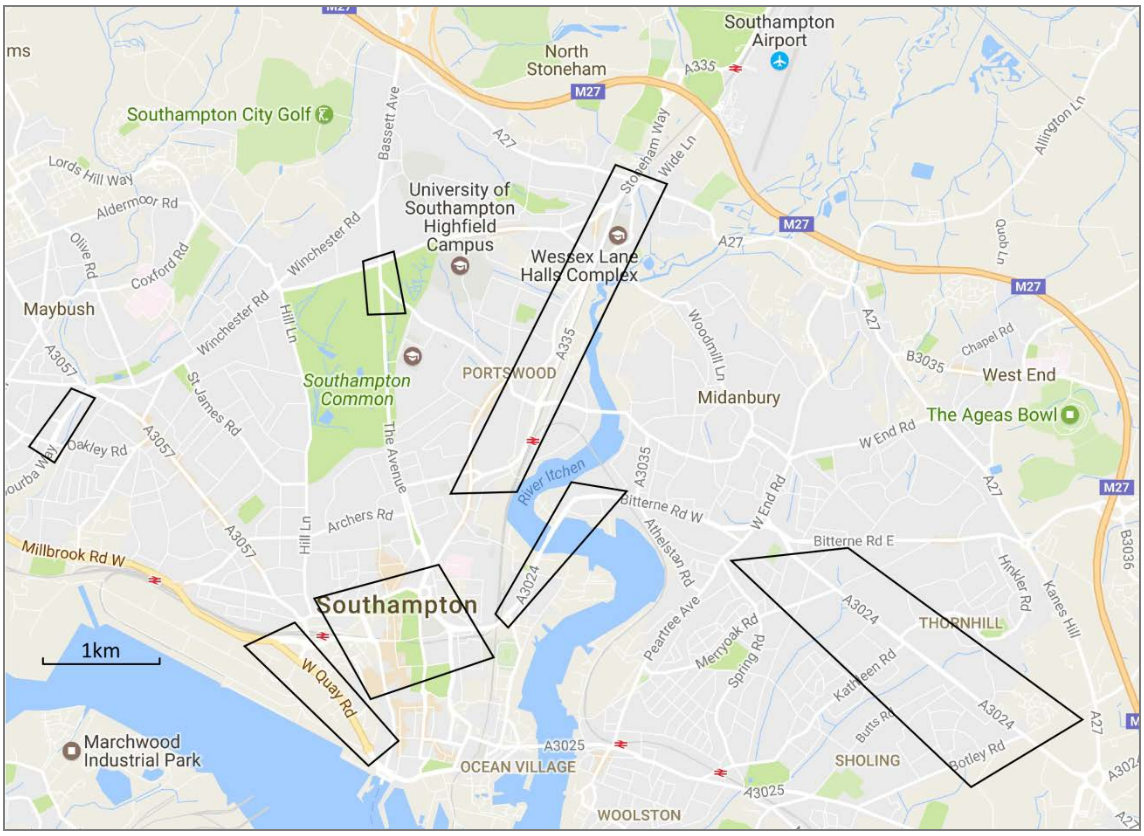

Figure 5-5: Map of the regions of Southampton within which operational ILDs are located.

- Operational ILDs are located within the regions marked by black quadrilaterals.
- Scale bar indicates a distance of 1 kilometre.
- Source: Base map obtained from Google Maps.

5.4.3 Traffic Variable Calculation

The following paragraphs detail how the ILD data were used to calculate values for four of the five selected traffic variables. Calculation of the fifth traffic variable (access density) is also detailed, but was not based on ILD data.

1. Traffic average speed (km/h).

Traffic average speed was taken directly from the value returned by the U07 message. This value is the average of the estimated speeds of all vehicles crossing an ILD in a five minute period, which is essentially a measure of time-mean-speed (i.e. an average of spot speeds). For further discussion of the accuracy of ILD speed data refer to Section 5.4.4.

2. Traffic average speed squared $(km/h)^2$.

The square of traffic average speed was calculated by squaring the traffic average speed value returned by the U07 message.

3. Traffic density (vehicles/km).

The U07 message returns a count of the number of vehicles crossing an ILD in a five minute period (based on the number of occasions the ILD switches from occupied to unoccupied), which was multiplied by 12 and converted to traffic flow (vehicles/hour). Traffic density was then calculated using traffic flow and the ILD estimate of traffic average speed as inputs to Equation 11.

4. Traffic average delay rate (seconds/vehicle.km).

Traffic average delay rate was estimated from the data available in the U07 message based on an assumption about traffic free-flow speed. The assumption used was that traffic free-flow speed is equal to the speed limit on a link (although free-flow speed may in reality be slightly in excess of the speed limit). Therefore, for a given link length, average delay per vehicle was calculated from the difference between travel time at traffic average speed and travel time at the speed limit. Traffic average delay rate was then obtained through dividing average delay per vehicle by link length.

5. Access density (intersections/km).

Access density is a network characteristic, and was calculated by inspection of the trip segments using the Q-Travel software. Q-Travel provides a background map display, on which it was possible to count the number of intersections along the route of a trip segment. The intersections at the start and end points of a segment were excluded from the count so that, if a segment was to constitute a single link (which did not occur in this project due to the definition of a trip segment), this would have an access density of zero.

5.4.4 Accuracy and Assumptions for ILD Data

In general, there are a number of factors that can influence the accuracy of data generated by ILDs. For example, in congested traffic conditions ILDs can be susceptible to nose-to-tail masking, where two (or more) slow moving, closely spaced vehicles may be registered as a single vehicle; although ILDs are usually located at the upstream end of a link to minimise the likelihood of slow moving or stationary vehicles in their vicinity (Boddy *et al.* 2005). Other factors that can affect ILD accuracy include vehicle chassis height (e.g. cars typically sit closer to the road surface than vans or HGVs), vehicle metallic content, and ILD responsiveness, which is in turn dictated by features such as pavement characteristics (e.g. condition and material), design standards, and installation depth under the road surface (Cherrett *et al.* 2002; Boddy *et al.* 2005; Lee and Coifman 2012). Responsiveness typically varies from ILD to ILD.

Therefore, ILDs usually have a user-selectable sensitivity setting. However, in practice, it is difficult to ascertain an ILD's responsiveness in-situ, which in turn makes it difficult to set the appropriate sensitivity. An ILD will not perform well if its sensitivity and responsiveness are poorly matched (Lee and Coifman 2012). Boddy *et al.* (2005) reported an assessment of the accuracy of SCOOT ILD data through comparison with direct observations of the traffic on arterial roads within the city of York, UK. For three of the four links observed in the study (comprising off-peak and PM peak period observations) ILDs captured an average of 96% of the observed flow. The fourth link had a lower capture rate of 90% of the observed flow, which was attributed to nose-to-tail masking due to heavy congestion causing traffic queues that often covered the entire length of the link throughout the majority of the day.

ILDs can be single-loop or double-loop, with the most common installation being single-loop (Cherrett *et al.* 2001; Coifman and Kim 2009; Li 2009), and this is the configuration used by SCOOT UTC systems (Han *et al.* 2010) such as that installed in Southampton. Single-loop ILDs only detect whether or not they are occupied. Therefore, rather than a true measurement of vehicle speed, single-loop ILDs can only provide an estimate of vehicle speed based on occupancy data. For example, based on the length of time for which an ILD is occupied and an assumption about the average length of vehicles (Guo *et al.* 2009), or the development of a relationship between ALOTPV and vehicle speed (Cherrett *et al.* 2001). Double-loop ILDs overcome this speed estimation problem by calculating a vehicle's speed from the distance between the two loops and the difference in vehicle arrival times at the two loops (Lee and Coifman 2012), i.e. double-loop ILDs <u>can</u> calculate a true measure of time-mean-speed in the strict sense (based on measurement of the time taken to travel between two points a known (small) distance apart). However, because single-loop ILDs are the most common installation, to provide the greatest utility for LGAs, it was desirable to investigate the prediction of CO_2 emissions based on data from this type of ILD. For example, emissions predictions based on data from double-loop ILDs would not have been of use to SCC because Southampton's SCOOT system is based on single-loop ILDs.

ILDs are frequently installed under each lane of a road, i.e. one ILD (single- or double-loop) per lane (Guo *et al.* 2009), and data generated are on a per lane basis. This situation is straightforward where a road is single lane (i.e. two lanes carrying traffic in opposite directions), with vehicles experiencing the traffic conditions in that lane and the associated ILD returning data for the same. The majority of roads in urban areas are single lane. However, some roads (typically larger arterial roads) are dual lane (or occasionally more than dual lane). In this situation, a judgement was made about which lane's ILD was appropriate for use as a data source based on a vehicle's direction of travel at the associated intersection (i.e. straight on or turning at the intersection). On other occasions, one ILD can be installed across both lanes of a dual lane road, or sometimes a dual lane road is monitored by two ILDs during peak periods which are then amalgamated into one ILD outside peak periods. For example, of the 169 operational ILDs identified in the U07 message for Southampton, 52 (31%) are installed across two lanes[116]. Where an ILD covers two lanes there is no way to accurately disaggregate the data for each lane, and Cherrett *et al.* (2001) found that relationships for estimating vehicle speed derived from ILDs covering a single lane did not transfer well to ILDs covering two lanes. For this reason ILDs covering two lanes were avoided as a source of data for traffic variable calculation in this project. A consequence of this was a further increase in locations around Southampton that lacked ILD coverage, further limiting the number of useable trip segments that could be extracted from the GPS trace of a particular vehicle's trip. An advantage of developing a relationship between traffic variables and EFs on a per lane basis is that PEMLA can then be applied to single- and multi-lane roads, with the multi-lane situation being calculated as the sum of multiple single-lane calculations.

Due to the limited availability of operational ILDs covering just one lane within Southampton's road network, from a practical perspective of collecting sufficient trip segment samples to allow statistical analysis, in the case of some trip segments it was necessary to use an ILD on a link adjacent to (but not forming part of) a trip segment to provide the data for calculating traffic variables. In these cases, an assumption was made that an ILD on an upstream or downstream link could provide data on the traffic conditions for the links of the trip segment. To test the validity of this assumption, 12 intersections were identified from different regions across Southampton where ILD data were available for both upstream and downstream locations. Values for traffic average speed and flow returned by the ILDs on either side of each intersection were compared because these were the data used as the basis for calculating the traffic variables associated with each trip segment. The arithmetic mean and standard deviation (SD) were calculated for the traffic average speed (km/h) and flow (vehicles/5 mins) values returned by the U07 message for each 5 minute period from 07:00 to 20:00 on a typical weekday (Friday 3rd July 2015). Results are shown in Table 5-5. Whilst it was not the

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[116] In fact, 2 of the 52 ILDs are installed across three lanes of a triple lane road.

expectation that upstream and downstream values would be the same, the differences are deemed to be small enough from the perspective of use in predicting emissions of CO_2 that their ability to stand as proxies for each other was acceptable on the occasions where this was necessary.

Table 5-5: Comparison of the mean and standard deviation for values of traffic average speed and flow for 5 minute periods from 07:00 to 20:00 returned by ILDs located upstream and downstream of test intersections.

Southampton Scoot region	ILD		5 minute traffic average speed (km/h)		5 minute flow (vehicles/5 mins)	
	Upstream	Downstream	Upstream Mean (SD)	Downstream Mean (SD)	Upstream Mean (SD)	Downstream Mean (SD)
SB	N10351A	N10361Y	37.1 (2.1)	29.0 (1.9)	55.9 (14.9)	53.4 (11.9)
SB	N10351E	N10331E	26.2 (3.2)	33.6 (2.4)	43.0 (9.1)	44.4 (9.9)
SG & SJ	N06211F	N06252D	21.1 (3.7)	29.2 (3.5)	20.7 (6.4)	36.4 (10.8)
SG & SJ	N06241C	N06251B	24.3 (1.7)	28.1 (2.7)	52.4 (12.9)	49.3 (10.5)
SJ	N06251A	N06221C	34.7 (2.8)	36.7 (2.8)	64.8 (13.6)	60.9 (13.0)
SG & SJ	N06252E	N06231D	30.2 (3.3)	19.8 (4.6)	24.9 (7.3)	19.3 (6.0)
SG & SM	N06251B	N05141A	28.1 (2.7)	27.4 (2.7)	49.3 (10.5)	56.6 (11.0)
SI	N07764F	N07754C	21.9 (5.8)	22.5 (3.9)	13.9 (5.1)	18.0 (7.6)
SM	N05141A	N05151B	27.4 (2.7)	26.3 (2.4)	56.6 (11.0)	58.6 (11.2)
SM	N05142B	N05111C	26.5 (3.2)	25.0 (3.3)	31.3 (7.9)	30.6 (6.8)
SY	N11121E	N11121M	28.7 (6.6)	21.2 (8.2)	52.3 (8.9)	63.9 (14.6)
SY	N11131F	N11131Z	27.4 (1.7)	29.9 (2.5)	54.2 (8.8)	52.6 (11.9)

- Data are for Friday 3rd July 2015.
- Data are extracted from the U07 message.
- SD is Standard Deviation.

A further assumption that underpinned the ILD data collected during this project was that the data were collected from a typical UTC system layout, which embodied the usual range of ILD positions across the network, in particular the position of ILDs relative to nearby intersections and traffic signals that will have affected the dynamics of vehicles as they crossed detectors (i.e. Southampton's UTC system layout was typical, and similar ILD data would therefore be found in other urban areas). Supporting this assumption was the fact that PEMLA was designed for network-level emissions predictions, and any ILD-specific variations in positioning will, to an extent, average-out over a network.

As a final and perhaps most important point, notwithstanding the issues relating to the accuracy of data generated by ILDs that have been outlined in this section, it is these data that are readily available to LGAs for use as inputs to the emissions modelling process. Therefore, the concern of this project was to investigate whether these data (with all their inherent inaccuracies) could be used to predict road traffic CO_2 emissions.

5.4.5 Traffic Variable Averaging Process

The statistical analysis used to calibrate PEMLA required samples (trip segments) consisting of a single value for each predictor variable (each traffic variable) and an associated value for the outcome variable (EF). Therefore, an averaging process for the data returned by the ILDs a vehicle crossed over the length of a trip segment was required for the four traffic variables obtained from the U07 message. To achieve this, values of the traffic variables were sampled at 1 minute intervals during a trip segment, followed by calculation of the arithmetic mean of all the sampled values[117]. For convenience and synchronisation with time periods in the U07 message, the timing of samples was coincident with whole minutes of the time of day. The sampled value was from the link on which the vehicle was located at sample time, and was the value returned by the ILD situated on that link for the minute preceding the sample time. Occasionally, an error was introduced because a vehicle had not been on the link from which the traffic variable values were obtained for the entirety of the 1 minute interval preceding the sample time. For example, when vehicles pass from one link to the next, or when start and end times of trip segments did not occur exactly on whole minutes. This error could have been reduced by increasing the sample rate, but 1 minute intervals were chosen as a practical compromise between the time taken to process an average traffic variable value for each segment and the accuracy of that value.

Also, due to the mismatch between the U07 message data averaging interval of 5 minutes and the sampling interval of 1 minute, when a vehicle remained on the same link with the same ILD at successive sample times within the same 5 minute U07 averaging interval, the same values in the U07 message data were sampled multiple times. The sampling interval could have been increased to 5 minutes to match the U07 averaging interval, but this was deemed to be too coarse in terms of capturing a vehicle's spatial position. This was because, within a given 5 minute U07 averaging interval, a vehicle will often have travelled to another link with a different ILD returning different U07 data (i.e. a 1 minute sampling interval allowed a vehicle's movement onto other links with other ILDs to be better captured).

[117] For simplicity, traffic average speed squared was actually calculated as the square of the average value for a trip segment of traffic average speed, rather than the average of the squares of traffic average speed values for each minute, which would give a slightly different result.

Essentially therefore, the traffic variable averaging process calculated a weighted average of the U07 message data that applied to a given trip segment. For example, a five minute trip segment where the vehicle spent three minutes on one link, before spending two minutes on the next link would have an average traffic variable value calculated from three samples of the U07 data from the ILD on the first link and two samples of the U07 data from the ILD on the second link.

5.5 STATISTICAL ANALYSIS

5.5.1 Statistical Analysis Method

5.5.1.1 Method Selection

On completion of data collection and processing, a dataset of results for each of the 24 PEMLA vehicle categories was produced containing trip segment samples, each consisting of values for the five traffic variables and for the EF. An appropriate method for exploring any relationships between a set of predictor variables (traffic variables) and an outcome variable (EF) is Multiple Linear Regression (MLR) analysis (Field 2009), and this was the method selected for use in this project, with all analyses performed using IBM SPSS 22 software. Very briefly, MLR analysis involves fitting a linear model to the data sample through application of the Ordinary Least Squares (OLS) estimator[118], which minimises the sum of squared residuals (SS_R) (Kennedy 2003), where residuals are the differences between observed values for the outcome variable and those predicted by the model (i.e. representative of model error) (Field 2009).

MLR (or simple linear regression in cases with a single predictor variable) has previously been successfully used in the development of a number of EMs, for example the DCM (refer to Section 2.5.7.4), VERSIT+LD (refer to Section 2.5.8.1), the Velocity and Payload EM for HGVs (refer to Section 2.5.8.4) and the ESC (refer to Section 2.5.10.5). However, there are some instances where MLR was not successful, such as the attempt to predict roadside CO concentrations from traffic variables (refer to Section 2.5.10.2). In general, in the literature relating to EM development, unsuccessful examples of MLR analysis are outnumbered by successful examples; although this may be subject to reporting bias, with unsuccessful examples less likely to be reported.

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[118] An estimator is the formula (algebraic function of the data sample) used to estimate the parameters (constant and predictor variable coefficients) that define the model (Kennedy 2003).

5.5.1.2 Sample size for Multiple Linear Regression

Perhaps the simplest expression of the minimum sample size necessary for MLR analysis is as many samples as can be collected within the resources available. However, to find quantifiable guidance on the minimum number of trip segments that needed to be collected per vehicle category, literature concerning the sample size necessary to obtain reliable MLR models was consulted. Field (2009) highlighted two commonly used rules of thumb, which were to multiply the number of predictor variables by 10 or by 15. This project had five traffic variables as predictor variables, which eventually increased to seven following the addition of two more traffic variables during preliminary statistical analysis (refer to Section 5.5.2), giving a sample size of either n=70 or n=105 per vehicle category. However, Green (1991) suggests the minimum acceptable sample size should be the greater of: minimum sample size for a reliable overall model of 50+8k, where k is the number of predictor variables (n=106 with seven predictor variables); and minimum sample size for a reliable contribution from individual predictor variables of 104+k (n=111 with seven predictor variables); giving a sample size of n=111 per vehicle category. Miles and Shevlin (2001) suggest that required sample size depends on the number of predictor variables and the size of expected effect (i.e. how well the predictor variables can predict the outcome variable in terms of the size of correlation expected between predicted and observed values of the outcome variable), with effect sizes defined as small, medium or large in accordance with Cohen (1988) and Cohen (1992)[119]. The work of Miles and Shevlin (2001) is summarised in a graphical format in Field (2009). Entering this graph with seven predictor variables gives sample sizes of n=700, n=110 and n=50 per vehicle category for small, medium and large effect sizes, respectively. For the purposes of this project, taking account of the different sources of guidance, n=110 was selected as an appropriate minimum sample size, and at least this number of trip segments were collected for each vehicle category (refer to Table 5-2).

5.5.1.3 Neural network analysis for comparison

It is possible for complex data relationships to go undetected when analysis is performed using standard conventional statistical methods such as MLR. Therefore, it is worth employing advanced methods such as neural network analysis as well (Sewak and Singh 2015). The Multilayer Perceptron (MLP) is the most commonly used type of feed-forward (i.e. non-cyclical)

[119] Cohen defines the following effect sizes:
Small effect size: Pearson's correlation coefficient of r=0.1 (effect explains 1% of the total variance).
Medium effect size: Pearson's correlation coefficient of r=0.3 (effect explains 9% of the total variance).
Large effect size: Pearson's correlation coefficient of r=0.5 (effect explains 25% of the total variance).

neural network in the atmospheric sciences, and can represent relationships between predictor and outcome variables that are unconstrained by assumptions such as those that underpin MLR analysis (Gaudart *et al.* 2004; Agirre-Basurko *et al.* 2006).
However, from a practical perspective, the results of MLR analysis are easier to interpret and utilise than the results of MLP analysis (IBM 2013a). Hence, the purpose of MLP analysis in this project was to act as a standard against which MLR analysis could be judged. Accordingly, for each MLR analysis conducted, an MLP analysis was also conducted in parallel using the default settings in IBM SPSS 22, which were deemed to not need fine-tuning for the model generated by MLP to function as a comparative indicator.

When SPSS default settings were used, automatic architecture selection created a MLP neural network that had three layers (Figure 5-6): an input layer; a hidden layer (with the number of hidden nodes in the hidden layer automatically optimised by SPSS); and an output layer (IBM 2013a). Nodes in the input layer corresponded to the different predictor variables (i.e. the same set of predictor variables as were used in the parallel MLR analysis to which comparison was being made), and the node in the output layer corresponded to the outcome variable (i.e. accurate EFs). All nodes were connected to all nodes in neighbouring layers. A node sums the inputs it receives from the previous layer, and then applies a non-linear transfer function, before passing the result to the next layer (Catalano *et al.* 2016). The non-linear transfer function (selected automatically when using SPSS default settings) applied by the hidden nodes in all the MLP analyses conducted during this project was the hyperbolic tangent function[120].

The collected samples (i.e. the trip segment samples) were partitioned into two sets[121], a set for training the network (the training set) and a set for testing and validation (the testing set). Using SPSS default settings, the samples were randomly partitioned into 70% for the training set and 30% for the testing set (IBM 2013a).

[120] The hyperbolic tangent function is of the form: $\tanh(x) = (e^{2x} - 1)/(e^{2x} + 1)$ (IBM 2013a).

[121] It is possible in IBM SPSS 22 to have a third set of independent samples (the hold-out set). However, three sets of samples (training, testing and hold-out sets) are only required when it is necessary to choose between different model architectures produced as a result of fine-tuning (i.e. a set to train the models, a set to choose the model architecture producing the smallest error, and a set to validate the final selected model) (Catalano *et al.* 2016; Hastie *et al.* 2009). In this project, there were no fine-tuned model architecture options to choose between (because SPSS default automatic architecture was used instead and deemed to not need fine-tuning to serve adequately as a comparative indicator). Therefore, the default setting in SPSS of only a training set and a testing set was sufficient.

Network training is an iterative process. Each node-to-node connection has a weighting (synaptic weight). During training, at each iteration, the MLP predicts values for the outcome variable (i.e. accurate EFs) for all samples in the training set (batch training was used under SPSS default settings which ensured all samples in the training set were used to calibrate the model), which are then compared to observed values and an error signal back-propagated through the network to adjust the synaptic weights to reduce the magnitude of the error (Catalano *et al.* 2016; IBM 2013a).

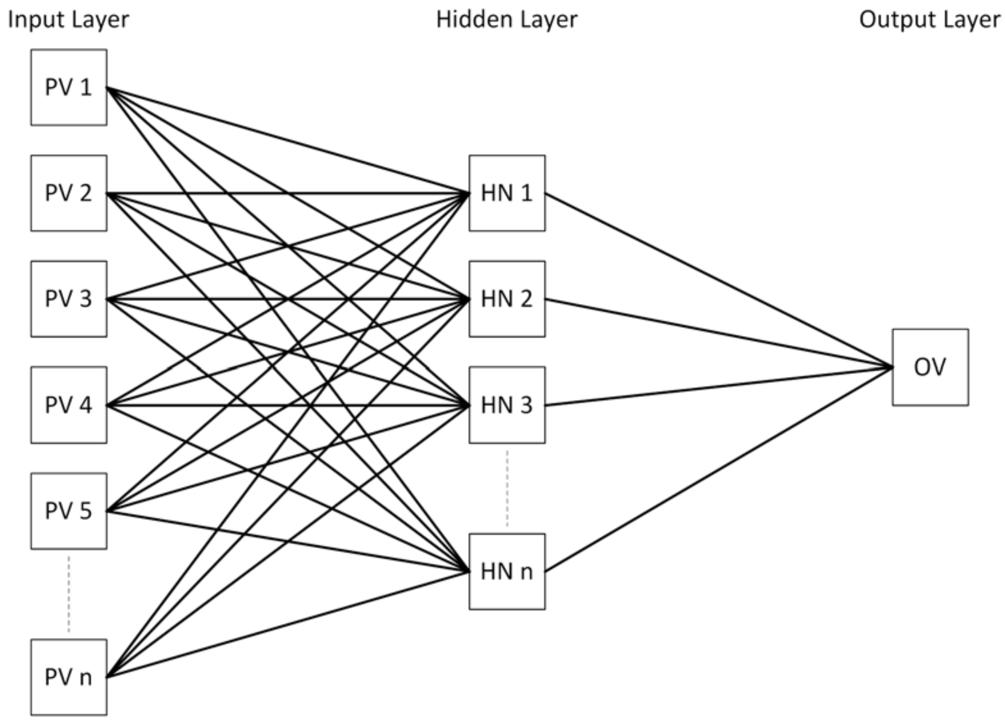

Figure 5-6: Diagram of a Multilayer Perceptron (MLP) neural network.

- PV is Predictor Variable; HN is Hidden Node; and OV is Outcome Variable.
- Source: adapted from Catalano *et al.* (2016).

At each iteration, values for the outcome variable (i.e. accurate EFs) for the testing set are predicted as well. However, the testing set is not used in calibration of the network (i.e. the testing set does not contribute to the error signal back-propagated to adjust synaptic weights). Instead, the testing set is used to prevent over-training, which is the situation where an overly complex model is a good fit to the training data, but is poor at generalising to make predictions from unseen data. In other words, the testing set validates the model, ensuring it can make accurate predictions when applied to unseen data (Catalano *et al.* 2016; IBM 2013a). Typically, during network training, the training set error tends to reduce with an increasing number of iterations; whereas the testing set error initially tends to reduce, before beginning to increase as the model starts to over-train. Stopping the iterations at the point of minimum error in the testing set therefore prevents over-training (Catalano *et al.* 2016).

The coefficient of determination (R^2) is a measure often used to assess the results of MLR analysis[122], and for a linear relationship estimated by OLS (i.e. as in MLR analysis) it represents the proportion of variation in the outcome variable that can be explained by variation in the predictor variables (Kennedy 2003). However, MLP analysis in SPSS does not output an R^2 value for the model generated. Therefore, to allow comparison with MLR analysis, a R^2 value for MLP analysis was derived through a bivariate linear correlation between MLP predicted and observed outcome values, and then squaring of the resulting Pearson linear correlation coefficient (r) (Field 2009). This provided an indication of the likely maximum R^2 value for the relationship between predictor and outcome variables when freed from any constraints imposed by MLR analysis.

5.5.2 Preliminary Statistical Analysis

During the preliminary phase, rather than analyse all 24 PEMLA vehicle categories, four representative categories were selected, one from each of the (more aggregate) trip segment collection vehicle categories: category 01 (representing LDV); category 20 (representing HDV (except bus)); category 22 (representing bus); and category 24 (representing two-wheel vehicle). In addition to analysing all cases within a particular vehicle category, to investigate any effect on EFs caused by different road types or times of day, cases were split according to these criteria. Hence, for each category, analysis was conducted for: (1) all cases; (2) cases split according to road type as determined by the speed limit (either 30 or 40 mph); and (3) cases split according to time of day (either peak period or off-peak period). On some occasions these splits led to sample sizes that were too small for sensible MLR analysis; although these occasions are retained in the results for the sake of completeness. Other methods for splitting cases according to road type were considered, such as according to UK national road classification (A-Road, B-Road or Other Road) or according to a more subjective assessment of road type (i.e. degree of segregation from potential hazards). However, these methods were rejected for two main reasons: (1) they often led to sample sizes being too small for MLR analysis; and (2) road type classification according to speed limit was seen as a more practical method for use by LGAs.

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[122] Adjusted R^2 (Adj. R^2) is often used instead. R^2 is valid for a model based on MLR analysis of a sample of data, whereas the adjusted value is an estimate of what R^2 would be if the model had been based on analysis of the entire population (Field 2009).

The final part of the preliminary analysis explored whether any correlations other than linear were present between predictor and outcome variables. Using the curve estimation function in SPSS, different non-linear correlations were assessed (compound, cubic, exponential, growth, inverse, logarithmic, power, quadratic and s-curve models, with equations as defined in IBM (2013b)). Considering the different forms of regression analysis, MLR is very well understood mathematically, and from a practical perspective is most easily interpreted. Hence, linear correlations between predictor and outcome variables were the preferred option. The objectives of this part of the analysis were to check whether any non-linear correlations existed; and if so, whether they offered considerable improvement (i.e. large increase in R^2) over any linear correlation and whether they could be incorporated into MLR analysis (e.g. linear combination of a non-linear function of a predictor variable). The only alternative non-linear correlation that showed a statistically significant R^2 improvement consistently across the large majority of vehicle categories was the cubic form of access density (refer to Section 6.3.4), and therefore the square and cube of access density were added to the five original traffic variables for the principal statistical analysis.

5.5.3 Principal Statistical Analysis

During the principal phase, all 24 PEMLA vehicle categories were considered. Rather than run a separate analysis for each vehicle category, all categories were analysed together using a MLR analysis that included vehicle category as a predictor variable in addition to the five original traffic variables (plus the square and cube of access density). This was achieved by combining the data from the separate PEMLA vehicle categories into a single dataset on which the analysis was conducted. Consequently, PEMLA was developed as a single EM covering all 24 vehicle categories. Also included as predictor variables were road type and time of day, which were encoded using Dummy Variables (DVs). For road type (DV-Road Type by Speed Limit), a value of 0 indicated a 30 mph limit and a value of 1 indicated a 40 mph limit (i.e. 30 mph limit was the default). For time of day (DV-Time Period), a value of 0 indicated an off-peak period and a value of 1 indicated a peak period (i.e. off-peak period was the default).

An outlier was visually identified (during the preliminary statistical analysis) in the scatter plot of traffic average delay rate against EF for the two-wheel data (TDP017). This case had a traffic average delay rate of 2074 s/veh.km (equivalent to approximately 35 minutes delay per km for each vehicle), which was over 3 times the next highest value (600 s/veh.km) and well outside the range for all other cases. On investigation, the traffic average speed returned by the ILD for this case was found to be very low (1km/h over a 5 minute period). This may have been a genuine measurement of traffic average speed in congested conditions. However, in congested conditions there is a likelihood that the ILD speed measurement was inaccurate (e.g. nose-to-tail masking where two or more slow moving, closely spaced vehicles are registered as continuous loop occupancy by a single vehicle). This likelihood, coupled with its outlying nature, led to the case (one out of 111 cases for the two-wheel category and 3206 cases for the combined vehicle categories) being excluded from the principal statistical analysis.

5.5.3.1 PEMLA versions

Three different calibration methods to incorporate vehicle category into the MLR analysis were investigated, which initially led to development of three different versions of PEMLA[123] (PEMLA v.1 to v.3). Subsequently, the PEMLA v.3 method was further developed, which led to another three versions of PEMLA (PEMLA v.4, v.5 and v.7). In PEMLA v.1, DVs were used to encode vehicle category. Category 01 was used as the default, and 23 DVs (DV-Cat 02 to DV-Cat 24) were used to encode the vehicle category for each trip segment (i.e. a value of 1 if a vehicle was from the relevant category and a value of 0 otherwise). MLR analysis was conducted by four blockwise entries of predictor variables: forced entry of all vehicle category DVs in the first block; forced entry of the road type DV in the second; forced entry of the time of day DV in the third; and forced entry of the seven traffic variables in the fourth.

PEMLA v.2 used the same vehicle category DVs as PEMLA v.1. In addition, known relationships established in previous research between average speed and EFs were forced into PEMLA v.2 through the use of the WebTAG average speed formulae for EFs (refer to Section 2.5.5.3 and Table 5-6). The outcome variable for the MLR analysis was defined as: EF from AIRE minus EF from WebTAG (gCO_2/VKM). According to this definition, for each case, a value for the new outcome variable was calculated, with the ILD traffic average speed for a case used as input to the appropriate WebTAG formula because it is these data that are intended to be used by LGAs as inputs to PEMLA.

The MLR analysis generated a model of the form shown in Equation 12. The final form of PEMLA v.2 could then be found by rearranging Equation 12 to give Equation 13, which now also includes the relationship between EFs and average speed as described by the WebTAG

[123] It should be noted that PEMLA versions are purely chronological in order and do not imply any incremental improvement with advancing version numbers. Also, some PEMLA versions were unsuccessful and were omitted from this thesis. PEMLA version numbers are therefore not consecutive.

formulae. WebTAG does not include a formula for calculating EFs for two-wheel vehicles. Therefore, for Category 24, there was no EF from WebTAG to be deducted from EF from AIRE prior to the MLR analysis, and no WebTAG formula to be added back to the function of predictor variables resulting from the analysis. MLR analysis was again conducted by four blockwise entries of predictor variables: forced entry of all vehicle category DVs in the first block; forced entry of the road type DV in the second; forced entry of the time of day DV in the third; and forced entry of the seven traffic variables in the fourth.

Table 5-6: WebTAG formulae used in construction of PEMLA v.2.

WebTAG Vehicle Category	Equation Parameters					PEMLA Vehicle Categories to which Equation Applied
	E	a	b	c	d	
Car Petrol	2189	0.98758	0.03883	-0.00007	0.000002	Cats. 01 to 09
Car Diesel	2602	0.42995	0.05432	-0.00052	0.000004	Cats. 10 to 15
LGV Petrol	2189	1.894989	0.033540	0.000066	0.000004	Cat. 16
LGV Diesel	2602	1.188764	0.028490	-0.000196	0.000007	Cats. 17 to 19
OGV1 Diesel	2602	1.431446	0.258021	-0.003907	0.000034	Cat. 20
OGV2 Diesel	2602	2.670111	0.557156	-0.007976	0.000060	Cat. 21
PSV Diesel	2602	5.980055	0.245278	-0.003065	0.000031	Cats. 22 and 23

- EF from WebTAG is given by the equation EF (gCO_2e/VKM) = $E(a/v + b + c.v + d.v^2)$.
- v is average speed (km/h).
- Data are for 2016.
- Decimal places are quoted as in the original source material.
- Other Goods Vehicle 1 (OGV1) is rigid vehicles over 3.5 tonnes Gross Vehicle Mass (GVM) with two or three axles; Other Goods Vehicle 2 (OGV2) is rigid vehicles with four or more axles, and all articulated vehicles; and Public Service Vehicle (PSV) is buses and coaches over 3.5 tonnes GVM.
- WebTAG formulae calculate gCO_2e/VKM (CO_2 constitutes 99% of CO_2e for traffic emissions). However, because EF from WebTAG was subtracted from, and then added back to, EF from AIRE during the model calibration process, this small inaccuracy is less important; instead, it is inclusion of the functional form of the WebTAG formulae that is desired.
- Source: DfT (2015d).

Equation 12

$$\text{EF from AIRE} - \text{EF from WebTAG formula} = f\,(\text{predictor variables})$$

Equation 13

$$\text{EF from AIRE} = f\,(\text{predictor variables}) + \text{EF from WebTAG formula}$$

In PEMLA v.3, Interaction Variables (IVs) were created. IVs were used to encode the interaction between vehicle category and the five original traffic variables (plus the square and cube of access density). For each vehicle category, seven IVs were created, one for each traffic variable (total IVs = 24 vehicle categories x 7 predictor variables = 168). For the seven IVs associated with a given vehicle category, for cases of vehicles from that category the value of each of the IVs corresponded to the value of each of the traffic variables; and for cases of vehicles from other categories the value of each of the IVs was zero. For example, the IV encoding category 01 and traffic average speed (IV-Cat 01 & Traffic Average Speed) took the value of traffic average speed for all cases involving category 01 vehicles, but was zero for cases involving vehicles from the other 23 categories. MLR analysis was conducted by three blockwise entries of predictor variables: forced entry of all IVs in the first block; forced entry of the road type DV in the second; and forced entry of the time of day DV in the third.

Following comparison of the three methods (PEMLA v.1 to v.3) to incorporate vehicle category in the MLR analysis (refer to Section 7.2.2), PEMLA v.3 was identified as offering the most potential for further development. PEMLA v.4 was therefore based on PEMLA v.3 (i.e. using the IVs) but with the dataset split into two parts, part one covering LDVs (and two-wheel vehicles) and part two covering HDVs. As for PEMLA v.3, for both parts, MLR analysis was conducted by three blockwise entries of predictor variables: forced entry of all IVs in the first block; forced entry of the road type DV in the second; and forced entry of the time of day DV in the third.

PEMLA v.5 was developed as a re-estimation of PEMLA v.3 but with the MLR analysis conducted using an OLS Heteroscedasticity-Consistent Standard Error (HCSE) estimator[124] (Hayes and Cai 2007) rather than the standard OLS estimator. Three blockwise entries of predictor variables were used: forced entry of all IVs in the first block; forced entry of the road type DV in the second; and forced entry of the time of day DV in the third.

PEMLA v.7 was developed as a re-estimation of PEMLA v.3 but with a transformation applied to the outcome variable prior to the MLR analysis[125], which was again conducted using an OLS HCSE estimator. Three blockwise entries of predictor variables were used: forced entry of all IVs in the first block; forced entry of the road type DV in the second; and forced entry of the time of day DV in the third.

[124] For an explanation of the use of an HCSE estimator refer to Section 6.4.3.2.
[125] For an explanation of the use of a transformation of the outcome variable refer to Section 6.4.3.3.

5.5.3.2 Outlying and influential cases

For all MLR analyses conducted during principal statistical analysis, casewise diagnostics (i.e. examined on a case-by-case basis) were used to identify any outlying cases, and to assess whether these outliers were exerting any undue influence over the results. Hence, these diagnostics established whether (or not) a MLR model was stable across the data sample (Field 2009). To perform the diagnostic process, widely used threshold values for a series of diagnostic statistics (as detailed in the following paragraph and associated footnotes) were obtained from Washington *et al.* (2003), Kennedy (2003) and Field (2009).

Initially, any case with an absolute value for its Standardised Residual[126] greater than two (i.e. outlying cases) was selected for further investigation. This further investigation assessed the influence of the case, and consisted of checking thresholds for a case's Cook's Distance[127], Centred Leverage[128], Mahalanobis Distance[129], Standardised DFFit[130], Standardised DFBeta[131] associated with each model parameter, and Covariance Ratio[132]. The default position for dealing with any influential cases was that, in the absence of a compelling reason for deletion (e.g. obvious measurement error for the case concerned), they should be retained. This was because deleting influential cases without good reason is generally seen as bad practice, i.e. to make the data fit the model, in contrast to the objective of MLR analysis which is to make the model fit the data (Washington *et al.* 2003). Particular importance was attached to a case's Cook's distance because, even where values for other diagnostic statistics highlighted a case as potentially influential, if Cook's distance was < 1 then the case was not having a large effect on the overall MLR analysis and deletion would make little difference to results (Field 2009).

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[126] Standardising the residuals (or any variable) involves dividing a residual's difference from the mean by an estimate of the standard deviation from the mean as a method of conversion into a standard unit of measurement (i.e. measured in standard deviations).

[127] Cook's Distance quantifies the overall impact on all the model parameters (constant and predictor variable coefficients) when the model is calculated excluding a case. Values greater than one were cause for concern.

[128] Centred Leverage is a measure of the influence of a case's observed value of the outcome variable over the predicted values for the outcome variable. Average leverage is defined as (k + 1)/n, where k is the number of predictor variables and n is the number of cases. Centred Leverage values greater than twice the average leverage value were cause for concern.

[129] Mahalanobis Distance is a measure of the distance of a case from the means of the predictor variables. Critical values above which there was cause for concern vary with k and n, and were estimated using a table in Barnett and Lewis (1984).

[130] Standardised DFFit is the difference between the predicted value for the outcome variable when the model is calculated using all cases and when the model is calculated excluding a case. Absolute values greater than one were cause for concern.

[131] Standardised DFBeta is the difference between a model parameter when the model is calculated using all cases and when the model is calculated excluding a case. Absolute values greater than one were cause for concern.

[132] Covariance Ratio is a measure of whether a case influences the variance of the model parameters. Covariance Ratio values outside [1± (3 x Average Leverage)] were cause for concern.

5.5.3.3 MLR assumptions

To be able to generalise a model developed using MLR analysis beyond the sample on which it is based and make predictions about the wider population, a number of assumptions must be satisfied. In practice, it is unlikely these assumptions will be perfectly satisfied, but as long as severe violations are avoided, it is likely the model can be generalised (Field 2009; Washington *et al.* 2003). The way in which MLR assumptions are described varies between different sources of literature, but combining information contained in Washington *et al.* (2003), Kennedy (2003) and Field (2009), the main assumptions can be summarised as follows:

1. Relationships between predictor and outcome variables are linear in nature.
2. There is no strong linear relationship between two (or more) of the predictor variables, i.e. no strong multicollinearity. Variance Inflation Factor [133] was used to diagnose any problems of multicollinearity.
3. Residuals have a mean of zero.
4. Residuals are normally distributed. A histogram and a normal P-P plot [134] of the standardised residuals were used to visually inspect for normality. Additionally, the Kolmogorov-Smirnov test was applied to the standardised residuals to statistically test for normality, with significant results ($p<0.05$) indicating the assumption had been violated. However, results of the Kolmogorov-Smirnov test had to be treated with caution because with large sample sizes (as in this project) even small deviations from normality can produce a significant result (Field 2009). Therefore, a significant result does not necessarily indicate that the deviation from normality is sufficient to compromise the MLR analysis, particularly as MLR analysis is reasonably robust to violation of this assumption (Osborne and Waters 2002; Zou *et al.* 2003). Hence, a subjective judgement was necessary concerning the severity of any violation of the normality assumption based on interpretation of both the visual and statistical tests. Even where this assumption is judged to be severely violated, the only consequence is that, rather than being the Best

[133] Variance Inflation Factor is a measure of the inflation of the variances of predictor variable coefficients due to the existence of multicollinearity (i.e. VIF=1 represents the perfect situation of no collinearity), and therefore indicates the extent to which a predictor variable has a strong linear relationship with any other predictor variables. Values greater than 10 for individual predictor variables were cause for concern. Also cause for concern was a mean value considerably greater than one (Field 2009).

[134] A normal P-P plot of the standardised residuals plots the cumulative probability of the observed values against the cumulative probability of the expected values if the residuals were normally distributed. If the residuals are indeed normally distributed the P-P plot results in a straight diagonal line.

Unbiased Estimator (BUE)[135], the OLS estimator is the Best Linear Unbiased Estimator (BLUE)[136] and it is possible superior non-linear estimators exist (Kennedy 2003).

5. Predictor variables are uncorrelated with external variables, where an external variable is defined as a variable that has not been included in the MLR analysis, and which exerts an influence on the outcome variable.
6. Residuals are homoscedastic, i.e. the variance of the residuals is constant across observations. If not, then a problem of heteroscedasticity exists. Scatterplots of standardised residuals against standardised predicted outcome values were used to visually inspect for homoscedasticity, which should produce a random array of dots evenly dispersed around zero. Additionally, the Breusch-Pagan test (sometimes called the Breusch-Pagan-Godfrey test) and the Koenker test[137] were used to statistically test for homoscedasticity, with significant results ($p<0.05$) indicating the assumption had been violated (Breusch and Pagan 1979; Koenker and Bassett Jr. 1982; Waldman 1983; Kennedy 2003; Garson 2013).
7. Residuals are independent so that the residual for an observation is not correlated with the residual for any other observation, i.e. no autocorrelation is present. In practice, this means that no single observation in the data is dependent on any other observation in the data. It is possible to violate this assumption when collecting time series data (such as data from a vehicle moving through a road network over time) because an observation can be dependent on the observation in the preceding time interval. To minimise this issue, observations were made as far apart in time as practical; and additionally, with the observations ordered chronologically, the Durbin-Watson statistic[138] was used to diagnose any problems of autocorrelation (Durbin and Watson 1951; Washington *et al.* 2003; Field 2009).

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[135] 'Best' means an estimator that (if parameters were estimated repeatedly from many different data samples) produces minimum variance in parameter estimate distributions; and 'Unbiased' means an estimator that produces parameter estimate distributions where the means are equal to the actual parameter values (Kennedy 2003).

[136] The addition of 'Linear' means an estimator that is a linear function of the observations of the outcome variable. For example, the OLS estimator minimises the sum of squared residuals, i.e. it is a linear function of the errors between predicted and observed values for the outcome variable (Kennedy 2003).

[137] The Breusch-Pagan test is more powerful when residuals are normally distributed, whereas the Koenker test is a development of the Breusch-Pagan test that does not rely on the normality of residuals (Waldman 1983; Kennedy 2003). The use of both tests therefore provided a measure of redundancy.

[138] The Durbin-Watson statistic tests whether adjacent residuals are correlated. The test statistic can vary between zero and four, with a value close to two indicating residuals are uncorrelated and the assumption is tenable, i.e. no evidence of autocorrelation. Values less than one or greater than three were cause for concern.

5.5.4 Model Comparison and Partial Validation

Full validation of PEMLA with PEMS data would have been the ideal validation method. However, due to the difficulties inherent in collecting real-world emissions measurements such as PEMS data (refer to Section 2.5.2 and Section 5.3.1), true validation of PEMLA (i.e. by comparison of predictions with independent real-world emissions measurements) was not practical within the resources of this project (i.e. installing PEMS equipment on vehicles from each of the 24 PEMLA vehicle categories was impractical). Instead, the two main methods used to evaluate the different versions of PEMLA (refer to Section 5.5.4.1 and Section 5.5.4.2) both constituted model comparison as an alternative to validation. Even though the two evaluation methods were not true validation, positive results when compared with two well-established EMs would give confidence in the use of PEMLA (Barlow and Boulter 2009). That said, fifty three trip segments in the PEMLA category 'Bus, All' (category 22) did have PEMS data available, and the third evaluation method (refer to Section 5.5.4.3) therefore did constitute true validation, although it was only partial validation of a very limited sample size from only one vehicle category.

5.5.4.1 Leave-one-out cross validation

The first evaluation method was by model comparison to AIRE, through comparing EFs predicted by PEMLA with EFs predicted by AIRE (i.e. comparison with observed values for the outcome variable, EF from AIRE[139]). The method involved splitting trip segment samples into those used for PEMLA calibration, and those reserved for model comparison. However, trip segment samples were limited in number. This meant both the calibration process and the model comparison process were competing for a limited number of samples, with both processes benefiting (ideally) from the largest sample size possible. A solution to this was Cross-Validation (CV), where assessment is conducted over multiple, different splits of the samples, with Leave-One-Out (LOO) being the most classical, exhaustive data-splitting CV process (Arlot and Celisse 2010). LOO CV has the term 'validation' in its name, but it is important to note that the process (as it was used in this project) still constituted model comparison with AIRE.

In LOO CV each case was left out of the PEMLA calibration process in turn, a new model without that particular case was then calibrated and used to predict an EF for the excluded

[139] For two-wheel vehicles, the outcome variable is actually EF from TRL/NAEI EM based on GPS vehicle average speed as input because AIRE does not have a two-wheel vehicle category. However, for brevity, EF from AIRE is used as a general description of the outcome variable.

case which was compared to the observed value for EF from AIRE. The differences between predicted EFs and EFs from AIRE for all cases as they were excluded in turn were used to evaluate the overall PEMLA model calibrated including all cases. For each case, an Accuracy Factor (AF) was calculated using Equation 14, and an Absolute Percentage Error[140] (APE) calculated using Equation 15.

Equation 14

$$AF = \frac{\text{Predicted EF when case excluded from PEMLA calibration}}{\text{EF from AIRE}}$$

Equation 15

$$APE = \frac{|\text{Predicted EF when case excluded from PEMLA calibration} - \text{EF from AIRE}|}{\text{EF from AIRE}} \times 100\%$$

5.5.4.2 TRL/NAEI EM comparison

The second evaluation method was by model comparison to TRL/NAEI EM, through comparing EFs predicted by PEMLA with EFs predicted by TRL/NAEI EM. For each case, the TRL/NAEI EM was used to predict an EF using GPS vehicle average speed (as opposed to ILD traffic average speed) as input because (as suggested by Smit *et al.* (2008b)) this was the most accurate method for applying an Average Speed EM. To allow comparison with PEMLA, EFs predicted by TRL/NAEI EM had to be for vehicle categories that matched those in PEMLA, i.e. TRL/NAEI EM categories were (where necessary) aggregated to match the PEMLA categories. The differences between PEMLA predicted EFs and TRL/NAEI predicted EFs were then used to evaluate PEMLA. For each case, an AF was calculated using Equation 16, and an APE calculated using Equation 17.

Equation 16

$$AF = \frac{\text{Predicted EF}}{\text{EF from TRL/NAEI (vehicle average speed)}}$$

Equation 17

$$APE = \frac{|\text{Predicted EF} - \text{EF from TRL/NAEI (vehicle average speed)}|}{\text{EF from TRL/NAEI (vehicle average speed)}} \times 100\%$$

[140] It is acknowledged that this is not ‘error’ in the strict sense of the difference between model predicted EFs and true real-world EFs.

5.5.4.3 PEMS partial validation

The third evaluation method was by comparison to EFs calculated from PEMS[141] data. Fifty three trip segments in the PEMLA category 'Bus, All' (category 22) were collected from a bus being operated with a PEMS on board. Hence, these cases also had EFs calculated from the PEMS data. Comparison of PEMLA predicted EFs to PEMS EFs constituted true validation (i.e. PEMS data are true real-world measurements), but was only partial validation because PEMS data were only available for 53 cases within a single vehicle category. For each case, an AF was calculated using Equation 18, and an APE calculated using Equation 19.

Equation 18

$$AF = \frac{\text{Predicted EF}}{\text{EF from PEMS}}$$

Equation 19

$$APE = \left|\frac{\text{Predicted EF} - \text{EF from PEMS}}{\text{EF from PEMS}}\right| \times 100\%$$

PEMS data used in this project were collected during another project conducted by the Transportation Research Group at the University of Southampton, which was the Southampton City Bus Emissions Monitoring Project[142]. The author was part of the project team that carried out the PEMS data collection. The PEMS equipment used in the Emissions Monitoring project was the On Board Emission Measurement System OBS-2200 manufactured by Horiba, which was installed on a Wrightbus Streetlite bus operated in Southampton by First Group, with vehicle details as shown in Table 5-7. During testing, two passenger seats were removed to accommodate the installation of the PEMS equipment as shown in Figure 5-7.

[141] In this thesis PEMS is used generically to encompass all Portable Emissions Measurement System equipment designed to be carried aboard road vehicles during real-world emissions tests on a test track or on public roads; as opposed to static laboratory emissions measurement equipment used during laboratory emissions tests (DfT 2016b). The make and model of the specific PEMS equipment used to collect data for partial validation in this project are detailed later in Section 5.5.4.3.

[142] The aim of the Southampton City Bus Emissions Monitoring Project was to assess the impact on bus tailpipe emissions of the retro-fitting of thermal management emissions abatement systems. Thermal management is designed to reduce NO_X emissions by optimising the operating temperature of the Selective Catalytic Reduction (SCR) system. SCR involves spraying urea (AdBlue) into the exhaust gas, which reacts with NO_X in the presence of a catalyst and produces less harmful compounds. The SCR reaction only occurs when exhaust gas is above a certain temperature. Therefore, thermal management is employed to maintain the engine at the correct temperature to optimise exhaust gas temperature.

Table 5-7: Vehicle characteristics for the bus used in the Southampton City Bus Emissions Monitoring Project.

Characteristic	Vehicle used for testing
Registration plate	SK63 KNB
Registration date	29th November 2013
Fuel type	Diesel
Engine size	4461cc
Euro Standard compliance	Euro V
Revenue weight	13,139kg
TRL/NAEI EM vehicle category	Bus, Midi, <15 tonnes, Euro V
PEMLA vehicle category	Bus, All
Maximum passenger load	37 seated plus 31 standing: Total = 4,420kg
Payload during test	6 passengers, 34 bags of grit (25kg each), PEMS equipment: Total = 1,360kg

- Engine capacity is shown in cubic centimetres (cc).
- Revenue weight is defined by the DfT as the maximum gross weight of a vehicle.
- Vehicle loads are calculated assuming an average passenger mass of 65kg, which was the assumption used in the development of TRL EFs 2009 (Barlow 2009).
- Mass of the PEMS equipment (including batteries) minus the mass of the 2 seats removed assumed to be 120kg.

Figure 5-7: PEMS equipment installation on the bus used in the Southampton City Bus Emissions Monitoring Project.

5.5.5 Accuracy Comparison

Investigation of Research Question 3 required the predictive accuracies of the different versions of PEMLA to be assessed in comparison to the predictive accuracy of TRL/NAEI EM, which is the next-best alternative EM available to UK LGAs (i.e. TRL EFs 2009 as the officially recognised EM recommended for use in the UK and the basis of the DfT Basic Local Authority Carbon Tool, refer to Sections 2.5.5.1 and 2.5.5.2). For this comparison, EFs from AIRE were assumed to be 'real-world' EFs, which was a reasonable assumption given that AIRE is a detailed Instantaneous EM (refer to Section 2.5.9.4) that has been independently verified by TRL (i.e. AIRE predictions are likely to be closer to true real-world EFs than predictions from either TRL/NAEI EM or PEMLA). For each case, an AF was calculated using Equation 20, and an APE calculated using Equation 21. For the TRL/NAEI EM predictions, ILD traffic average speeds (as opposed to GPS vehicle average speeds) were used as inputs. This was for two reasons: (1) these are the data which are readily available to LGAs; and (2) to ensure a like-for-like comparison because ILD data (plus access density) were used as inputs to PEMLA. As was the situation for evaluation by model comparison to TRL/NAEI EM (refer to Section 5.5.4.2), to allow comparison of predictions, TRL/NAEI EM categories were (where necessary) aggregated to match the PEMLA categories.

Equation 20

$$AF = \frac{\text{Predicted EF}}{\text{EF from AIRE}}$$

Equation 21

$$APE = \frac{|\text{Predicted EF} - \text{EF from AIRE}|}{\text{EF from AIRE}} \times 100\%$$

5.6 CONCLUSIONS

The PEMLA development methodology described in this chapter (Chapter 5) was built on the key findings of the literature review and the survey of British LGAs, which were: that Traffic Variable EMs potentially offer an improved ability to capture congestion impacts compared to the widely used alternative of Average Speed EMs, through inclusion of other traffic variables (in addition to traffic average speed) as quantifiable measures of congestion, with little associated increase in complexity; and that ILDs are a readily available source of these traffic variables, where collection does not entail additional expenditure of resources by or on behalf of LGAs. The methodology, therefore, was designed to develop a new CO_2 Traffic Variable EM based on ILD inputs (i.e. PEMLA), and then compare the accuracy of its emissions predictions with those of the existing Average Speed EM recommended for use by LGAs in the UK (i.e. TRL EFs 2009 as the basis of the DfT Basic Local Authority Carbon Tool).

For reasons of practicality, both in the analyses conducted within the resources of this project and in the future use by LGAs of PEMLA, the initial step in the development methodology was to create a manageable number of vehicle categories for PEMLA, with the target being to reduce by approximately an order of magnitude the number of categories found in the (highly disaggregated) NAEI national fleet model (over 200 categories). This vehicle category reduction analysis ultimately resulted in 24 PEMLA vehicle categories (refer to Section 5.2.2).

The principal data collection part of the PEMLA development methodology can be summarised as collection of two parallel sets of data, which were: (1) an accurate EF for each trip segment performed by test vehicles, calculated using AIRE based on driving pattern inputs recorded by GPS loggers carried in the vehicles around Southampton's road network; and (2) traffic variables for each trip segment calculated from U07 SCOOT message data collected from ILDs crossed by test vehicles during trip segments.

For calculation of accurate EFs, the ideal data collection method would have been real-world emissions measurements using on-board PEMS equipment, but fitting such equipment to vehicles in each of the 24 PEMLA vehicle categories was not practical within project resources. Therefore, calculation of EFs based on collection of real-world GPS driving patterns for use as inputs to an Instantaneous EM (AIRE) was used instead as the next-best alternative.

For calculation of traffic variables from the U07 ILD data, the issues relating to the accuracy of data generated by ILDs were acknowledged (refer to Section 5.4.4). However, despite these issues, it is ILD data that are readily available to LGAs for use as inputs to the emissions modelling process, and the concern of this project was, therefore, to investigate whether these data (with all their inherent inaccuracies) could be used to predict road traffic CO_2 emissions.

The two parallel sets of data were then brought together through Multiple Linear Regression (MLR) statistical analysis, which was used to investigate relationships between the traffic variables (predictor variables) and accurate EFs (outcome variable). Three different model calibration methods were used to incorporate vehicle category as an additional predictor variable: (1) the use of Dummy Variables (DVs) to encode vehicle category, which led to PEMLA v.1; (2) the use of the same DVs alongside the forced inclusion of the WebTAG formulae, which led to PEMLA v.2; and (3) the use of Interaction Variables (IVs) to encode the interaction of the traffic variables and vehicle category, which led to PEMLA v.3.

Following comparison of the three methods to incorporate vehicle category in the MLR analysis (refer to Section 7.2.2), PEMLA v.3 was identified as having the greatest potential. Therefore, three further versions of PEMLA (PEMLA v.4, v.5 and v.7) were subsequently developed based on the PEMLA v.3 calibration method (i.e. using IVs). These further PEMLA versions sought to investigate solutions to the violation of certain MLR assumptions evident in the calibration of PEMLA v.3 (PEMLA v.4 and v.5 both investigated violation of the assumption of homoscedasticity, refer to Section 6.4.3.1 and Section 6.4.3.2, respectively; and PEMLA v.7 investigated (the less serious) violation of the assumption of normally distributed residuals, refer to Section 6.4.3.3).

For each PEMLA version calibrated by MLR analysis, a parallel Multilayer Perceptron (MLP) neural network statistical analysis was also performed as a comparative indicator to assess the explanatory power of the associated MLR analysis through comparison of respective R^2 values. This was because it is possible for complex data relationships to go undetected when analysis is performed using standard conventional statistical methods such as MLR. In contrast, MLP can represent relationships between predictor and outcome variables that are unconstrained by assumptions such as those that underpin MLR analysis. Therefore, comparison of R^2 values allowed the extent to which any explanatory power was being lost due to the more restrictive constraints of MLR assumptions to be assessed.

Despite its more restrictive assumptions, MLR was preferred as the primary statistical analysis method because it is a widely used method for exploring relationships between a set of predictor variables and an outcome variable, it is very well understood mathematically, its results are easily interpreted (e.g. it is easy to see how a change in a predictor variable affects the outcome variable), and it has been widely used in the calibration of different EMs (refer to Section 5.5.1.1). MLP served only as a comparative indicator because it is more of a ‘black box’ method, in that it is not as easy to interpret results or see the significance and effect of predictor variables (IBM 2013a). It is also more difficult to distribute because the final model is saved in SPSS (or exported in an XML-based[143] file format) and so requires SPSS (or other neural network software) to apply the model to new data (IBM 2013a); whereas a model produced by MLR analysis is relatively straightforward to encode in a simple spreadsheet format (such as the widely used Microsoft Excel software).

In an ideal situation, the PEMLA versions would have been validated by comparing their predictions to independent real-world emissions measurements made using on-board PEMS equipment. However, (as was the case for collection of the data used to calculate accurate EFs for PEMLA calibration) this was not practical within project resources. Instead, the performance of each PEMLA version was evaluated by comparison of predicted EFs to those predicted by two existing well-established EMs (i.e. model comparison rather than true validation). The first model comparison was with EFs predicted by AIRE using a LOO CV method, and the second was with EFs predicted by TRL/NAEI EM (using GPS vehicle average speed as inputs). Additionally, a small number of trip segments (53 bus trip segments) did have EFs calculated from on-board PEMS measurements, which allowed true (partial) validation of PEMLA versions to be performed for these trip segments.
The final part of the PEMLA development methodology was to assess the predictive accuracies of the PEMLA versions in comparison to the predictive accuracy of TRL/NAEI EM, which is the next-best alternative EM available to UK LGAs (i.e. TRL EFs 2009 as the officially recognised EM recommended for use in the UK and the basis of the DfT Basic Local Authority Carbon Tool). This was accomplished by comparing EFs predicted by PEMLA and EFs predicted by TRL/NAEI EM (using ILD traffic average speed as inputs) to EFs predicted by AIRE, based on the assumption that EFs from AIRE are likely to be closer to real-world EFs due to it being a detailed Instantaneous EM.

[143] XML is Extensible Mark-up Language which allows the model format and data to be shared using ASCII text.

Chapter 6 PEMLA DEVELOPMENT RESULTS

6.1 INTRODUCTION

Presentation of results from the development of PEMLA has been divided into six main sections. Section 6.2 explains where the dataset compiled as a result of the data collection effort can be found. Section 6.3 details results from the preliminary statistical analysis of the four, separate representative vehicle categories (categories 01, 20, 22 and 24). Section 6.4 details results from the principal statistical analysis of the combined dataset for all 24 vehicle categories, which includes presentation of the six versions (v.1 to v.5, and v.7) of PEMLA. Sections 6.5 and 6.6 provide results from evaluation by model comparison and partial validation of the different PEMLA versions, and from accuracy comparison with TRL/NAEI EM, respectively. Finally, although the discussion and conclusions of the results are mainly detailed in Chapter 7 and Chapter 8, a summary of the main conclusions drawn from the results is included in this chapter in Section 6.7.

6.2 DATA COLLECTION RESULTS

The main results of data collection constitute a set of 24 spreadsheets, one for each PEMLA vehicle category, with details of each trip segment, including values for the four traffic variables (traffic average speed, traffic density, traffic average delay rate and access density; with the square of traffic average speed being computed later when the data were imported to SPSS) and a value for the EF. Rather than including these spreadsheets as large tables in an appendix to this thesis, the data have been electronically deposited in the University of Southampton repository and are openly available at http://dx.doi.org/10.5258/SOTON/400894.

6.3 PRELIMINARY STATISTICAL ANALYSIS

6.3.1 Data Exploration

For each of the four representative vehicle categories (categories 01, 20, 22 and 24), to gain an initial appreciation of the data, descriptive statistics for key variables were produced (Table 6-1 to Table 6-4), along with scatter plots of predictor (traffic variables) against outcome (EF from AIRE) variables (e.g. Figure 6-1), and statistics from bivariate linear correlations between predictor and outcome variables (Table 6-5). By inspection of the scatter plots, any visually obvious outliers were investigated to determine if they were being consistently produced by the same driver. In other words, to determine if a particular driver's behaviour (aggressive or passive) was causing excessively high or low EFs. Results showed that outliers were not all produced by one driver and were therefore deemed to not be biased by driver behaviour. In general, the bivariate linear correlations showed fairly weak relationships between predictor and outcome variables, only some of which were statistically significant. The non-parametric Spearman's rho[144] was used to assess the correlations (and used to assess other linear correlations throughout the statistical analysis) because the outcome variable (and in most instances the predictor variable as well) was non-normally distributed (Field 2009).

In general, for reasons of brevity, EF from AIRE (gCO_2/VKM) has been used in the results to describe the outcome variable. For two-wheel cases (PEMLA vehicle category 24), the outcome variable EFs were actually calculated using TRL/NAEI EM based on GPS vehicle average speed (refer to Section 5.3.5.4), and (where appropriate) the use of EF from AIRE to describe the outcome variable should be taken to include this fact.

Table 6-1: Descriptive statistics for variables measured for PEMLA vehicle category 01 (representing LDV).

Statistic	Predictor Variables					Outcome Variable	GPS Vehicle Average Speed (km/h)
	Traffic Average Speed (km/h)	Traffic Density (veh/km)	Traffic Average Delay Rate (s/veh.km)	Access Density (int/km)	Traffic Average Speed Squared $(km/h)^2$	EF from AIRE (gCO_2/VKM)	
Mean	25	21	90	8.54	666	208	27
Median	25	19	75	8.76	625	199	25
SD	6	14	55	3.84	324	39	10
Range	31 (9 to 40)	77 (1 to 78)	315 (15 to 331)	18.97 (1.08 to 20.06)	1519 (81 to 1600)	228 (146 to 374)	48 (9 to 57)
Interquartile Range	10	13	58	5.22	490	51	12
Normality of Distribution	Normal	Non-normal	Non-normal	Non-normal	Normal	Non-normal	Non-normal

- n = 137.
- SD is Standard Deviation.
- Normality of distributions assessed using Kolmogorov-Smirnov tests. Significant result ($p<0.05$) indicates non-normal.

[144] The Spearman linear correlation coefficient (Spearman's rho) is based on first ranking the data, and then applying the Pearson linear correlation coefficient (r) to the ranks.

Table 6-2: Descriptive statistics for variables measured for PEMLA vehicle category 20 (representing HDV (except bus)).

Statistic	Predictor Variables					Outcome Variable	GPS Vehicle Average Speed (km/h)
	Traffic Average Speed (km/h)	Traffic Density (veh/km)	Traffic Average Delay Rate (s/veh.km)	Access Density (int/km)	Traffic Average Speed Squared $(km/h)^2$	EF from AIRE (gCO_2/VKM)	
Mean	26	22	85	8.65	735	1410	26
Median	27	21	69	8.56	729	1378	25
SD	6	12	64	3.55	326	358	8
Range	34 (7 to 41)	57 (1 to 58)	455 (20 to 475)	19.24 (1.10 to 20.34)	1637 (44 to 1681)	2323 (506 to 2829)	42 (8 to 50)
Interquartile Range	8	12	52	4.57	405	401	11
Normality of Distribution	Normal	Non-normal	Non-normal	Non-normal	Normal	Non-normal	Normal

- n = 113.
- SD is Standard Deviation.
- Normality of distributions assessed using Kolmogorov-Smirnov tests. Significant result ($p<0.05$) indicates non-normal.

Table 6-3: Descriptive statistics for variables measured for PEMLA vehicle category 22 (representing bus).

Statistic	Predictor Variables					Outcome Variable	GPS Vehicle Average Speed (km/h)
	Traffic Average Speed (km/h)	Traffic Density (veh/km)	Traffic Average Delay Rate (s/veh.km)	Access Density (int/km)	Traffic Average Speed Squared $(km/h)^2$	EF from AIRE (gCO_2/VKM)	
Mean	20	21	150	8.30	455	1648	16
Median	20	15	115	7.88	393	1579	14
SD	8	17	120	4.23	325	447	8
Range	34 (4 to 38)	80 (2 to 82)	805 (20 to 825)	16.16 (1.81 to 17.96)	1428 (16 to 1444)	2515 (802 to 3316)	41 (5 to 45)
Interquartile Range	10	18	109	6.90	380	614	10
Normality of Distribution	Non-normal	Non-normal	Non-normal	Non-normal	Non-normal	Non-normal	Non-normal

- n = 153.
- SD is Standard Deviation.
- Normality of distributions assessed using Kolmogorov-Smirnov tests. Significant result ($p<0.05$) indicates non-normal.

Table 6-4: Descriptive statistics for variables measured for PEMLA vehicle category 24 (representing two-wheel vehicle).

Statistic	Predictor Variables					Outcome Variable	GPS Vehicle Average Speed (km/h)
	Traffic Average Speed (km/h)	Traffic Density (veh/km)	Traffic Average Delay Rate (s/veh.km)	Access Density (int/km)	Traffic Average Speed Squared $(km/h)^2$	EF from TRL/NAEI EM (gCO_2/VKM)	
Mean	22	38	167	5.11	555	117	27
Median	22	34	101	4.78	484	114	26
SD	9	20	217	3.63	399	20	9
Range	30 (8 to 38)	118 (7 to 126)	2037 (37 to 2074)	10.49 (0.97 to 11.46)	1380 (64 to 1444)	90 (89 to 179)	44 (10 to 55)
Interquartile Range	14	28	176	6.19	588	28	13
Normality of Distribution	Non-normal	Non-normal	Non-normal	Non-normal	Non-normal	Non-normal	Normal

- n = 111.
- SD is Standard Deviation.
- Normality of distributions assessed using Kolmogorov-Smirnov tests. Significant result ($p<0.05$) indicates non-normal.
- The outcome variable of EF from TRL/NAEI EM was based on using GPS vehicle average speed as input.

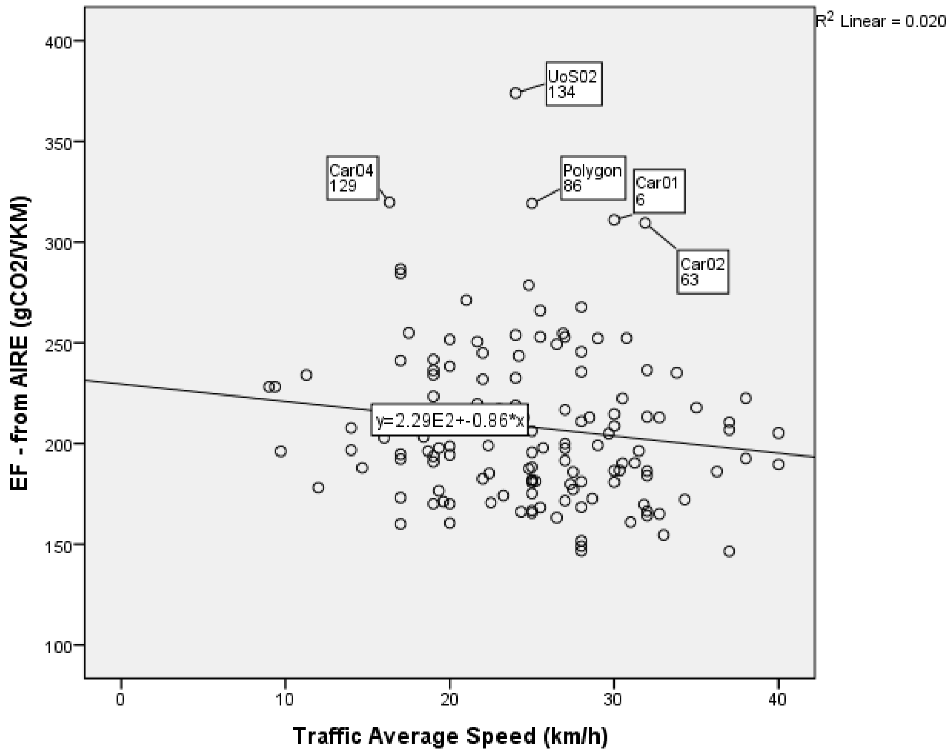


Figure 6-1: Example scatter plot for PEMLA vehicle category 01 (representing LDV) showing the outcome variable (EF from AIRE) plotted against one of the predictor variables (traffic average speed).

- Visually obvious outliers are labelled with Driver ID (e.g. Car04) and case number (e.g. 129) for the trip segment to which the data point relates.

Table 6-5: **Statistics for bivariate linear correlations between predictor and outcome variables for PEMLA vehicle categories 01, 20, 22 and 24.**

PEMLA Vehicle Category	Data Split		n	Traffic Average Speed (km/h)	Traffic Density (veh/km)	Traffic Average Delay Rate (s/veh.km)	Access Density (int/km)	Traffic Average Speed Squared (km/h)^2
				Rho	Rho	Rho	Rho	Rho
Cat. 01	All cases		137	-.17*	-.11	.09	.26*	-.17*
	Road Type	30	84	-.18	.01	.19	-.00	-.18
		40	53	-.28*	.14	.21	.33*	-.28*
	Peak Period	Off	83	-.25*	-.18	.15	.31*	-.25*
		On	54	-.07	-.12	.05	.15	-.07
Cat. 20	All cases		113	.08	-.09	-.08	-.02	.08
	Road Type	30	59	-.04	.00	.04	-.10	-.04
		40	54	.23	-.03	-.13	-.16	.23
	Peak Period	Off	64	.31*	-.22	-.31*	-.08	.31*
		On	49	-.18	.14	.16	-.08	-.18
Cat. 22	All cases		153	-.12	-.19*	.09	.09	-.12
	Road Type	30	114	-.01	-.06	.01	.16	-.01
		40	39	-.35*	.40*	.31	-.09	-.35*
	Peak Period	Off	75	-.20	-.31*	.15	.08	-.20
		On	78	.01	-.13	-.03	.09	.01
Cat. 24	All cases		111	-.57*	.46*	.49*	.32*	-.57*
	Road Type	30	54	-.53*	.54*	.56*	.22	-.53*
		40	57	-.43*	.35*	.36*	.10	-.43*
	Peak Period	Off	8	-.36	-.32	.30	-.24	-.36
		On	103	-.53*	.38*	.44*	.35*	-.53*

- Outcome variable is EF from AIRE (gCO_2/VKM).
- n is sample size.
- Rho is the non-parametric Spearman's rho linear correlation coefficient.
- * indicates correlation is significant ($p<0.05$).
- Category 01 represents LDV; category 20 represents HDV (except bus); category 22 represents bus; and category 24 represents two-wheel vehicle.
- Road type is defined by a 30 or 40 mph speed limit.

6.3.2 Preliminary MLR Analysis

Preliminary MLR analysis was conducted using a single block, forced entry method for all five traffic variables (predictor variables) with the objective of exploring their general ability to predict values for EF from AIRE (outcome variable). In general, results (Table 6-6) indicated that the predictor variables had limited ability to explain variation in the outcome variable, i.e.

small Adj. R^2 values. Typically, Multilayer Perceptron (MLP) R^2 values were similarly small, indicating it is unlikely that there were other strong relationships between predictor and outcome variables that MLR analysis failed to capture.

Table 6-6: Statistics from preliminary MLR analysis of PEMLA vehicle categories 01, 20, 22 and 24.

<table>
<tr><th rowspan="2">PEMLA Vehicle Category</th><th rowspan="2" colspan="2">Data Split</th><th rowspan="2">n</th><th rowspan="2">k</th><th colspan="3">MLR Analysis</th><th rowspan="2">MLP Analysis R^2</th></tr>
<tr><th>R^2</th><th>Adj. R^2</th><th>Predictor Variables Making Statistically Significant Contribution (t-statistic)</th></tr>
<tr><td rowspan="5">Cat. 01</td><td colspan="2">All cases</td><td>137</td><td>5</td><td>.10</td><td>.06</td><td>Constant (2.23*)
Access Density (2.58*)</td><td>.04</td></tr>
<tr><td rowspan="2">Road Type</td><td>30</td><td>85</td><td>5</td><td>.05</td><td>-.01</td><td>None</td><td>.08</td></tr>
<tr><td>40</td><td>52</td><td>5</td><td>.12</td><td>.02</td><td>Access Density (2.06*)</td><td>.05</td></tr>
<tr><td rowspan="2">Peak Period</td><td>Off</td><td>83</td><td>5</td><td>.11</td><td>.05</td><td>Constant (2.13*)</td><td>.19</td></tr>
<tr><td>On</td><td>54</td><td>5</td><td>.11</td><td>.02</td><td>None</td><td>.08</td></tr>
<tr><td rowspan="5">Cat. 20</td><td colspan="2">All cases</td><td>113</td><td>5</td><td>.05</td><td>.00</td><td>Constant (2.36*)</td><td>.00</td></tr>
<tr><td rowspan="2">Road Type</td><td>30</td><td>59</td><td>5</td><td>.09</td><td>.00</td><td>Constant (2.49*)</td><td>.14</td></tr>
<tr><td>40</td><td>54</td><td>5</td><td>.07</td><td>-.03</td><td>None</td><td>.05</td></tr>
<tr><td rowspan="2">Peak Period</td><td>Off</td><td>64</td><td>5</td><td>.09</td><td>.01</td><td>None</td><td>.19</td></tr>
<tr><td>On</td><td>49</td><td>5</td><td>.16</td><td>.06</td><td>Constant (3.63*)
Traffic Average Speed (-2.19*)</td><td>.01</td></tr>
<tr><td rowspan="5">Cat. 22</td><td colspan="2">All cases</td><td>153</td><td>5</td><td>.08</td><td>.05</td><td>Constant (4.29*)
Traffic Density (-2.18*)
Access Density (2.57*)</td><td>.12</td></tr>
<tr><td rowspan="2">Road Type</td><td>30</td><td>114</td><td>5</td><td>.08</td><td>.03</td><td>Constant (3.11*)
Access Density (2.44*)</td><td>.00</td></tr>
<tr><td>40</td><td>39</td><td>5</td><td>.32</td><td>.22</td><td>Constant (2.66*)
Traffic Average Speed (-2.32*)
Traffic Density (2.38*)
Traffic Average Delay Rate (-2.42*)
Traffic Average Speed Squared (2.37*)</td><td>.33</td></tr>
<tr><td rowspan="2">Peak Period</td><td>Off</td><td>75</td><td>5</td><td>.17</td><td>.10</td><td>Constant (3.18*)
Traffic Average Speed (-2.58*)
Traffic Average Speed Squared (2.65*)</td><td>.23</td></tr>
<tr><td>On</td><td>78</td><td>5</td><td>.05</td><td>-.02</td><td>Constant (2.56*)</td><td>.09</td></tr>
<tr><td rowspan="5">Cat. 24</td><td colspan="2">All cases</td><td>111</td><td>5</td><td>.31</td><td>.28</td><td>Constant (5.78*)
Traffic Average Delay Rate (-2.56*)</td><td>.38</td></tr>
<tr><td rowspan="2">Road Type</td><td>30</td><td>54</td><td>5</td><td>.37</td><td>.30</td><td>Traffic Average Speed (2.97*)
Traffic Average Delay Rate (3.09*)
Traffic Average Speed Squared (-3.10*)</td><td>.22</td></tr>
<tr><td>40</td><td>57</td><td>5</td><td>.35</td><td>.28</td><td>None</td><td>.36</td></tr>
<tr><td rowspan="2">Peak Period</td><td>Off</td><td>8</td><td>5</td><td>.71</td><td>-.03</td><td>None</td><td>.25</td></tr>
<tr><td>On</td><td>103</td><td>5</td><td>.28</td><td>.25</td><td>Constant (5.68*)
Traffic Average Delay Rate (-2.08*)</td><td>.28</td></tr>
</table>

- Outcome variable is EF from AIRE (gCO_2/VKM).
- n is sample size.

- k is number of predictor variables.
- The t-statistic indicates whether a predictor variable coefficient is statistically significantly different from zero i.e. whether a predictor variable is making a statistically significant contribution to the model (further details in notes for Table 6-11).
- * indicates t-statistic is significant ($p<0.05$).
- For comparison, equivalent MLP neural network analysis R^2 was calculated by squaring Pearson's linear correlation coefficient (r) for the linear correlation between MLP predicted values and observed values for EF.
- Category 01 represents LDV; category 20 represents HDV (except bus); category 22 represents bus; and category 24 represents two-wheel vehicle.
- Road type is defined by a 30 or 40 mph speed limit.

6.3.3 GPS Vehicle Average Speed as a Predictor Variable

In previous research (e.g. development of Average Speed EMs, refer to Section 2.5.5) it has been well established that vehicle emissions are strongly related to vehicle average speeds calculated over longer distances, e.g. link length or longer (i.e. as in the calculation of traffic average speed expressed as space-mean-speed). Therefore, an analysis of how well ILD traffic average speeds (which are estimates of time-mean-speed) correlated with GPS vehicle average speeds (calculated over the length of trip segments) was completed, with the expectation that a better correlation between the two measures would be likely to lead to better prediction of EFs from ILD data. In general, results in Table 6-7 showed small correlations between the two measures of speed, only some of which were statistically significant. Due to these small correlations, a further MLR analysis was conducted to examine how much improvement in ability to predict EFs (in terms of increased Adj. R^2) would be generated by using GPS speed as a predictor variable instead of the original five (ILD-based, except access density) traffic variables. Both GPS speed and the square of GPS speed were entered into the MLR analysis for each vehicle category. However, for the range of speeds collected during the study, speed and speed^2 were found to be highly linearly correlated (category 01 r=.98, category 20 r=.98, category 22 r=.97, category 24 r=.98). For all four vehicle categories, speed^2 had the smallest t-statistic (i.e. least likely to be making a statistically significant contribution to the model), and for this reason was selected as the predictor variable to exclude to satisfy the MLR assumption of no multicollinearity (refer to Section 5.5.3.3). Considering previous results in Table 6-6 (All Cases rows) alongside results in Table 6-8 revealed that Adj. R^2 values from MLR analysis (and also R^2 values from MLP analysis) based on GPS vehicle average speed as the predictor variable were all much improved when compared to those based on the original five traffic variables (in many instances, an order of magnitude greater).

Table 6-7: Statistics for bivariate linear correlations between ILD traffic average speed and GPS vehicle average speed for PEMLA vehicle categories 01, 20, 22 and 24.

PEMLA Vehicle Category	Data Split		n	Rho
Cat. 01	All cases		137	.23*
	Road Type	30	84	.31*
		40	53	.29*
	Peak Period	Off	83	.30*
		On	54	.18
Cat. 20	All cases		113	.04
	Road Type	30	59	.24
		40	54	-.16
	Peak Period	Off	64	-.13
		On	49	.26
Cat. 22	All cases		153	.19*
	Road Type	30	114	.13
		40	39	.16
	Peak Period	Off	75	.24*
		On	78	.08
Cat. 24	All cases		111	.57*
	Road Type	30	54	.53*
		40	57	.43*
	Peak Period	Off	8	.36
		On	103	.53*

- n is sample size.
- Rho is the non-parametric Spearman's rho linear correlation coefficient.
- * indicates correlation is significant ($p<0.05$).
- Category 01 represents LDV; category 20 represents HDV (except bus); category 22 represents bus; and category 24 represents two-wheel vehicle.
- Road type is defined by a 30 or 40 mph speed limit.

Table 6-8: Statistics from MLR analysis using GPS vehicle average speed as the predictor variable for PEMLA vehicle categories 01, 20, 22 and 24.

PEMLA Vehicle Category	n	k	MLR Analysis			MLP Analysis R^2
			R^2	Adj. R^2	t-statistic	
Cat. 01	137	1	.61	.60	-14.41*	.78
Cat. 20	113	1	.52	.52	-11.01*	.51
Cat. 22	153	1	.64	.64	-16.29*	.84
Cat. 24	111	1	.85	.85	-24.82*	1.00

- Outcome variable is EF from AIRE (gCO_2/VKM).
- n is sample size.
- k is number of predictor variables (GPS vehicle average speed was the only predictor variable used).
- The t-statistic indicates whether a predictor variable coefficient is statistically significantly different from zero i.e. whether a predictor variable is making a statistically significant contribution to the model (further details in notes for Table 6-11).
- * indicates t-statistic is significant ($p<0.05$).
- For comparison, equivalent MLP neural network analysis R^2 was calculated by squaring Pearson's linear correlation coefficient (r) for the linear correlation between MLP predicted values and observed values for EF.
- Category 01 represents LDV; category 20 represents HDV (except bus); category 22 represents bus; and category 24 represents two-wheel vehicle.
- Accurate EFs for two-wheel vehicles (category 24) were calculated with TRL/NAEI EM using GPS vehicle average speed as input. Therefore, high R^2 for this category was expected.

6.3.4 Non-Linear Correlations

The final part of the preliminary statistical analysis explored whether any correlations other than linear were present between predictor and outcome variables. Using the curve estimation function in SPSS, nine different non-linear correlations were assessed (compound, cubic, exponential, growth, inverse, logarithmic, power, quadratic and s-curve models, with equations as defined in IBM (2013b)). Results are shown in Table 6-9, where it should be noted that the underlying data for category 01 (i.e. values of traffic variables and GPS driving patterns used as inputs to AIRE) were reused in all other LDV categories (categories 02 to 19), meaning the curve estimation results for category 01 carried more weight when all 24 categories were considered as a combined dataset (as in the subsequent Principal Statistical Analysis, refer to Section 6.4). Based on these results, the only alternative non-linear correlation that showed a statistically significant R^2 improvement consistently across the large majority of vehicle categories was the cubic form of access density, and for this reason the square and cube of access density were added as predictor variables in the next phase of analysis.

Table 6-9: Statistics for bivariate linear and non-linear correlations between predictor and outcome variables for PEMLA vehicle categories 01, 20, 22 and 24.

PEMLA Vehicle Category	n	Predictor Variable Correlated with the Outcome Variable									
		Traffic Average Speed (km/h)		Traffic Density (veh/km)		Traffic Average Delay Rate (s/veh.km)		Access Density (int/km)		Traffic Average Speed Squared $(km/h)^2$	
		Linear R^2	Best Other R^2	Linear R^2	Best Other R^2	Linear R^2	Best Other R^2	Linear R^2	Best Other R^2	Linear R^2	Best Other R^2
Cat. 01	137	.02	None	.00	None	.01	None	.08*	Cubic .14*	.02	None
Cat. 20	113	.00	None	.02	None	.00	None	.00	None	.00	None
Cat. 22	153	.00	None	.03*	Comp .03*	.00	None	.02	Cubic .06*	.00	None
Cat. 24	111	.26*	Comp .29*	.10*	Cubic .19*	.01	Cubic .31*	.12*	Cubic .13*	.26*	Comp .29*

- Outcome variable is EF from AIRE (gCO_2/VKM).
- n is sample size.
- R^2 for linear correlations was calculated by squaring Pearson's linear correlation coefficient (r).
- Best Other is the equation form (other than linear) for the curve having the highest R^2 value.
- None in the Best Other column indicates no other form of curve had a statistically significant correlation with the data.
- Comp is compound curve (equation: $Y = a.b^X$); and Cubic is cubic curve (equation: $Y = a + b.X + c.X^2 + d.X^3$).
- * indicates correlation is significant ($p<0.05$).
- Category 01 represents LDV; category 20 represents HDV (except bus); category 22 represents bus; and category 24 represents two-wheel vehicle.

6.4 PRINCIPAL STATISTICAL ANALYSIS

6.4.1 Combined Dataset Descriptive Statistics

In general, evidence from the results of the preliminary statistical analysis of the four separate PEMLA vehicle categories suggested that the original five traffic variables measured during the study possessed only moderate performance as predictors of EFs. Therefore, it was decided to incorporate vehicle category as an additional predictor variable, and to perform the MLR analysis on a single dataset constituting the combined data for all 24 PEMLA vehicle categories. Descriptive statistics for key variables (including the square and cube of access density as additional traffic variables) in this combined dataset are shown in Table 6-10. As described in Section 5.5.3, the visually obvious outlier in the two-wheel vehicle traffic average delay rate data (=2074s/veh.km) led to the associated trip segment (TDP017) being excluded from the principal statistical analysis, which gave a total sample size of n=3205.

Table 6-10: Descriptive statistics for variables measured for all 24 PEMLA vehicle categories combined.

Statistic	Predictor Variables							Outcome Variable	GPS Vehicle Average Speed (km/h)
	Traffic Average Speed (km/h)	Traffic Density (veh/km)	Traffic Average Delay Rate (s/veh.km)	Access Density (int/km)	Traffic Average Speed Squared $(km/h)^2$	Access Density Squared $(int/km)^2$	Access Density Cubed $(int/km)^3$	EF from AIRE (gCO_2/VKM)	
Mean	25	22	95	8.43	660	85.91	968.55	444	26
Median	25	19	75	8.42	625	70.83	596.14	248	25
SD	7	15	66	3.86	331	66.34	1089.20	515	10
Range	37 (4 to 41)	91 (1 to 92)	810 (15 to 825)	19.36 (0.97 to 20.34)	1665 (16 to 1681)	412.72 (0.95 to 413.67)	8412.79 (0.93 to 8413.71)	3530 (89 to 3619)	53 (5 to 57)
Interquartile Range	10	14	61	5.22	480	91.00	1225.95	152	12
Normality of Distribution	Non-normal	Non-normal	Non-normal	Non-normal	Non-normal	Non-normal	Non-normal	Non-normal	Non-normal

- n = 3205.
- SD is Standard Deviation.
- Normality of distributions assessed using Kolmogorov-Smirnov tests. Significant result ($p<0.05$) indicates non-normal.

6.4.2 Three Calibration Methods (PEMLA v.1 to v.3)

Three different calibration methods to incorporate vehicle category into the MLR analysis were investigated, which initially led to development of three different versions of PEMLA (PEMLA v.1 to v.3, refer to Section 5.5.3.1). In general, in MLR analysis of all PEMLA versions, where two (or more) predictor variables were collinear, one (or more) of the predictor variables was removed from the analysis to satisfy the MLR assumption of no multicollinearity (refer to Section 5.5.3.3), with the predictor variable(s) having the smallest t-statistic selected for removal (i.e. least likely to be making a statistically significant contribution to the model). Also removed were any predictor variables having non-significant t-statistics (i.e. not making a statistically significant contribution to the model)[145] (Field 2009). In the presentation of results for all PEMLA versions, the underlying assumptions of MLR (refer to Section 5.5.3.3) are only discussed in instances where a violation has potentially occurred. Additionally, unless otherwise stated, no cases were found to be exerting undue influence over results.

6.4.2.1 PEMLA v.1

Dummy Variables (DVs) were used to encode vehicle categories in PEMLA v.1. Category 01 was the default, and 23 DVs (DV – Cat 02 to DV – Cat 24) used to encode the other vehicle categories (refer to Section 5.5.3.1). Results for PEMLA v.1 are shown in Table 6-11. Results of

[145] These removal criteria are similar to those used by SPSS in the backward stepwise method for MLR, where all predictor variables are initially entered into the analysis, then SPSS is allowed to remove predictor variables automatically based on defined removal thresholds for absolute values of, or probability values associated with, t-statistics (Field 2009).

a Kolmogorov-Smirnov test ($p<0.05$) indicated the assumption of normally distributed residuals had been violated (although this test is very sensitive to small deviations from normality in large samples (Field 2009), refer to Section 5.5.3.3). Inspection of the charts in Figure 6-2 also confirmed that the residuals were non-normally distributed, with positive kurtosis being evident. However, the extent of the violation was assessed as not being severe enough to compromise the analysis and therefore judged to be acceptable due to a combination of four reasons: (1) MLR is reasonably robust to violation of the assumption of normally distributed residuals (refer to Section 5.5.3.3); (2) MLR was the preferred analysis option because it is a relatively simple and practical method to estimate model parameters. Deviation of the residuals from a perfect normal distribution was therefore acceptable to an extent because it allowed MLR to be retained as the analysis method; (3) the distribution of residuals was approximately normal in shape (i.e. symmetrically clustered around a central value, with a mean of zero), and was not obviously another type of distribution (e.g. bimodal or exponential); and (4) even if the violation was severe enough to compromise the analysis, the consequence would be that the OLS estimator was BLUE rather than BUE and superior non-linear estimators may exist (refer to Section 5.5.3.3). However, MLP analysis gave a similar R^2 (=.90) to the MLR analysis Adj. R^2 (=.89). Therefore, even when freed from the constraints imposed by MLR assumptions (such as the normality assumption), predictions were not greatly improved. This assessment of the violation of the assumption of normally distributed residuals was typical for all PEMLA versions, and for brevity is not repeated.

More serious was the violation of the assumption of homoscedasticity, with heteroscedasticity indicated by the characteristic funnelling-out pattern of data points in Figure 6-3. This was confirmed by the results of Breusch-Pagan ($p<0.05$) and Koenker ($p<0.05$) tests. Again, this assessment was typical of all PEMLA versions, and for brevity is not repeated. The solution used to overcome the problem is detailed in Section 6.4.3.2.

Table 6-11: Statistics from the MLR analysis to calibrate PEMLA v.1.

Predictor Variable	B	Std. Error of B	Standardized Coefficient β	t-statistic
(Constant)	206.50	5.80	-	35.60*
DV - Cat 07 (1=Cat 07, else 0)	149.14	15.37	.06	9.71*
DV - Cat 08 (1=Cat 08, else 0)	118.12	15.37	.05	7.69*
DV - Cat 09 (1=Cat 09, else 0)	91.83	15.37	.04	5.98*
DV - Cat 13 (1=Cat 13, else 0)	80.15	15.37	.03	5.22*
DV - Cat 14 (1=Cat 14, else 0)	53.74	15.37	.02	3.50*
DV - Cat 15 (1=Cat 15, else 0)	31.18	15.37	.01	2.03*
DV - Cat 16 (1=Cat 16, else 0)	184.97	15.37	.07	12.04*
DV - Cat 17 (1=Cat 17, else 0)	84.20	15.37	.03	5.48*
DV - Cat 18 (1=Cat 18, else 0)	78.47	15.37	.03	5.11*
DV - Cat 19 (1=Cat 19, else 0)	73.62	15.37	.03	4.79*
DV - Cat 20 (1=Cat 20, else 0)	1220.01	16.78	.44	72.70*
DV - Cat 21 (1=Cat 21, else 0)	1385.65	16.78	.50	82.58*
DV - Cat 22 (1=Cat 22, else 0)	1439.09	14.67	.60	98.07*
DV - Cat 23 (1=Cat 23, else 0)	1430.78	16.78	.51	85.27*
DV - Cat 24 (1=Cat 24, else 0)	-91.27	17.30	-.03	-5.28*
DV - Road Type by Speed Limit (1=40, 0=30)	-70.95	6.29	-.07	-11.28*
DV - Time Period (1=Peak Period, 0=Off-Peak Period)	40.54	6.32	.04	6.41*

- Outcome variable is EF from AIRE (gCO_2/VKM).
- n = 3205.
- Adj. R^2 = .89.
- For comparison, equivalent MLP neural network analysis resulted in R^2 = .90.
- Durbin-Watson statistic = 1.66 (i.e. close to 2), which indicates the MLR assumption of independent residuals is tenable.
- Average VIF = 1.06 (i.e. not considerably greater than 1) and all individual predictor variable VIF values <10, which indicates the MLR assumption of no strong multicollinearity is tenable.
- The default vehicle category is ‘Car, Petrol or Diesel, <2000cc, All Euro’ (i.e. encompassing categories 01-06 and 10-12).
- B is the coefficient associated with a particular predictor variable.
- Standard Error of B is defined as the Standard Deviation (SD) of a distribution of repeated measures of B calculated from many different samples; i.e. SE is a measure of the similarity of B-values across different samples (Field 2009).
- Standardized Coefficient β is a standardised version of B and represents the number of SDs the outcome variable will change as a result of one SD change in the associated predictor variable, and provides an indication of the relative importance of predictor variables (Field 2009).
- The t-statistic (= B/Std. Error of B) tests whether B is statistically significantly different from zero, i.e. whether a predictor variable makes a statistically significant contribution to the model (Field 2009).
- * indicates t-statistic is significant (p<0.05).

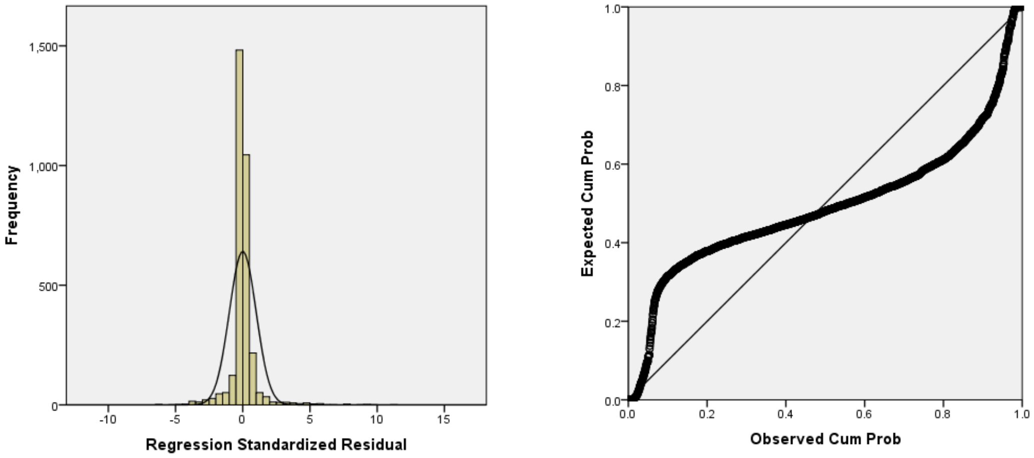


Figure 6-2: Histogram and normal P-P plot of standardised residuals from MLR analysis of PEMLA v.1.

- Positive kurtosis is evident in the histogram.
- In the normal P-P plot the straight line represents a normal distribution. Positive kurtosis is evident because initially the observed cumulative probability of the residuals is less than the expected cumulative probability for a normal distribution; and after approximately the mid-point (0.5 on the axes) the observed cumulative probability of the residuals is greater than the expected cumulative probability for a normal distribution (refer to Footnote 134 in Section 5.5.3.3).

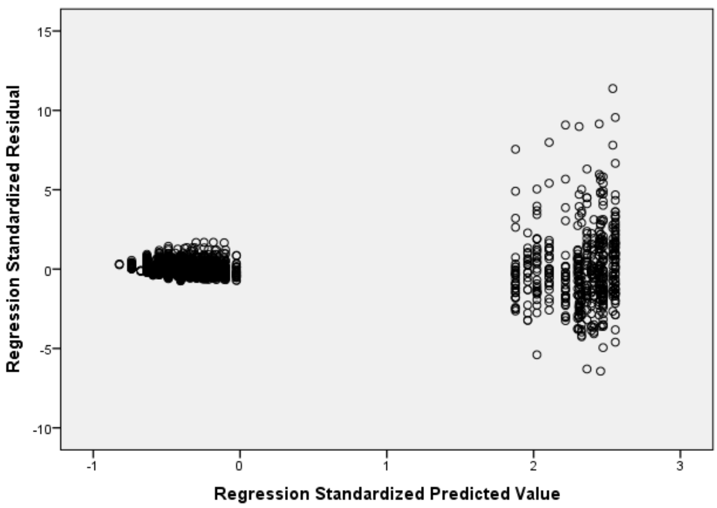


Figure 6-3: Scatter plot of standardised residuals against standardised predicted values from MLR analysis of PEMLA v.1.

- Funnelling-out pattern of the data points is characteristic of heteroscedasticity.

6.4.2.2 PEMLA v.2

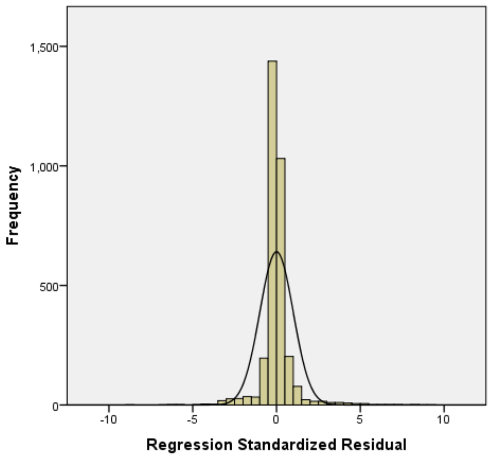
The same vehicle category DVs were used in PEMLA v.2 as in PEMLA v.1. In addition, known relationships established in previous research between average speed and EFs were forced into PEMLA v.2 through the use of the WebTAG average speed formulae for EFs (refer to Section 5.5.3.1). The reason behind the forced inclusion of the WebTAG formulae was to provide a strong relationship between average speed and EFs to compensate for the moderate performance in predicting emissions of the original five traffic variables.

Results for PEMLA v.2 are shown in Table 6-12. The outcome variable in the MLR analysis was EF from AIRE minus EF from WebTAG, and the model in this form had an Adj. R^2=.47. The final form of PEMLA v.2 was given by: EF from AIRE = *f*(predictor variables) + EF from WebTAG formula (i.e. converting back to EF from AIRE as outcome variable by rearranging Equation 12 to give Equation 13, refer to Section 5.5.3.1). Therefore, in order to calculate predicted values for EF from AIRE for PEMLA v.2, the EF from the appropriate WebTAG formula was added to the predicted value for the outcome variable in the MLR analysis for each case (i.e. in accordance with Equation 13). When observed values for EF from AIRE were linearly correlated with these predicted values for EF from AIRE, squaring of the resulting Pearson linear correlation coefficient (r) gave R^2=.86 for the final form of PEMLA v.2. Whilst it is acknowledged that this R^2 is not the same as Adj. R^2 (which is an estimate of what R^2 would be if the model had been based on analysis of the entire population, refer to Footnote 122 in Section 5.5.1.3), the statistic provided an approximate measure to assess the goodness of fit for the final form of PEMLA v.2. The increase from Adj. R^2=.47 to R^2=.86 represented the proportion of variation in EF from AIRE that can be explained by the WebTAG formulae when they are added back in during the conversion to the final form of PEMLA v.2 (i.e. in accordance with Equation 13).

Table 6-12: Statistics from the MLR analysis to calibrate PEMLA v.2.

Predictor Variable	B	Std. Error of B	Standardised Coefficient β	t-statistic
Constant	260.90	35.40	-	7.37*
DV - Cat 07 (1=Cat 07, else 0)	144.16	17.54	.11	8.22*
DV - Cat 08 (1=Cat 08, else 0)	113.13	17.54	.09	6.45*
DV - Cat 09 (1=Cat 09, else 0)	86.84	17.54	.07	4.95*
DV - Cat 13 (1=Cat 13, else 0)	90.12	17.54	.07	5.14*
DV - Cat 14 (1=Cat 14, else 0)	63.71	17.54	.05	3.63*
DV - Cat 15 (1=Cat 15, else 0)	41.15	17.54	.03	2.35*
DV - Cat 16 (1=Cat 16, else 0)	94.90	17.54	.07	5.41*
DV - Cat 17 (1=Cat 17, else 0)	49.32	17.54	.04	2.81*
DV - Cat 18 (1=Cat 18, else 0)	43.58	17.54	.03	2.48*
DV - Cat 19 (1=Cat 19, else 0)	38.74	17.54	.03	2.21*
DV - Cat 20 (1=Cat 20, else 0)	763.08	19.18	.53	39.79*
DV - Cat 21 (1=Cat 21, else 0)	246.24	19.18	.17	12.84*
DV - Cat 22 (1=Cat 22, else 0)	254.16	17.18	.20	14.80*
DV - Cat 23 (1=Cat 23, else 0)	465.18	19.18	.32	24.26*
DV - Cat 24 (1=Cat 24, else 0)	157.67	20.24	.11	7.79*
DV - Road Type by Speed Limit (1=40, 0=30)	-39.84	8.74	-.07	-4.56*
DV - Time Period (1=Peak Period, 0=Off-Peak Period)	41.84	7.49	.08	5.59*
Traffic Average Speed (km/h)	-4.60	1.03	-.12	-4.45*
Traffic Density (veh/km)	1.42	0.34	.08	4.19*
Traffic Av Delay Rate (s/veh.km)	-1.84	0.11	-.45	-16.58*
Access Density Cubed $(\text{int./km})^3$	0.01	0.00	.04	3.14*

- Outcome variable is (EF from AIRE – EF from WebTAG average speed formulae) (gCO_2/VKM).
- ILD traffic average speeds were used in the WebTAG formulae because these are the data to which LGAs have access.
- n = 3205.
- Adj. R^2 = .47.
- For comparison, equivalent MLP neural network analysis resulted in R^2 = .53.
- Durbin-Watson statistic = 1.89 (i.e. close to 2), which indicates the MLR assumption of independent residuals is tenable.
- Average VIF = 1.46 (i.e. not considerably greater than 1) and all individual predictor variable VIF values <10, which indicates the MLR assumption of no strong multicollinearity is tenable.
- The default vehicle category is 'Car, Petrol or Diesel, <2000cc, All Euro' (i.e. encompassing categories 01-06 and 10-12).
- B, Standard Error of B, Standardized Coefficient β and t-statistic are detailed in notes for Table 6-11.
- * indicates t-statistic is significant ($p<0.05$).



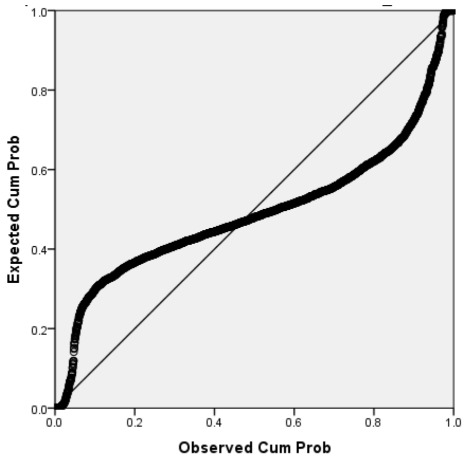


Figure 6-4: Histogram and normal P-P plot of standardised residuals from MLR analysis of PEMLA v.2.

- Positive kurtosis is evident in the plots (refer to notes for Figure 6-2).

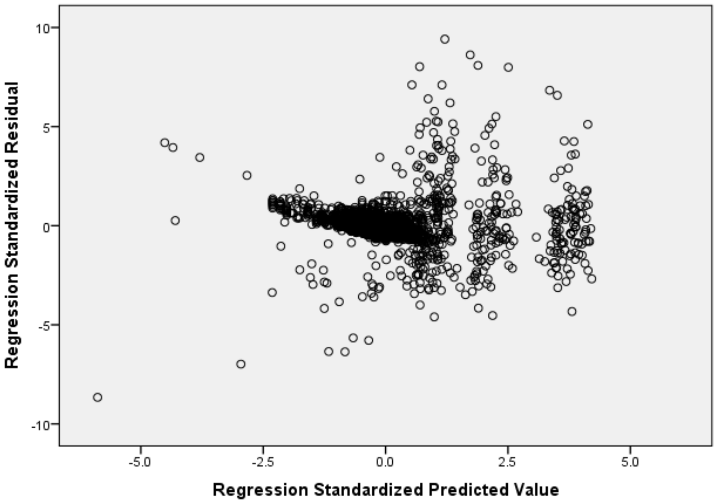


Figure 6-5: Scatter plot of standardised residuals against standardised predicted values from MLR analysis of PEMLA v.2.

- Funnelling-out pattern of the data points is characteristic of heteroscedasticity.

6.4.2.3 PEMLA v.3

Interaction Variables (IVs) were created for PEMLA v.3, which were used to encode the interaction between vehicle category and the five original traffic variables (plus the square and cube of access density). For each vehicle category, seven IVs were created, one for each traffic variable. For example, IV-Cat 01 & Traffic Average Speed was the IV encoding the interaction between vehicle category 01 and traffic average speed (refer to Section 5.5.3.1). Results for PEMLA v.3 are shown in Table 6-13.

Table 6-13: Statistics from the MLR analysis to calibrate PEMLA v.3.

Predictor Variable	B	Std. Error of B	Standardised Coefficient β	t-Statistic
Constant	544.55	35.04	-	15.54*
IV - Cat01 & TraffAvSpd	-9.58	1.31	-.10	-7.32*
IV - Cat01 & TraffAvDlyRt	-0.97	0.23	-.04	-4.13*
IV - Cat02 & TraffAvSpd	-10.12	1.31	-.10	-7.74*
IV - Cat02 & TraffAvDlyRt	-1.03	0.23	-.04	-4.38*
IV - Cat03 & TraffAvSpd	-10.58	1.31	-.11	-8.09*
IV - Cat03 & TraffAvDlyRt	-1.08	0.23	-.05	-4.59*
IV - Cat04 & TraffAvSpd	-8.63	1.31	-.09	-6.60*
IV - Cat04 & TraffAvDlyRt	-0.84	0.23	-.04	-3.56*
IV - Cat05 & TraffAvSpd	-9.27	1.31	-.09	-7.09*
IV - Cat05 & TraffAvDlyRt	-0.91	0.23	-.04	-3.86*
IV - Cat06 & TraffAvSpd	-9.81	1.31	-.10	-7.50*
IV - Cat06 & TraffAvDlyRt	-0.96	0.23	-.04	-4.11*
IV - Cat07 & TraffAvSpd	-5.93	1.31	-.06	-4.54*
IV - Cat07 & TraffAvDlyRt	-0.49	0.23	-.02	-2.09*
IV - Cat08 & TraffAvSpd	-6.82	1.31	-.07	-5.21*
IV - Cat08 & TraffAvDlyRt	-0.59	0.23	-.02	-2.50*
IV - Cat09 & TraffAvSpd	-7.57	1.31	-.08	-5.79*
IV - Cat09 & TraffAvDlyRt	-0.67	0.23	-.03	-2.85*
IV - Cat10 & TraffAvSpd	-10.09	1.31	-.10	-7.71*
IV - Cat10 & TraffAvDlyRt	-1.04	0.23	-.04	-4.42*
IV - Cat11 & TraffAvSpd	-10.60	1.31	-.11	-8.11*
IV - Cat11 & TraffAvDlyRt	-1.09	0.23	-.05	-4.66*
IV - Cat12 & TraffAvSpd	-11.03	1.31	-.11	-8.43*
IV - Cat12 & TraffAvDlyRt	-1.14	0.23	-.05	-4.86*
IV - Cat13 & TraffAvSpd	-7.78	1.31	-.08	-5.95*
IV - Cat13 & TraffAvDlyRt	-0.73	0.23	-.03	-3.13*
IV - Cat14 & TraffAvSpd	-8.52	1.31	-.09	-6.52*
IV - Cat14 & TraffAvDlyRt	-0.82	0.23	-.03	-3.49*
IV - Cat15 & TraffAvSpd	-9.16	1.31	-.09	-7.00*
IV - Cat15 & TraffAvDlyRt	-0.89	0.23	-.04	-3.80*
IV - Cat16 & TraffAvSpd	-4.85	1.31	-.05	-3.71*
IV - Cat16 & TraffAvDlyRt	-0.39	0.23	-.02	-1.67
IV - Cat17 & TraffAvSpd	-7.55	1.31	-.08	-5.78*
IV - Cat17 & TraffAvDlyRt	-0.75	0.23	-.03	-3.19*
IV - Cat18 & TraffAvSpd	-7.72	1.31	-.08	-5.90*
IV - Cat18 & TraffAvDlyRt	-0.76	0.23	-.03	-3.26*
IV - Cat19 & TraffAvSpd	-7.86	1.31	-.08	-6.01*
IV - Cat19 & TraffAvDlyRt	-0.78	0.23	-.03	-3.32*
IV - Cat20 & TraffAvSpd	24.35	1.36	.24	17.85*
IV - Cat20 & TraffAvDlyRt	2.33	0.24	.09	9.91*
IV - Cat20 & AccDensCubd	0.03	0.02	.02	2.16*
IV - Cat21 & TraffAvSpd	28.86	1.36	.28	21.15*
IV - Cat21 & TraffAvDlyRt	2.70	0.24	.10	11.49*

Table 6-13 continued.

Predictor Variable	B	Std. Error of B	Standardised Coefficient β	t-Statistic
IV - Cat21 & AccDensCubd	0.05	0.02	.02	3.12*
IV - Cat22 & TraffAvSpd	32.19	1.49	.29	21.65*
IV - Cat22 & TraffAvDlyRt	2.18	0.11	.18	19.12*
IV - Cat22 & AccDensCubd	0.11	0.01	.07	9.52*
IV - Cat23 & TraffAvSpd	29.72	1.36	.29	21.79*
IV - Cat23 & TraffAvDlyRt	2.92	0.24	.11	12.45*
IV - Cat23 & AccDensCubd	0.05	0.02	.03	3.21*
IV - Cat24 & TraffAvSpd	-12.65	1.41	-.11	-8.95*
IV - Cat24 & TraffAvDlyRt	-0.65	0.14	-.04	-4.68*
IV - Cat24 & AccDensCubd	-0.14	0.04	-.03	-3.68*
DV - Road Type by Speed Limit (1=40, 0=30)	-58.13	7.06	-.06	-8.23*
DV - Time Period (1=Peak Period, 0=Off-Peak Period)	38.65	6.71	.04	5.76*

- Outcome variable is EF from AIRE (gCO_2/VKM).
- n = 3205.
- Adj. R^2 = .88.
- For comparison, equivalent MLP neural network analysis resulted in R^2 = .89.
- Durbin-Watson statistic = 1.71 (i.e. close to 2), which indicates the assumption of independent residuals is tenable.
- Average VIF = 3.38 (i.e. not considerably greater than 1) and all individual predictor variable VIF values <10, which indicates the MLR assumption of no strong multicollinearity is tenable.
- B, Standard Error of B, Standardized Coefficient β and t-statistic are detailed in notes for Table 6-11.
- * indicates t-statistic is significant (p<0.05).
- IV – Cat16 & TraffAvDlyRt has a t-statistic significant at only the 0.1 level, but is retained for consistency with predictor variables for other vehicle categories.

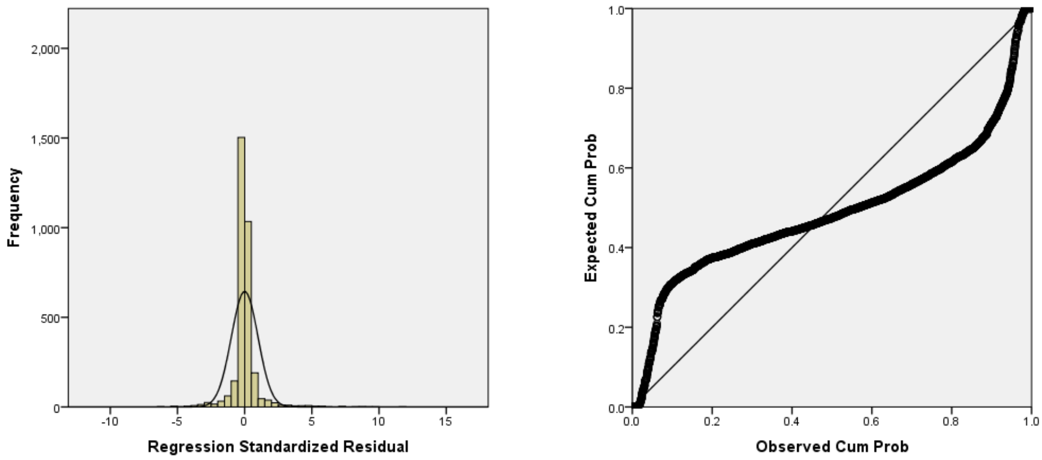


Figure 6-6: Histogram and normal P-P plot of standardised residuals from MLR analysis of PEMLA v.3.

- Positive kurtosis is evident in the plots (refer to notes for Figure 6-2).

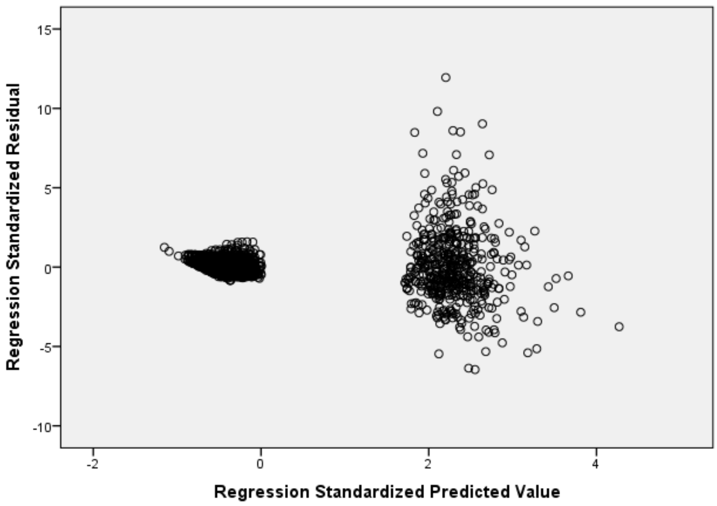


Figure 6-7: Scatter plot of standardised residuals against standardised predicted values from MLR analysis of PEMLA v.3.

- Funnelling-out pattern of the data points is characteristic of heteroscedasticity.

6.4.3 Development of the IV (PEMLA v.3) Calibration Method

After comparison of the three different calibration methods (represented by PEMLA v.1 to v.3) used to incorporate vehicle category as a predictor variable, PEMLA v.3 was identified as offering the most potential for further development (refer to Section 7.2.2). Therefore, three more versions of PEMLA (PEMLA v.4, v.5 and v.7) were subsequently developed based on the PEMLA v.3 calibration method (i.e. using IVs). PEMLA v.4 and v.5 both sought to investigate solutions to the violation of the assumption of homoscedasticity, and PEMLA v.7 sought to investigate the extent to which the (less serious) deviation from the assumption of normally distributed residuals could be reduced.

6.4.3.1 PEMLA v.4

As well as showing a funnelling-out pattern characteristic of heteroscedasticity, the scatter plots of standardised residuals against standardised predicted values for PEMLA v.1 and v.3 (Figure 6-3 and Figure 6-7, respectively) both showed a distinct lateral gap between a cluster of standardised predicted values for LDV (and two-wheel) vehicle categories at the mean and below (between approximately -1 and 0 on the x-axis), and a cluster for HDV vehicle categories well above the mean (between approximately 2 and 3 on the x-axis). The same scatter plot for PEMLA v.2 (Figure 6-5) showed a different pattern. This was due to the different method used to calibrate PEMLA v.2 where EF from AIRE minus EF from WebTAG was used as the outcome variable, in contrast to calibration of PEMLA v.1 and v.3 where EF from AIRE was used as the outcome variable. In general, using EF from AIRE minus EF from WebTAG meant values for the outcome variable were closer to zero (if the EF from AIRE for a case had been in exact agreement with the EF predicted for the case by the WebTAG formula the value of the outcome variable would be zero). This resulted in the two distinct clusters seen for PEMLA v.1

and v.3 being placed in close proximity in the scatter plot for PEMLA v.2, which superficially appeared to have reduced the heteroscedasticity problem. However, funnelling-out was still evident in Figure 6-5, albeit with the gap now closed between LDV and HDV data, and the results of Breusch-Pagan ($p<0.05$) and Koenker ($p<0.05$) tests confirmed that heteroscedasticity was still present.

Due to the marked difference in variance of the residuals between the LDV and HDV clusters, the potential benefit (in terms of reduced heteroscedasticity) of splitting PEMLA into two parts (i.e. LDV and HDV) was investigated. Results for PEMLA v.4-LDV (and two-wheel) and PEMLA v.4-HDV are shown in Table 6-14 and Table 6-15, respectively.

The data points in Figure 6-9 show a funnelling-out pattern, and the results of Breusch-Pagan ($p<0.05$) and Koenker ($p<0.05$) tests confirmed the continued presence of heteroscedasticity for PEMLA v.4-LDV (and two-wheel). Although less distinct than in Figure 6-9, there is still evidence of funnelling-out in Figure 6-11, and the assumption of homoscedasticity is likely to be violated for PEMLA v.4-HDV as well. The results of the statistical tests were not conclusive for the HDV part. The Breusch-Pagan test gave a significant result ($p<0.05$) indicating heteroscedasticity, while the Koenker test gave a non-significant result ($p=.09$) indicating the assumption of homoscedasticity was tenable (although more weight should be given to the Koenker test results because this test is more powerful if the distribution of residuals deviates from normality (Waldman 1983; Kennedy 2003), refer to Footnote 137 in Section 5.5.3.3).

In general, splitting PEMLA into two parts did not provide a satisfactory solution to the problem of heteroscedasticity of residuals (heteroscedasticity was still present in the LDV part, and was likely to still be present in the HDV part), and also resulted in small Adj. R^2 values (LDV=.59 and HDV=.12). PEMLA v.4 was therefore abandoned as a viable option. This led to investigation of an alternative solution to the problem, which produced PEMLA v.5.

Table 6-14: Statistics from the MLR analysis to calibrate PEMLA v.4-LDV (and two-wheel).

Predictor Variable	B	Std. Error of B	Standardised Coefficient β	t-Statistic
(Constant)	267.59	4.30		62.30*
IV - Cat01 & TraffAvSpd	-2.04	0.23	-.14	-8.81*
IV - Cat02 & TraffAvSpd	-2.75	0.23	-.19	-11.88*
IV - Cat03 & TraffAvSpd	-3.35	0.23	-.23	-14.49*
IV - Cat04 & TraffAvSpd	-0.71	0.23	-.05	-3.05*
IV - Cat05 & TraffAvSpd	-1.55	0.23	-.11	-6.68*
IV - Cat06 & TraffAvSpd	-2.25	0.23	-.16	-9.73*
IV - Cat07 & TraffAvSpd	3.00	0.23	.21	12.97*
IV - Cat08 & TraffAvSpd	1.84	0.23	.13	7.93*
IV - Cat09 & TraffAvSpd	0.85	0.23	.06	3.67*
IV - Cat10 & TraffAvSpd	-2.75	0.23	-.19	-11.88*
IV - Cat11 & TraffAvSpd	-3.42	0.23	-.24	-14.78*
IV - Cat12 & TraffAvSpd	-3.99	0.23	-.28	-17.22*
IV - Cat13 & TraffAvSpd	0.45	0.23	.03	1.92
IV - Cat14 & TraffAvSpd	-0.54	0.23	-.04	-2.35*
IV - Cat15 & TraffAvSpd	-1.39	0.23	-.10	-6.00*
IV - Cat16 & TraffAvSpd	4.37	0.23	.30	18.89*
IV - Cat17 & TraffAvSpd	0.63	0.23	.04	2.73*
IV - Cat18 & TraffAvSpd	0.41	0.23	.03	1.79
IV - Cat19 & TraffAvSpd	0.23	0.23	.02	1.00
IV - Cat24 & TraffAvSpd	-5.87	0.27	-.33	-22.14*
DV - Road Type by Speed Limit (1=40, 0=30)	-32.70	2.13	-.19	-15.34*
DV - Time Period (1=Peak Period, 0=Off-Peak Period)	15.43	2.17	.09	7.10*

- Outcome variable is EF from AIRE (gCO_2/VKM).
- n = 2713.
- Adj. R^2 = .59.
- For comparison, equivalent MLP neural network analysis resulted in R^2 = .64.
- Durbin-Watson statistic = 1.89 (i.e. close to 2), which indicates the assumption of independent residuals is tenable.
- Average VIF = 1.61 (i.e. not considerably greater than 1) and all individual predictor variable VIF values < 10, which indicates the MLR assumption of no strong multicollinearity is tenable.
- B, Standard Error of B, Standardized Coefficient β and t-statistic are detailed in notes for Table 6-11.
- * indicates t-statistic is significant (p<0.05).
- IV – Cat13 & TraffAvSpd and IV – Cat18 & TraffAvSpd have t-statistics significant at only 0.1 level, but are retained for practical model use.
- IV – Cat19 & TraffAvSpd has a non-significant t-statistic, but is also retained for practical model use.

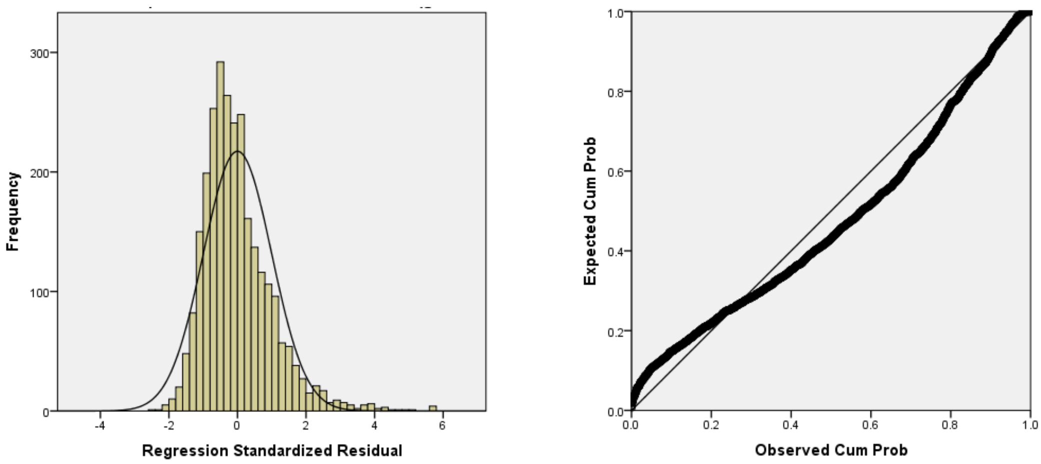


Figure 6-8: Histogram and normal P-P plot of standardised residuals from MLR analysis of PEMLA v.4-LDV (and two-wheel).

- Positive kurtosis is evident in the plots (refer to notes for Figure 6-2).
- Skewness is evident in the plots, i.e. a lack of symmetry to the left and right of the mid-point.

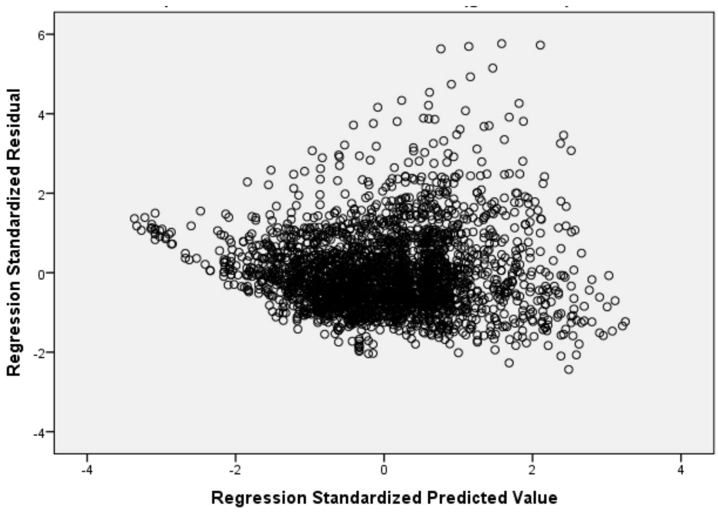


Figure 6-9: Scatter plot of standardised residuals against standardised predicted values from MLR analysis of PEMLA v.4-LDV (and two-wheel).

- Funnelling-out pattern of the data points is characteristic of heteroscedasticity.

Table 6-15: Statistics from the MLR analysis to calibrate PEMLA v.4-HDV.

Predictor Variable	B	Std. Error of B	Standardised Coefficient β	t-Statistic
(Constant)	1649.93	30.55	-	54.00*
IV - Cat20 & TraffDens	-5.99	1.73	-.15	-3.46*
DV - Road Type by Speed Limit (1=40, 0=30)	-234.06	38.11	-.27	-6.14*
DV - Time Period (1=Peak Period, 0=Off-Peak Period)	101.21	37.04	.12	2.73*

- Outcome variable is EF from AIRE (gCO_2/VKM).
- n = 492.
- Adj. R^2 = .12.
- For comparison, equivalent MLP neural network analysis resulted in R^2 = .13.
- Durbin-Watson statistic = 1.66 (i.e. close to 2), which indicates the assumption of independent residuals is tenable.
- Average VIF = 1.02 (i.e. not considerably greater than 1) and all individual predictor variable VIF values < 10, which indicates the MLR assumption of no strong multicollinearity is tenable.
- B, Standard Error of B, Standardized Coefficient β and t-statistic are detailed in notes for Table 6-11.
- * indicates t-statistic is significant (p<0.05).

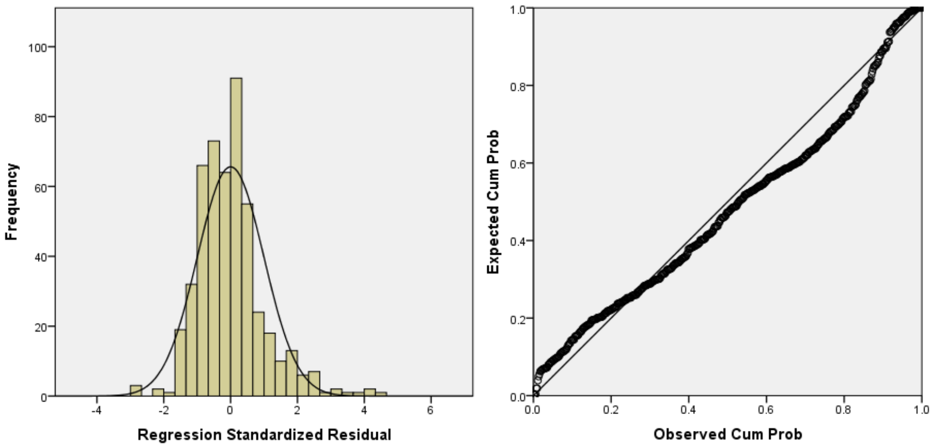


Figure 6-10: Histogram and normal P-P plot of standardised residuals from MLR analysis of PEMLA v.4-HDV.

- Positive kurtosis is evident in the plots (refer to notes for Figure 6-2).
- Skewness is evident in the plots (refer to notes for Figure 6-8).

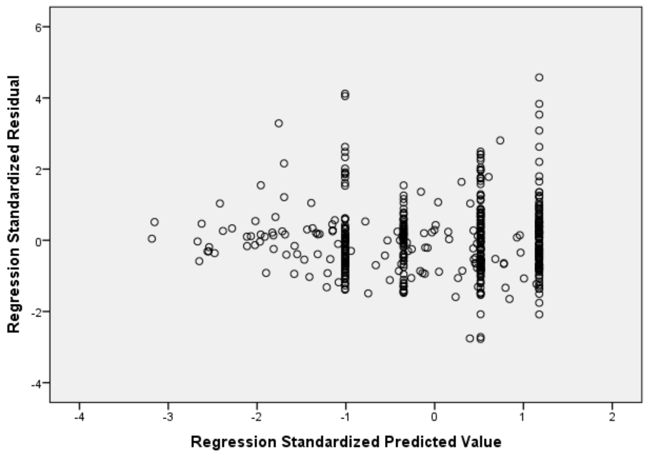


Figure 6-11: Scatter plot of standardised residuals against standardised predicted values from MLR analysis of PEMLA v.4-HDV.

- Funnelling-out pattern of the data points is characteristic of heteroscedasticity.

6.4.3.2 PEMLA v.5

Violation of the assumption of homoscedasticity occurred in PEMLA v.1 to v.3, and splitting PEMLA into LDV and HDV parts (PEMLA v.4) did not eliminate the problem. The presence of heteroscedasticity diminishes the accuracy with which the OLS estimator calculates the standard error (SE) of predictor variable coefficients (B). Consequently, because t-statistics are calculated as the ratio of B to SE (refer to notes for Table 6-11), the statistical power of the hypothesis test based on the probability value for a predictor variable's t-statistic is reduced (i.e. the hypothesis test that a predictor variable's coefficient is statistically significantly different from zero is less reliable because the accuracy of the SE is questionable[146]) (Hayes and Cai 2007).

One approach to overcoming heteroscedasticity is Weighted Least Squares (WLS) regression (as opposed to OLS regression) where each case is weighted differently in calculating the sum of squared residuals. However, this approach requires knowledge of the functional form of heteroscedasticity so that the appropriate weights can be applied to each case (Montgomery *et al.* 2012). If the weights do not closely match the form of heteroscedasticity, the WLS estimates of SEs may still be inaccurate due to the heteroscedasticity that remains unaccounted for in the selected weights (Hayes and Cai 2007).

An alternative method that does not rely on knowledge of the functional form of heteroscedasticity is the use of OLS with a Heteroscedastic-Consistent Standard Error estimator (OLS HCSE). This method estimates model parameters using OLS, but with an HCSE estimator that can estimate standard errors even when residuals display heteroscedasticity (i.e. the assumption of homoscedasticity is no longer necessary for the MLR analysis) (Kennedy 2003; Hayes and Cai 2007). Due to obviating the requirement for knowledge of the form of heteroscedasticity, OLS HCSE was the method selected. PEMLA v.3 was therefore re-estimated using OLS HCSE. Results were designated PEMLA v.5 and are shown in Table 6-16. Figure 6-13 and the results of Breusch-Pagan ($p<0.05$) and Koenker ($p<0.05$) tests indicated heteroscedasticity was still present, but this was no longer a problem because of the estimation method used.

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[146] In the hypothesis test the null hypothesis is that a predictor variable's coefficient is not significantly different from zero (i.e. a predictor variable is not making a statistically significant contribution to the model). A significant result for the t-statistic ($p<0.05$) allows the null hypothesis to be rejected, and the alternative hypothesis that the coefficient is significantly different from zero is accepted.

Table 6-16: Statistics from the MLR analysis to calibrate PEMLA v.5.

Predictor Variable	B	Std. Error of B (HC)	Standardised Coefficient β	t-Statistic (HC)
(Constant)	557.62	52.27	-	10.67*
IV - Cat01 & TraffAvSpd	-9.94	1.54	-0.10	-6.45*
IV - Cat01 & TraffAvDlyRt	-1.01	0.20	-0.04	-5.15*
IV - Cat02 & TraffAvSpd	-10.49	1.54	-0.11	-6.80*
IV - Cat02 & TraffAvDlyRt	-1.07	0.20	-0.05	-5.40*
IV - Cat03 & TraffAvSpd	-10.95	1.54	-0.11	-7.09*
IV - Cat03 & TraffAvDlyRt	-1.12	0.20	-0.05	-5.61*
IV - Cat04 & TraffAvSpd	-9.00	1.54	-0.09	-5.85*
IV - Cat04 & TraffAvDlyRt	-0.88	0.19	-0.04	-4.52*
IV - Cat05 & TraffAvSpd	-9.64	1.54	-0.10	-6.25*
IV - Cat05 & TraffAvDlyRt	-0.95	0.20	-0.04	-4.84*
IV - Cat06 & TraffAvSpd	-10.17	1.54	-0.10	-6.60*
IV - Cat06 & TraffAvDlyRt	-1.00	0.20	-0.04	-5.09*
IV - Cat07 & TraffAvSpd	-6.30	1.54	-0.06	-4.09*
IV - Cat07 & TraffAvDlyRt	-0.53	0.19	-0.02	-2.76*
IV - Cat08 & TraffAvSpd	-7.19	1.54	-0.07	-4.66*
IV - Cat08 & TraffAvDlyRt	-0.63	0.19	-0.03	-3.23*
IV - Cat09 & TraffAvSpd	-7.94	1.54	-0.08	-5.14*
IV - Cat09 & TraffAvDlyRt	-0.71	0.20	-0.03	-3.63*
IV - Cat10 & TraffAvSpd	-10.46	1.54	-0.11	-6.78*
IV - Cat10 & TraffAvDlyRt	-1.08	0.20	-0.05	-5.45*
IV - Cat11 & TraffAvSpd	-10.97	1.54	-0.11	-7.11*
IV - Cat11 & TraffAvDlyRt	-1.13	0.20	-0.05	-5.67*
IV - Cat12 & TraffAvSpd	-11.40	1.54	-0.12	-7.38*
IV - Cat12 & TraffAvDlyRt	-1.18	0.20	-0.05	-5.86*
IV - Cat13 & TraffAvSpd	-8.15	1.54	-0.08	-5.30*
IV - Cat13 & TraffAvDlyRt	-0.77	0.19	-0.03	-4.02*
IV - Cat14 & TraffAvSpd	-8.89	1.54	-0.09	-5.78*
IV - Cat14 & TraffAvDlyRt	-0.86	0.19	-0.04	-4.42*
IV - Cat15 & TraffAvSpd	-9.53	1.54	-0.10	-6.18*
IV - Cat15 & TraffAvDlyRt	-0.93	0.20	-0.04	-4.75*
IV - Cat16 & TraffAvSpd	-5.22	1.54	-0.05	-3.39*
IV - Cat16 & TraffAvDlyRt	-0.43	0.19	-0.02	-2.29*
IV - Cat17 & TraffAvSpd	-7.92	1.54	-0.08	-5.16*
IV - Cat17 & TraffAvDlyRt	-0.79	0.19	-0.03	-4.14*
IV - Cat18 & TraffAvSpd	-8.09	1.54	-0.08	-5.26*
IV - Cat18 & TraffAvDlyRt	-0.80	0.19	-0.03	-4.22*
IV - Cat19 & TraffAvSpd	-8.23	1.54	-0.08	-5.36*
IV - Cat19 & TraffAvDlyRt	-0.82	0.19	-0.03	-4.28*
IV - Cat20 & TraffAvSpd	24.76	2.40	0.24	10.32*
IV - Cat20 & TraffAvDlyRt	2.40	0.45	0.09	5.34*
IV - Cat21 & TraffAvSpd	29.62	2.64	0.29	11.20*
IV - Cat21 & TraffAvDlyRt	2.81	0.51	0.11	5.54*
IV - Cat22 & TraffAvSpd	31.77	2.86	0.28	11.13*

Table 6-16 continued.

Predictor Variable	B	Std. Error of B (HC)	Standardised Coefficient β	t-Statistic (HC)
IV - Cat22 & TraffAvDlyRt	2.15	0.30	0.17	7.09*
IV - Cat22 & AccDensCubd	0.11	0.03	0.07	4.01*
IV - Cat23 & TraffAvSpd	30.51	2.91	0.30	10.49*
IV - Cat23 & TraffAvDlyRt	3.05	0.56	0.12	5.47*
IV - Cat24 & TraffAvSpd	-13.03	1.68	-0.11	-7.78*
IV - Cat24 & TraffAvDlyRt	-0.67	0.15	-0.05	-4.43*
IV - Cat24 & AccDensCubd	-0.15	0.02	-0.03	-6.18*
DV - Road Type by Speed Limit (1=40, 0=30)	-59.77	7.86	-0.06	-7.61*
DV - Time Period (1=Peak Period, 0=Off-Peak Period)	40.03	7.26	0.04	5.51*

- Outcome variable is EF from AIRE (gCO_2/VKM).
- n = 3205.
- Adj. R^2 = .88.
- For comparison, equivalent MLP neural network analysis resulted in R^2 = .89.
- HC is Heteroscedastic-Consistent.
- Durbin-Watson statistic = 1.69 (i.e. close to 2), which indicates the assumption of independent residuals is tenable.
- Average VIF = 3.45 (i.e. not considerably greater than 1) and all individual predictor variable VIF values < 10, which indicates the MLR assumption of no strong multicollinearity is tenable.
- B, Standard Error of B, Standardized Coefficient β and t-statistic are detailed in notes for Table 6-11.
- * indicates t-statistic is significant (p<0.05).

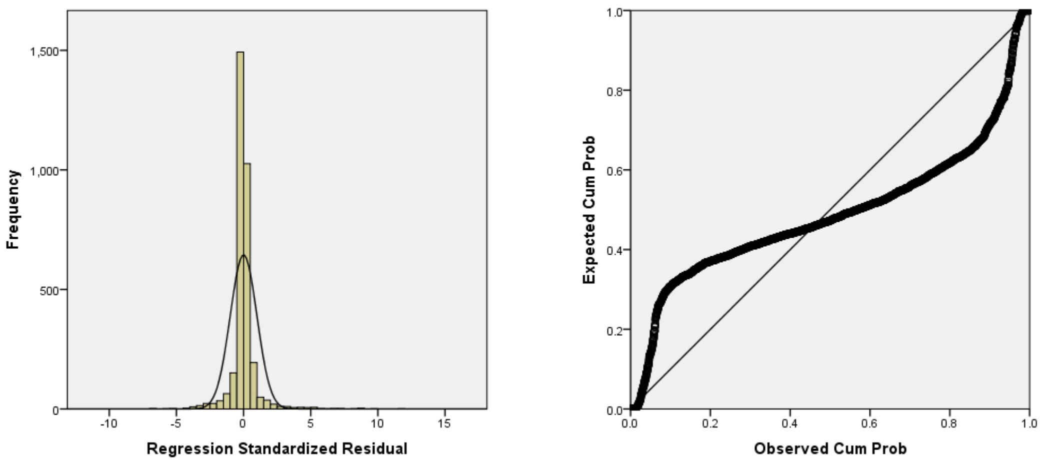

Figure 6-12: Histogram and normal P-P plot of standardised residuals from MLR analysis of PEMLA v.5.

- Positive kurtosis is evident in the plots (refer to notes for Figure 6-2).

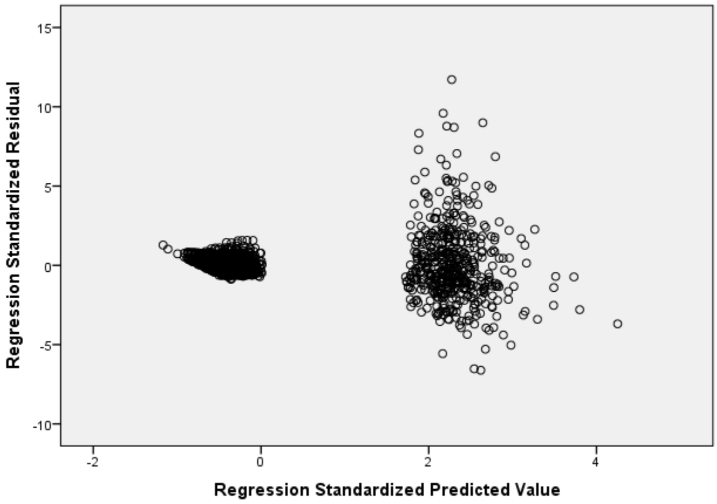

Figure 6-13: Scatter plot of standardised residuals against standardised predicted values from MLR analysis of PEMLA v.5.

- Funnelling-out pattern of the data points is characteristic of heteroscedasticity.

6.4.3.3 PEMLA v.7

Violation of the assumption of normally distributed residuals occurred to an extent in all PEMLA versions calibrated so far. For the reasons detailed in Section 6.4.2.1 the violations were judged to be acceptable and not severe enough to compromise the analysis. However, a method commonly used to correct for non-normally distributed residuals was investigated to establish what benefits (if any) it might provide. The method employed was a log transformation of the outcome variable (Kleinbaum *et al.* 2007). The outcome variable for the MLR analysis was therefore defined as the natural log of EF from AIRE (gCO_2/VKM). According to this definition, for each case, a value for the new outcome variable was calculated.

Results for PEMLA v.7 are shown in Table 6-17. The MLR analysis (again conducted using an OLS HCSE estimator) generated a model of the form shown in Equation 22, which in this form had an Adj. R^2=.93. The final form of PEMLA v.7 was given by: EF from AIRE = $e^{f(\text{predictor variables})}$ (i.e. converting back to EF from AIRE as outcome variable by rearranging Equation 22 to give Equation 23). Therefore, in order to calculate predicted values for EF from AIRE for PEMLA v.7, e was raised to the power of the predicted value for the natural log of EF from AIRE for each case (i.e. in accordance with Equation 23). When observed values for EF from AIRE were linearly correlated with these predicted values for EF from AIRE, squaring of the resulting Pearson linear correlation coefficient (r) gave R^2 = .85 for the final form of PEMLA v.7. As was the case for PEMLA v.2, whilst it is acknowledged that this R^2 is not the same as Adj. R^2 (which is an estimate of what R^2 would be if the model had been based on analysis of the entire population, refer to Footnote 122 in Section 5.5.1.3), the statistic provided an approximate measure to assess the goodness of fit for the final form of PEMLA v.7. The decrease from Adj.

R^2=.93 to R^2=.85 was due to residuals being magnified by the exponential nature of the conversion to the final form of PEMLA v.7, i.e. an error in a predicted value for ln(EF from AIRE) was magnified when e was raised to the power of that predicted value.

Results of a Kolmogorov-Smirnov test ($p<0.05$) indicated the assumption of normally distributed residuals had still been violated. However, inspection of both charts in Figure 6-14 indicated the distribution of residuals was a closer approximation to normality than in previous PEMLA versions, i.e. reduced kurtosis shown in the histogram and a straighter line shown in the normal P-P plot. Figure 6-15 and the results of Breusch-Pagan ($p<0.05$) and Koenker ($p<0.05$) tests indicated heteroscedasticity was still present, but again this was not a problem because of the estimation method used (i.e. OLS HCSE estimator).

Equation 22

$$\ln(\text{EF from AIRE}) = f(\text{predictor variables})$$

Equation 23

$$\text{EF from AIRE} = e^{f(\text{predictor variables})}$$

Table 6-17: Statistics from the MLR Analysis to Calibrate PEMLA v.7.

Predictor Variable	B	Std. Error of B (HC)	Standardised Coefficient β	t-Statistic (HC)
(Constant)	5.9485	0.0152	-	392.54*
IV - Cat01 & TraffAvSpd	-0.0183	0.0009	-0.13	-20.14*
IV - Cat01 & TraffAvDlyRt	-0.0016	0.0002	-0.05	-8.09*
IV - Cat02 & TraffAvSpd	-0.0212	0.0010	-0.15	-21.73*
IV - Cat02 & TraffAvDlyRt	-0.0019	0.0002	-0.05	-8.47*
IV - Cat03 & TraffAvSpd	-0.0239	0.0010	-0.17	-22.88*
IV - Cat03 & TraffAvDlyRt	-0.0021	0.0002	-0.06	-8.69*
IV - Cat04 & TraffAvSpd	-0.0140	0.0009	-0.10	-15.55*
IV - Cat04 & TraffAvDlyRt	-0.0011	0.0002	-0.03	-5.56*
IV - Cat05 & TraffAvSpd	-0.0170	0.0010	-0.12	-17.46*
IV - Cat05 & TraffAvDlyRt	-0.0013	0.0002	-0.04	-6.26*
IV - Cat06 & TraffAvSpd	-0.0197	0.0010	-0.14	-18.84*
IV - Cat06 & TraffAvDlyRt	-0.0016	0.0002	-0.05	-6.70*
IV - Cat07 & TraffAvSpd	-0.0057	0.0009	-0.04	-6.38*
IV - Cat07 & AccDensCubd	4×10^{-5}	0.0000	0.02	2.60*
IV - Cat08 & TraffAvSpd	-0.0095	0.0010	-0.07	-9.78*
IV - Cat08 & AccDensCubd	4×10^{-5}	0.0000	0.02	2.31*
IV - Cat09 & TraffAvSpd	-0.0114	0.0011	-0.08	-10.66*
IV - Cat09 & TraffAvDlyRt	-0.0007	0.0002	-0.02	-2.70*
IV - Cat09 & AccDensCubd	5×10^{-5}	0.0000	0.02	2.77*
IV - Cat10 & TraffAvSpd	-0.0210	0.0010	-0.15	-21.90*
IV - Cat10 & TraffAvDlyRt	-0.0019	0.0002	-0.05	-8.93*

Table 6-17 continued.

Predictor Variable	B	Std. Error of B (HC)	Standardised Coefficient β	t-Statistic (HC)
IV - Cat11 & TraffAvSpd	-0.0240	0.0010	-0.17	-23.34*
IV - Cat11 & TraffAvDlyRt	-0.0022	0.0002	-0.06	-9.20*
IV - Cat12 & TraffAvSpd	-0.0269	0.0011	-0.19	-24.36*
IV - Cat12 & TraffAvDlyRt	-0.0025	0.0003	-0.07	-9.35*
IV - Cat13 & TraffAvSpd	-0.0107	0.0009	-0.07	-11.87*
IV - Cat13 & TraffAvDlyRt	-0.0007	0.0002	-0.02	-3.73*
IV - Cat14 & TraffAvSpd	-0.0137	0.0010	-0.09	-14.35*
IV - Cat14 & TraffAvDlyRt	-0.0010	0.0002	-0.03	-4.85*
IV - Cat15 & TraffAvSpd	-0.0166	0.0010	-0.11	-16.33*
IV - Cat15 & TraffAvDlyRt	-0.0013	0.0002	-0.04	-5.67*
IV - Cat17 & TraffAvSpd	-0.0096	0.0008	-0.07	-12.19*
IV - Cat17 & TraffAvDlyRt	-0.0007	0.0001	-0.02	-4.91*
IV - Cat18 & TraffAvSpd	-0.0103	0.0008	-0.07	-12.77*
IV - Cat18 & TraffAvDlyRt	-0.0008	0.0002	-0.02	-5.13*
IV - Cat19 & TraffAvSpd	-0.0108	0.0008	-0.08	-13.24*
IV - Cat19 & TraffAvDlyRt	-0.0008	0.0002	-0.02	-5.30*
IV - Cat20 & TraffAvSpd	0.0374	0.0019	0.25	19.67*
IV - Cat20 & TraffAvDlyRt	0.0036	0.0006	0.09	5.82*
IV - Cat21 & TraffAvSpd	0.0405	0.0020	0.27	20.09*
IV - Cat21 & TraffAvDlyRt	0.0039	0.0007	0.10	5.92*
IV - Cat22 & TraffAvSpd	0.0439	0.0019	0.26	23.13*
IV - Cat22 & TraffAvDlyRt	0.0028	0.0003	0.15	8.51*
IV - Cat22 & AccDensCubd	0.0001	0.0000	0.04	5.15*
IV - Cat23 & TraffAvSpd	0.0410	0.0020	0.27	20.12*
IV - Cat23 & TraffAvDlyRt	0.0040	0.0006	0.10	6.25*
IV - Cat24 & TraffAvSpd	-0.0376	0.0009	-0.21	-40.90*
IV - Cat24 & TraffAvDlyRt	-0.0017	0.0002	-0.08	-7.60*
IV - Cat24 & AccDensCubd	-0.0003	0.0001	-0.04	-5.78*
DV - Road Type by Speed Limit (1=40, 0=30)	-0.1292	0.0082	-0.08	-15.68*
DV - Time Period (1=Peak Period, 0=Off-Peak Period)	0.0730	0.0077	0.05	9.47*

- Outcome variable is the natural log of EF from AIRE (gCO_2/VKM).
- n = 3205.
- B and Std. Error of B are quoted to four decimal places because values are approximately two orders of magnitude smaller than in PEMLA v.1 to v.5. Some values are too small to register at four decimal places. In instances where this applies to B, the values are included (and expressed in scientific notation) because they are required for EM application.
- Adj. R^2 = .93.
- For comparison, equivalent MLP neural network analysis resulted in R^2 = .93.
- HC is Heteroscedastic-Consistent.
- Durbin-Watson statistic = 1.90 (i.e. close to 2), which indicates the assumption of independent residuals is tenable.
- Average VIF = 2.06 (i.e. not considerably greater than 1) and all individual predictor variable VIF values < 10, which indicates the MLR assumption of no strong multicollinearity is tenable.
- B, Standard Error of B, Standardized Coefficient β and t-statistic are detailed in notes for Table 6-11.
- * indicates t-statistic is significant (p<0.05).

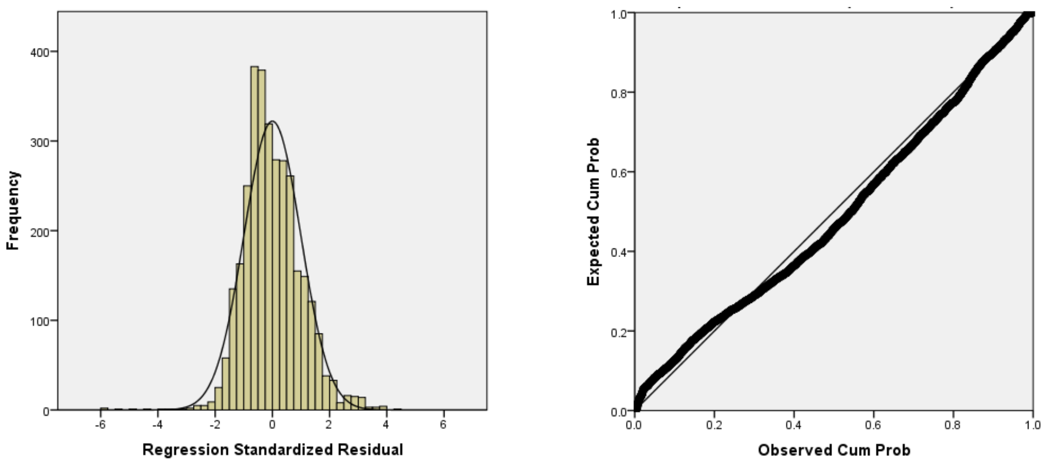

Figure 6-14: Histogram and normal P-P plot of standardised residuals from MLR analysis of PEMLA v.7.

- Positive kurtosis is evident in the plots (refer to notes for Figure 6-2).
- Skewness is evident in the plots (refer to notes for Figure 6-8).

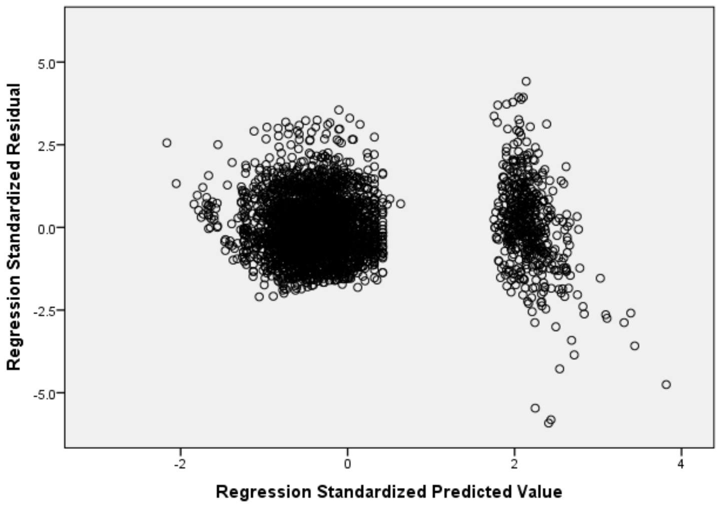

Figure 6-15: Scatter plot of standardised residuals against standardised predicted values from MLR analysis of PEMLA v.7.

- Funnelling-out pattern of the data points is characteristic of heteroscedasticity.

6.5 MODEL COMPARISON AND PARTIAL VALIDATION

Splitting PEMLA into two parts did not provide the solution to the problem of heteroscedasticity of residuals, and also resulted in small Adj. R^2 values (LDV=.59 and HDV=.12, refer to Section 6.4.3.1). Therefore, PEMLA v.4 did not offer any benefits over the other PEMLA versions that included all vehicle categories in a single model, and was not pursued any further. Consequently, model comparison and partial validation of PEMLA v.4 was considered to be redundant and not completed. Results from model comparison and partial validation of the other five versions of PEMLA (v.1 to v.3, v.5 and v.7) by the three different evaluation methods are shown in Table 6-18.

Due to the poor performance of all PEMLA versions when partially validated against EFs from PEMS data (refer to Table 6-18), the linear correlations between PEMLA predicted EFs and PEMS EFs were also examined to determine if there were any underlying relationships between the two sets of EFs. Results are shown in Table 6-19.

Table 6-18: Mean accuracy factors and mean absolute percentage errors from model comparison and partial validation of PEMLA versions.

Evaluation Method	n	MAF (SD)	MAPE (SD)
PEMLA v.1:			
LOO CV	3205	1.04 (0.24)	19% (16%)
TRL/NAEI EM (GPS vehicle average speed)	3205	1.24 (0.29)	30% (23%)
PEMS	53	2.23 (0.52)	123% (52%)
PEMLA v.2:			
LOO CV	3205	1.04 (0.43)	25% (36%)
TRL/NAEI EM (GPS vehicle average speed)	3205	1.24 (0.46)	36% (38%)
PEMS	53	2.24 (0.64)	124% (64%)
PEMLA v.3:			
LOO CV	3205	1.04 (0.28)	21% (19%)
TRL/NAEI EM (GPS vehicle average speed)	3205	1.23 (0.31)	31% (24%)
PEMS	53	2.24 (0.48)	124% (48%)
PEMLA v.5:			
LOO CV	3205	1.04 (0.28)	21% (19%)
TRL/NAEI EM (GPS vehicle average speed)	3205	1.23 (0.32)	31% (24%)
PEMS	53	2.24 (0.48)	124% (48%)
PEMLA v.7:			
LOO CV	3205	1.02 (0.22)	16% (15%)
TRL/NAEI EM (GPS vehicle average speed)	3205	1.21 (0.26)	26% (21%)
PEMS	53	2.21 (0.72)	121% (72%)

- n is sample size.
- MAF is Mean Accuracy Factor.
- MAPE is Mean Absolute Percentage Error.
- SD is Standard Deviation.

Table 6-19: Statistics for linear correlations between EFs predicted by PEMLA versions and EFs from PEMS.

PEMLA Version	Rho
PEMLA v.1	.50*
PEMLA v.2	.23
PEMLA v.3	.48*
PEMLA v.5	.48*
PEMLA v.7	.49*

- n = 53 for each correlation.
- Rho is the non-parametric Spearman's rho linear correlation coefficient.
- * indicates correlation is significant ($p<0.05$).

6.6 ACCURACY COMPARISON

Results of the comparison of the predictive accuracies of the PEMLA versions with the predictive accuracy of the TRL/NAEI Average Speed EM are shown in Table 6-20. As for the model comparison and partial validation results (refer to Section 6.5), accuracy comparison for PEMLA v.4 (LDV and HDV parts) was considered to be redundant and not completed.

Table 6-20: Prediction accuracy of PEMLA versions compared to the TRL/NAEI EM, assuming 'real-world' emissions are represented by EFs from AIRE.

EM Making the Prediction	n	MAF (SD)	MAPE (SD)
PEMLAv.1	3205	1.04 (0.24)	19% (16%)
PEMLAv.2	3205	1.04 (0.42)	25% (34%)
PEMLAv.3	3205	1.04 (0.27)	20% (18%)
PEMLA v.5	3205	1.04 (0.27)	21% (18%)
PEMLA v.7	3205	1.02 (0.21)	16% (14%)
TRL/NAEI EM (ILD traffic average speed)	3204	0.88 (0.24)	22% (16%)

- n is sample size.
- MAF is Mean Accuracy Factor.
- MAPE is Mean Absolute Percentage Error.
- SD is Standard Deviation.
- n = 3204 for the TRL/NAEI EM because, for one case, the ILD traffic average speed was below the minimum speed for use of the TRL emission function (for BDP159 traffic average speed = 4km/h, whereas emission function minimum speed = 6km/h).

6.7 DISCUSSION AND CONCLUSIONS

The main discussion and conclusions of the results presented in this chapter (Chapter 6) are detailed in the subsequent two chapters (Chapter 7 and Chapter 8), particularly in the section concerning the development process for PEMLA (refer to Section 7.2) which discusses the use of the results as the basis for selection of the recommended PEMLA version. However, a summary of the main conclusions drawn from the results is included here.

The main conclusion of the preliminary statistical analysis of the four separate PEMLA vehicle categories (one to represent each of the four driving pattern collection vehicle categories: HDV (except bus), LDV, bus and two-wheel) was that the original five traffic variables (traffic average speed, the square of traffic average speed, traffic density, traffic average delay rate and access density) possessed only moderate performance as predictors of EFs. As a result of this conclusion, it was decided to incorporate vehicle category as an additional predictor variable in the principal statistical analysis.

Three calibration methods for incorporating vehicle category as a predictor variable in the MLR analysis were investigated, which were: using dummy variables (DVs) to encode vehicle category (PEMLA v.1); using the same dummy variables in combination with the forced inclusion of the WebTAG relationship between average speed and EFs (PEMLA v.2); and using interaction variables (IVs) to encode the interaction between vehicle category and the seven traffic variables (i.e. the original five traffic variables plus the square and cube of access density) (PEMLA v.3). When results from PEMLA v.1 to v.3 were compared (refer to Section 7.2.2), it was concluded that the IV method (PEMLA v.3) offered the most potential for further development, and all subsequent PEMLA versions (PEMLA v.4, v.5 and v.7) were therefore based on this method.

Violation of the MLR assumption of homoscedastic residuals (i.e. the assumption that the variance of the residuals is constant across observations) occurred in PEMLA v.1 to v.3. For each of these PEMLA versions, heteroscedasticity was indicated by the characteristic funnelling-out pattern of data points in the scatter plots of standardised residuals against standardised predicted values (Figure 6-3, Figure 6-5 and Figure 6-7) and significant results ($p<0.05$) from the Breusch-Pagan and Koenker statistical tests. Three methods to overcome this problem were considered. The first method involved splitting PEMLA into two parts (PEMLA v.4-LDV and PEMLA v.4-HDV). However, this did not eliminate the problem of heteroscedasticity and also resulted in small Adj. R^2 values (LDV=.59 and HDV=.12). PEMLA v.4 was therefore abandoned. The second method was Weighted Least Squares (WLS) regression, but this approach was rejected because the functional form of heteroscedasticity was unknown, so the appropriate weights could not be applied to each case. The third method, which did not rely on knowledge of the functional form of heteroscedasticity, was Ordinary Least Squares (OLS) regression with a Heteroscedastic-Consistent Standard Error estimator (OLS HCSE). This method produced PEMLA v.5. The scatter plot of standardised residuals against standardised predicted values (Figure 6-13) and significant results ($p<0.05$) from the Breusch-Pagan and Koenker statistical tests indicated heteroscedasticity was still present in PEMLA v.5, but this was no longer a problem because of the estimation method used.

Violation of the MLR assumption of normally distributed residuals occurred to an extent in PEMLA v.1 to v.5, with the main method of diagnosis being visual inspection of histograms and normal P-P plots of standardised residuals for each PEMLA version (Figure 6-2, Figure 6-4, Figure 6-6, Figure 6-8, Figure 6-10 and Figure 6-12). These violations were judged to be acceptable and not severe enough to compromise the MLR analysis (refer to Section 6.4.2.1). Despite this judgement, a method commonly used to correct for non-normally distributed residuals was investigated to establish what benefits might be provided. The method employed was a log transformation of the outcome variable prior to the MLR analysis (which was again conducted using OLS HCSE to overcome any problems of heteroscedasticity). This method produced PEMLA v.7. Inspection of the histogram and normal P-P plot of standardised residuals for PEMLA v.7 (Figure 6-14) indicated compliance with the assumption of normally distributed residuals had been improved compared to PEMLA v.5.

All PEMLA versions (PEMLA v.1 to v.3 and the subsequent v.5 and v.7, with v.4 being abandoned prior to model comparison and partial validation) performed similarly during model comparison and partial validation. There are more detailed discussions in Chapter 7 (refer to Section 7.2.2.2 and Section 7.2.3.4), but the general conclusion was that MAF and MAPE results (refer to Table 6-18) showed good performance in model comparison by LOO CV and in model comparison to TRL/NAEI EM (using GPS vehicle average speed as inputs) (MAFs<1.24 and MAPEs<36%). For reference, in their review of the validation of road traffic EMs, Smit *et al.* (2010) found that mean prediction errors for CO_2 were generally within a factor of 1.3 of the observed values. Potential reasons for the poor performance of all PEMLA versions in partial validation by comparison to bus PEMS EFs (MAFs<2.24 and MAPEs<124%) are discussed in Section 7.2.2.2.

All PEMLA versions also performed similarly during accuracy comparison with TRL/NAEI EM (using ILD traffic average speed as inputs). There are more detailed discussions in Chapter 7 (refer to Section 7.2.2.3 and Section 7.2.3.5), but the general conclusion was that MAF and MAPE results (refer to Table 6-20) showed that PEMLA versions (MAFs<1.04 and MAPEs<25%) all out-performed TRL/NAEI EM (MAF=0.88 and MAPE=22%).

Further development of PEMLA v.3 (IV method) to address the violation of two MLR assumptions (assumptions of homoscedastic and normally distributed residuals) produced PEMLA v.5 and v.7, which both had potential to be the recommended version for use by LGAs. These two versions of PEMLA were therefore compared (refer to Section 7.2.3), which ultimately led to the final main conclusion that PEMLA v.7 be recommended for use by LGAs.

Chapter 7 PEMLA VERSION SELECTION AND APPLICATION

7.1 INTRODUCTION

Discussion of results from the development of PEMLA (refer to Chapter 6) and their wider context has been divided into three main sections. Section 7.2 discusses the results, leading to a chosen version of PEMLA being recommended for use by LGAs. Section 7.3 discusses the wider context of how PEMLA can be applied by LGAs. Finally, Section 7.4 identifies areas for future work.

7.2 PEMLA DEVELOPMENT

7.2.1 Original Five Traffic Variables

The original five traffic variables (traffic average speed, traffic average speed squared, traffic density, traffic average delay rate and access density), possessed only moderate performance as predictors of CO_2 emissions. A likely reason for this is that the traffic variables (except access density) were calculated from data generated by ILDs, which are point detectors[147], and vehicle motion over the length of a trip segment (which determines vehicle emissions) was only partially captured and characterised by the snapshots of vehicle activity provided by these data (although being based on inputs generated by point detectors does confer an important advantage on PEMLA, refer to Section 7.3.1). For example, in the preliminary statistical analysis of the four representative PEMLA vehicle categories, ILD traffic average speeds (time-mean-speeds) had small linear correlations with GPS vehicle average speeds measured over the length of trip segments (Spearman's rhos of: category 01=.23*, category 20=.04, category 22=.19* and category 24=.57* (*significant correlation at $p<0.05$) from the All Cases rows in Table 6-7), which is likely to be an important factor in the moderate performance of ILD traffic average speed as a predictor of emissions. Evidence for this was provided by comparison of the preliminary MLR analysis based on the original five traffic variables as predictor variables (Table 6-6) with the MLR analysis based on GPS vehicle average speed as the predictor variable (Table 6-8), where use of GPS speed produced considerable increases in Adj. R^2 values.

[147] Point detector is used to describe detectors that provide a snap-shot of vehicle activity data at a point location in a road network (e.g. ILD or SDR). This is in contrast to detectors that provide vehicle activity data over longer distances (e.g. GPS).

However, an important issue with the use of GPS vehicle average speed data for predicting emissions is that obtaining such data for every vehicle (or even a representative sample of vehicles), along each link in a road network, is a difficult and resource-intensive task, which is likely to make this option impractical for LGAs. In contrast, the comparative ease and affordability with which ILD data are available (as by-products of UTC systems) makes an EM that uses ILD-based inputs an appealing option for LGAs, and therefore worthy of development.

Another possible reason for the moderate performance of the original five traffic variables as predictors of CO_2 emissions was the relatively small ranges of values measured. In other words, the ranges may not have been wide enough to capture any relationships, and resulted in the situation exemplified in Figure 7-1 where the full, theoretical relationship between traffic average speed and EF (i.e. established in previous research studies and shown by the solid line) is not captured by the limited range of observations (measured in this project and shown by the grey circles). On a related point, as well as providing a strong relationship between average speed and EFs to compensate for the moderate performance of the original five traffic variables (refer to Section 6.4.2.2), a further reason behind the forced inclusion of the WebTAG average speed formulae for EFs in the method used to calibrate PEMLA v.2 was extension of PEMLA's limited range of validity for traffic average speed.

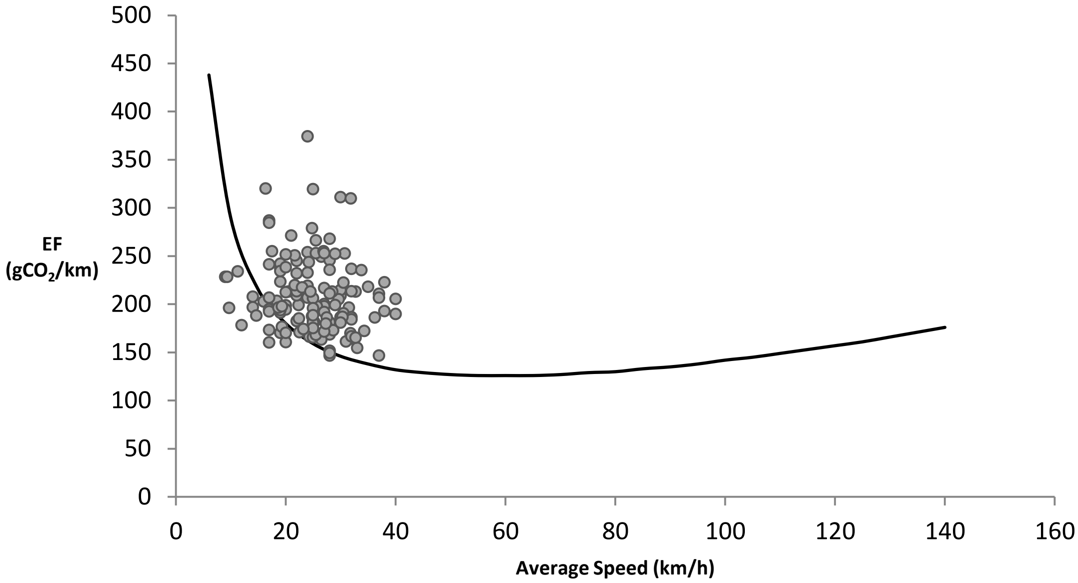

Figure 7-1: Observed and theoretical plot of traffic average speed against EF for petrol cars.

- Each data point (grey circle) represents the ILD traffic average speed and EF observations for PEMLA vehicle category 01 'Car, Petrol, <1400cc, Pre-Euro 5'.
- The black line represents the TRL EFs 2009 average speed emission function (i.e. theoretical relationship established in previous research studies) for the NAEI category 'Car, Petrol, <1400cc, Euro 4'.

7.2.2 Comparison of the Three Calibration Methods (PEMLA v.1 to v.3)

During the principal statistical analysis, individual PEMLA vehicle categories were combined into a single dataset, and three different calibration methods were used to incorporate vehicle category as a predictor variable into the MLR analysis, which led to development of three different versions of PEMLA (v.1 to v.3). To evaluate the strengths and weaknesses of each method, the results from PEMLA v.1 to v.3 (Table 6-11 to Table 6-13, respectively) have been compared.

7.2.2.1 Comparison of R^2 values for PEMLA v.1 to v.3

The Adj. R^2 values for PEMLA v.1, v.2 and v.3 were .89, .47 and .88, respectively (Table 6-11, Table 6-12 and Table 6-13). However, these values could not be compared to assess which model explained the greatest proportion of variation in the outcome variable. The Adj. R^2 values were not comparable because the outcome variable was different for PEMLA v.2 (i.e. EF from AIRE for PEMLA v.1 and v.3, and EF from AIRE minus EF from WebTAG for PEMLA v.2).

As an alternative, the Adj. R^2 values for PEMLA v.1 (.89) and v.3 (.88) were compared to the R^2 for PEMLA v.2 after conversion to its final form (.86 calculated by squaring the Pearson correlation coefficient (r) from the linear correlation between observed and predicted values for EF from AIRE, refer to Section 6.4.2.2). This comparison indicated all three calibration methods had a similar ability to explain variation in the outcome variable (EF from AIRE). However, this assessment was not an ideal like-for-like comparison, and only served as an approximate guide.

Also evident from this approximate comparison of R^2 values for the three methods was that the majority of predictive power in any MLR analysis was due to vehicle category inputs, with the inclusion of the seven traffic variables (original five traffic variables, plus the later addition of the square and cube of access density) having only a small impact on R^2 values: PEMLA v.1 (only vehicle category, road type and time of day as predictor variables) achieved an Adj. R^2=.89; whereas PEMLA v.2 and PEMLA v.3 (which both also included the influence of traffic variables in the predictor variables) achieved R^2=.86 and Adj. R^2=.88, respectively.

Despite this, LGAs are likely to prefer an EM that includes traffic variables in addition to vehicle category variables. Without the addition of traffic variables as inputs an EM can only be used to assess transport interventions that alter the mix of vehicle categories. This means PEMLA v.2 and v.3 are likely to be more favourable than PEMLA v.1, even though PEMLA v.1 is simpler to use and achieves a (slightly) greater Adj. R^2 value.

7.2.2.2 Model comparison and partial validation of PEMLA v.1 to v.3

During model comparison and partial validation, all three PEMLA versions performed similarly. Model comparison by LOO CV produced good agreement (MAFs<1.04 and MAPEs<25% in Table 6-18). For reference, in their review and meta-analysis of the validation of road traffic EMs, Smit *et al.* (2010) found that mean prediction errors for CO_2 were generally within a factor of 1.3 of the observed values. Again with reference to Smit *et al.* (2010), model comparison to the TRL/NAEI EM (using GPS vehicle average speeds as inputs) produced reasonable agreement (MAFs<1.24 and MAPEs<36% in Table 6-18). These MAFs showed that, on average, all PEMLA versions predicted higher EFs than the TRL/NAEI EM. This was expected because, even though GPS vehicle average speeds were used as inputs (which, as identified by Smit *et al.* (2008b), is more accurate than using traffic average speeds), this still falls short of fully accounting for increased emissions resulting from the impact of congestion on driving pattern dynamics, which is not well accounted for in Average Speed EMs (such as the TRL/NAEI EM). In contrast, PEMLA was purposefully designed to better account for this impact.

All three PEMLA versions performed poorly in partial validation against PEMS EFs (MAFs<2.24 and MAPEs<124% in Table 6-18). Three potential reasons for this were: (1) the sample size for PEMS validation was small (53 cases compared to 3205 cases for the model comparison methods) and drawn from only one PEMLA vehicle category (category 22 'Bus, All'); (2) comparison of the EFs used to calibrate PEMLA (i.e. EFs from AIRE) with PEMS EFs demonstrated a similar over-estimation by a factor of approximately two (MAF=2.08 and MAPE=108%); and (3) PEMLA category 22 is for a fleet-average bus, i.e. the category describes an average for buses of all masses and all Euro Standards (although a single AIRE category of 'Bus, Single Deck, Euro V' was used to represent category 22 in accurate EF calculations), whereas the PEMS data were collected from one bus at the light-weight end of the scale (revenue weight 13,139 kg) and compliant with a modern Euro Standard (Euro V) (refer to Table 5-7).

The TRL/NAEI EM was used to further examine reason (3) through calculating the likely maximum size of over-estimation of EFs due to using a fleet-average bus category rather than the lightest-weight, most modern Euro Standard (Euro VI) category (AIRE does not include Euro VI HDVs, so this analysis was not possible using AIRE). For those bus cases where PEMS data were collected, an EF was calculated using the TRL/NAEI EM (using GPS vehicle average speed as input) for the NAEI category 'Bus, Midi, <15 tonnes, Euro VI' (i.e. the lightest-weight, most modern Euro Standard category available), which was then compared to the EF (also calculated using the TRL/NAEI EM and GPS vehicle average speed) for the PEMLA category 'Bus, All' (i.e. a fleet-average category) using Equation 24 and Equation 25. Results showed that PEMLA's over-estimation compared to PEMS EFs (MAFs<2.24 and MAPEs<124% in Table 6-18) was greater than might be expected according to the TRL/NAEI EM analysis (MAF=1.23 and MAPE=23% in Table 7-1). A possible reason for this is that the forecast reduction in emissions achieved by Euro VI buses estimated when the TRL/NAEI EM was released in 2009 was an under-estimation of those actually achieved; although this reason does not seem likely to be sufficient to explain the total difference.

Equation 24

$$AF = \frac{\text{EF from TRL/NAEI (Bus, All)}}{\text{EF from TRL/NAEI (Bus, Midi, <15t, Euro VI)}}$$

Equation 25

$$APE = \frac{|\text{EF from TRL/NAEI (Bus, All)} - \text{EF from TRL/NAEI (Bus, Midi, <15t, Euro VI)}|}{\text{EF from TRL/NAEI (Bus, Midi, <15t, Euro VI)}} \times 100\%$$

Table 7-1: Statistics from comparison of EFs for 'Bus, All' with EFs for 'Bus, Midi, <15tonnes, Euro VI', both calculated with the TRL/NAEI EM using GPS vehicle average speed as inputs.

MAF (SD)	MAPE (SD)
1.23 (0.00)	23% (0%)

- n = 53.
- MAF is Mean Accuracy Factor.
- MAPE is Mean Absolute Percentage Error.
- Standard deviation (SD) is zero for MAF and MAPE because the ratio of EF for 'Bus, All' to EF for 'Bus, Midi, <15tonnes, Euro VI' remains constant with varying speed inputs to TRL/NAEI EM.

Due to the poor performance of all three PEMLA versions when partially validated against PEMS EFs, the linear correlations between PEMLA predicted EFs and PEMS EFs were also examined to determine if there were any underlying relationships between the two sets of EFs, i.e. to assess the extent to which the over-predictions by the PEMLA versions were consistent across all cases. Table 6-19 shows the analysis resulted in Spearman's rhos of: PEMLA v.1=.50*; PEMLA v.2=.23; and PEMLA v.3=.48* (*significant correlation at $p<0.05$). For comparison, a similar analysis of the linear correlation between EFs from AIRE and PEMS EFs resulted in a Spearman's rho=.83*. These results suggest that AIRE and PEMS are more consistent (albeit with AIRE over-estimating by a factor of approximately two compared to PEMS), and it is PEMLA that is less consistent; although it is to be expected that an IEM (AIRE) is more likely to be consistent with the real world (PEMS) than a Traffic Variable EM (PEMLA).

A final possible reason for the poor performance of all three PEMLA versions when partially validated against PEMS EFs was that the PEMS data themselves were erroneous. This possibility is discussed in Section 7.2.5.2.

7.2.2.3 Accuracy comparison of PEMLA v.1 to v.3

Comparing prediction accuracies with the next-best alternative EM available to LGAs (i.e. TRL/NAEI EM), when using the same source for inputs (ILD data) all three PEMLA versions have MAFs that outperform the MAF from the TRL/NAEI EM. MAF values in Table 6-20 suggest that on average (i.e. when applied to a whole network or substantially large parts of a network) the three PEMLA versions all over-estimate emissions by 4% (MAF=1.04), whereas the TRL/NAEI EM under-estimates emissions by 12% (MAF=0.88). These results were expected because PEMLA was designed to better capture the impact of congestion, which acts to increase emissions. Hence, PEMLA predictions are both greater than TRL/NAEI EM predictions and closer to the 'real-world' emissions. On a case-by-case basis, MAPE values in Table 6-20 suggest that on average the three PEMLA versions and the TRL/NAEI EM will all be in error by approximately 20% of the true value for emissions, with PEMLA v.1 and v.3 (19% and 20%, respectively) slightly out-performing the TRL/NAEI EM (22%), and PEMLA v.2 (25%) performing slightly worse.

7.2.2.4 Comparative advantages and disadvantages of PEMLA v.1 to v.3

All three PEMLA versions performed similarly in model comparison and partial validation, and showed similar potential to outperform the TRL/NAEI EM in accuracy comparisons (i.e. MAFs closer to unity than those achieved by the TRL/NAEI EM). Therefore, to distinguish the method with the greatest merit, the advantages and disadvantages associated with each approach were considered. PEMLA v.1 is the simplest to use, with only vehicle category, road type (30mph or 40mph speed limit), and time of day (peak or off-peak period) required as inputs. There is no requirement for LGAs to collect ILD data from which to calculate traffic variable values. However, model utility is limited by this lack of traffic variable inputs, which means PEMLA v.1 cannot (for a given road type and time period) be used to assess interventions that do not alter the fleet mix of vehicle categories. Another disadvantage is that MLR analysis to calibrate PEMLA v.1 resulted in further aggregation and loss of detail from the 24 PEMLA vehicle categories (i.e. analysis led to an aggregate category for smaller cars of 'Car, Petrol or

Diesel, <2000cc, All Euro'), which had already been aggregated from the more detailed NAEI vehicle categories.

PEMLA v.2 included traffic variables as predictor variables, and can therefore be used to assess interventions that do not alter the fleet mix of vehicle categories. The forced inclusion of the known relationship between average speed and EFs as described by the WebTAG average speed formulae (which are based on the TRL EFs 2009 average speed emission functions that have speed ranges of at least 6 to 75 km/h depending on vehicle category[148]) means PEMLA v.2 can be extended over a greater range of traffic average speeds than those collected during the study (4 to 41 km/h shown in Table 6-10); although this extension would need to be verified by comparison of PEMLA v.2 predicted EFs with observed EFs from trip segments with a greater range of traffic average speeds. However, the relationship that has been forced into PEMLA v.2 was (it could be argued) an artificial relationship not actually present in the data collected during the study. Also, similar to PEMLA v.1, MLR analysis to calibrate PEMLA v.2 resulted in further aggregation of vehicle categories (i.e. resulted in the same aggregate category of 'Car, Petrol or Diesel, <2000cc, All Euro').

In contrast to both other versions, PEMLA v.3 retained all 24 PEMLA vehicle categories. Also, through the use of IVs, PEMLA v.3 incorporated traffic variables into the predictor variables, and can therefore be used to assess interventions that do not alter the fleet mix of vehicle categories. From the perspective of MAPE results from accuracy comparison (refer to Section 7.2.2.3), PEMLA v.3 was one of the two PEMLA versions (PEMLA v.1 being the other) that slightly out-performed the TRL/NAEI EM. Weighing the advantages and disadvantages associated with each of the three PEMLA versions, PEMLA v.3 was judged to represent the calibration method with the most merit, and was therefore selected as having the most potential for further development into an EM suitable for use by LGAs.

7.2.3 Development of the IV (PEMLA v.3) Calibration Method

Three versions of PEMLA (PEMLA v.4, v.5 and v.7) were subsequently developed based on the PEMLA v.3 calibration method (i.e. using IVs). PEMLA v.4 involved splitting PEMLA into two parts (LDV and HDV), but did not provide the solution to the problem of heteroscedasticity and did not offer any benefits over other PEMLA versions that included all vehicle categories in a

[148] The moped vehicle category (i.e. two-wheel with <50cc engine capacity) was the only exception to this, having a speed range of 5 to 50 km/h.

single model. PEMLA v.4 was therefore discounted as an option prior to model comparison and partial validation (refer to Section 6.4.3.1). Hence, two versions of PEMLA remained for consideration: PEMLA v.5 which involved a straightforward re-estimation of PEMLA v.3 using OLS HCSE in the MLR analysis to overcome the problem of heteroscedasticity of residuals (results in Table 6-16); and PEMLA v.7 which involved a log transformation of the outcome variable prior to the MLR analysis (also conducted using OLS HCSE) to establish the benefits offered by this commonly used method to correct for non-normally distributed residuals (results in Table 6-17). PEMLA v.5 and v.7 were compared to allow a final version of PEMLA to be recommended as most suitable for use by LGAs.

7.2.3.1 PEMLA v.5 predictor variable coefficients

Table 6-16 shows the Time Period DV predictor variable coefficient was positive in PEMLA v.5, predicting an increase in emissions during peak periods, which was expected because increased congestion associated with peak periods increases stop-start events for vehicles and therefore increases emissions. The Road Type DV predictor variable coefficient was negative, predicting a decrease in emissions on roads with a 40mph speed limit. In UK urban areas, 40mph limits tend to apply to arterial roads, whereas 30mph limits tend to apply to collector and local roads. Arterial roads tend to have greater segregation from potential hazards, i.e. pedestrians, other road users (e.g. lane width, central reservation markings/barrier), access to residential and commercial premises, and priority for green traffic signals. This segregation is designed to give smoother traffic flow (i.e. decreases stop-start events), and therefore decreases emissions. Conversely, it could be argued that arterial routes carry greater traffic loads and are therefore more prone to congestion which acts to increase emissions; although this is not the finding in results for PEMLA v.5 (or any other PEMLA version).

Some of the IV predictor variable coefficients shown in Table 6-16 have signs (+ or -) that were (superficially) unexpected. For example, coefficients associated with traffic average speed were expected to be negative because higher traffic average speed is indicative of lower congestion; and also, over the range of speeds measured in the project (traffic average speeds of 4 to 41 km/h and vehicle average speeds of 5 to 57 km/h in Table 6-10), higher speeds tend to move vehicles closer to their optimal fuel efficiency speeds (Ramos *et al.* 2011). However, for HDV categories (categories 20, 21, 22 and 23) traffic average speed was associated with positive coefficients. Similarly, coefficients associated with traffic average delay rate were expected to be positive because higher traffic average delay rate is indicative of higher congestion. However, for LDV and two-wheel categories (categories 01 to 19 and 24) traffic average delay rate was associated with negative coefficients. Coefficients associated with access density cubed were expected to be positive because higher access density is likely to lead to higher congestion due to the increased interaction of vehicles at intersections. However, for the two-wheel category (category 24) the coefficient was negative.

The reason for these 'unexpected' signs was because the predictor variables were IVs and represented the effect on emissions of the interaction between vehicle category and the traffic variables, rather than the effect of the traffic variables alone. The effect of vehicle category far outweighed the effect of the traffic variables, and when in combination it was vehicle category that dominated and determined the sign of the coefficient. In relation to the constant in PEMLA v.5 (558 gCO_2/VKM in Table 6-16), the effect of a LDV or two-wheel vehicle category was always downwards (i.e. all IV predictor variables had a negative coefficient regardless of the associated traffic variable). This was expected because EFs from these vehicle categories were always less than the value of the constant. In contrast, the effect of an HDV vehicle category was always upwards (i.e. all IV predictor variables had a positive coefficient regardless of the associated traffic variable). Again, this was expected because EFs from these categories were always greater than the value of the constant.

The relationship between the relevant traffic variables (traffic average speed, traffic average delay rate and access density) and emissions can be seen in isolation (i.e. without the interaction of vehicle category) in Table 6-5, which shows statistics for bivariate linear correlations between the original five traffic variables and EF from AIRE for the individual, representative vehicle categories (category 01 for LDV, category 20 for HDV (except bus), category 22 for bus and category 24 for two-wheel vehicle). The All Cases row for each category in Table 6-5 shows that the correlations were as expected for categories 01, 22 and 24 (i.e. traffic average speed had a negative correlation, traffic average delay rate had a positive correlation and access density had a positive correlation). HDV (except bus) (category 20 in Table 6-5) was the exception, where each correlation had the opposite sign to that expected. A possible explanation is that traffic characteristics are set by LDVs (the large majority of vehicles in the traffic, constituting 95% of VKMs in urban areas in England outside London in 2016 in the NAEI national fleet model, refer to Table 5-1), and are not a good representation of HDV dynamics which may not follow the trend of the traffic due to lower power-to-mass ratios. For example, in this project, Spearman's rho for a bivariate linear correlation between ILD traffic average speed and GPS vehicle average speed was greater for

LDVs than HDVs[149] (LDV=.23* and HDV (except bus)=.04 (*significant correlation at $p<0.05$) from the All Cases rows in Table 6-7).

7.2.3.2 PEMLA v.7 predictor variable coefficients

In general, Table 6-17 shows that the signs (+ or -) of predictor variable coefficients in PEMLA v.7 followed a similar pattern to those in PEMLA v.5. As discussed for PEMLA v.5 (refer to Section 7.2.3.1), the reason for any 'unexpected' signs for the IV predictor variable coefficients was that the effect of vehicle category outweighed the effect of the traffic variables, and when in combination it was vehicle category that dominated and determined the sign of the coefficient. In relation to the EF represented by the constant in PEMLA v.7 ($e^{5.9485}$ = 383 gCO_2/VKM from Table 6-17 and Equation 23), the effect of a LDV or two-wheel vehicle category was always downwards (i.e. all IV predictor variables had a negative coefficient regardless of the associated traffic variable; although there were three exceptions to this, which are discussed in the next paragraph), and the effect of an HDV vehicle category was always upwards (i.e. all IV predictor variables had a positive coefficient regardless of the associated traffic variable).

The three IV predictor variable coefficients that were exceptions were: IV – Cat07 & AccDensCubd; IV – Cat08 & AccDensCubd; and IV – Cat09 & AccDensCubd. These IV predictor variables all had positive coefficients despite being LDV vehicle categories. A potential reason for this was that EFs for these vehicle categories (i.e. categories 07, 08 and 09) were typically in close proximity to the EF that corresponds to the constant in PEMLA v.7 (383 gCO_2/VKM, which is lower than the equivalent constant value in PEMLA v.5 of 558 gCO_2/VKM). Therefore, in relation to the constant, the effect of vehicle category was less dominant, which allowed the effect of the traffic variable (access density positively correlated with EF from AIRE for LDVs (rho=.26* significant at $p<0.05$) from the category 01 All Cases row in Table 6-5) to manifest.

A further difference from PEMLA v.5 was that PEMLA v.7 did not have any statistically significant IV predictor variables for category 16 (i.e. LGV Petrol All, which constitutes 0.3% of VKMs in urban areas in England outside London in 2016 in the NAEI national fleet model, refer

[149] Buses, however, which were distinguished as a separate category from other HDVs for the purposes of recording their dynamics due to the multi-stop nature of their operation (refer to Section 5.3.3), appear to be better aligned with traffic characteristics as set by LDVs, having correlations as expected in Table 6-5 and a similar sized Spearman's rho to LDVs in Table 6-7 (bus=.19* in the All Cases row).

to Table 5-1). Consequently, EFs for category 16 only vary by road type (30 or 40mph speed limit) and time of day (peak or off-peak period), and are unaffected by traffic variable values.

7.2.3.3 Comparison of R^2 values for PEMLA v.5 and v.7

The Adj. R^2 values for PEMLA v.5 and v.7 were .88 and .93, respectively (Table 6-16 and Table 6-17). However, as was the case for comparison of R^2 values for PEMLA v.1 to v.3 (refer to Section 7.2.2.1), these values could not be compared to assess which model explained the greatest proportion of variation in the outcome variable. The Adj. R^2 values were not comparable because the outcome variable was different in each case (i.e. EF from AIRE for PEMLA v.5 and ln(EF from AIRE) for PEMLA v.7).

As an alternative, the Adj. R^2 for PEMLA v.5 (.88) was compared to the R^2 for PEMLA v.7 after conversion to its final form (.85 calculated by squaring the Pearson correlation coefficient (r) from the linear correlation between observed and predicted values for EF from AIRE, refer to Section 6.4.3.3). This comparison indicated both versions of PEMLA had a similar ability to explain variation in the outcome variable (EF from AIRE). However, this assessment was not an ideal like-for-like comparison, and only served as an approximate guide.

A further method to overcome the incomparability of Adj. R^2 values was a comparison based on the linear (PEMLA v.5) and log-linear (PEMLA v.7) functional forms being special cases of the Box-Cox test[150], a process detailed in Maddala (1992). The process involved first creating a new outcome variable by dividing each value of the outcome variable (EF from AIRE) by the geometric mean of the outcome variable values (303 gCO_2/VKM). Then the MLR analyses for PEMLA v.5 and v.7 were re-estimated using the new outcome variable, i.e. PEMLA v.5 in the linear form used values of the new outcome variable, and PEMLA v.7 in the log-linear form used values of ln(new outcome variable). Comparison of the sum of squared residuals (SS_R) from each MLR analysis allowed a choice to be made between the linear or log-linear functional forms, with a smaller value indicating a better model. Results showed PEMLA v.7 (SS_R = 135) outperformed PEMLA v.5 (SS_R = 1077).

[150] The Box-Cox test is a widely used method for selecting an appropriate functional form for a given model (Washington *et al.* 2003). The Box-Cox transformation is of the form $y^*(\lambda) = (y^\lambda - 1)/\lambda$ for $\lambda \neq 0$ and log(y) for $\lambda=0$, where $y^*(\lambda)$ is the transformed outcome variable. The general form of the Box-Cox test evaluates the optimal value for the transformation parameter (λ) that minimises the sum of squared residuals in MLR analysis (Maddala 1992).

7.2.3.4 Model comparison and partial validation of PEMLA v.5 and v.7

Table 6-18 shows model comparison and partial validation of PEMLA v.5 produced very similar results to model comparison and partial validation of PEMLA v.1 to v.3: model comparison by LOO CV produced MAF=1.04 and MAPE=21%; model comparison to TRL/NAEI EM produced MAF=1.23 and MAPE=31%; and partial validation against PEMS EFs (for 53 'Bus, All' cases) produced MAF=2.24 and MAPE=124%. Table 6-18 also shows model comparison and partial validation of PEMLA v.7 produced similar (slightly better) results: model comparison by LOO CV produced MAF=1.02 and MAPE=16%; model comparison to TRL/NAEI EM produced MAF=1.21 and MAPE=26%; and partial validation against PEMS EFs produced MAF=2.21 and MAPE=121%.

7.2.3.5 Accuracy comparison of PEMLA v.5 and v.7

Comparing prediction accuracy with the next-best alternative EM available to LGAs (i.e. TRL/NAEI EM), PEMLA v.5 produced very similar results to PEMLA v.1 to v.3. MAF values in Table 6-20 show that on average PEMLA v.5 over-estimated emissions by 4% (MAF=1.04), whereas TRL/NAEI EM under-estimated by 12% (MAF=0.88). On a case-by-case basis, MAPE values in Table 6-20 show that on average both EMs will be in error by approximately 20% of the true value for emissions, with PEMLA v.5 (21%) slightly out-performing TRL/NAEI EM (22%).

Results for PEMLA v.7 indicated a better performance than both PEMLA v.5 and TRL/NAEI EM. MAF values in Table 6-20 show that on average PEMLA v.7 over-estimated emissions by 2% (MAF=1.02), which is less than the over-estimation by PEMLA v.5 (4%) and the under-estimation by TRL/NAEI EM (12%). On a case-by-case basis MAPE values in Table 6-20 show that on average PEMLA v.7 will be in error by 16%, which is less than PEMLA v.5 (21%) and TRL/NAEI EM (22%).

An additional important point for consideration in accuracy comparisons is the scaling factors suggested for use with TRL/NAEI EM. A 15% uplift factor to NEDC-based TRL EFs 2009 average speed emission functions (i.e. LDV categories in TRL/NAEI EM) was agreed between DfT and DEFRA to account for real-world effects such as use of auxiliaries and level of maintenance (refer to Section 2.5.5.1). Also, scaling factors are used in the DfT Basic Local Authority Carbon Tool to normalise the HGV TRL emission functions to agree with real-world statistics from haulage firms (rigid HGVs=1.351 and articulated HGVs=1.023) (refer to Section 2.5.5.2). AIRE was developed based on PHEM, which has the facility to alter vehicle-specific characteristics and can therefore better represent these real-world effects. However, the PHEM runs used in AIRE's development did not include the use of auxiliaries or the effects of vehicle maintenance levels (refer to Section 2.5.9.4). Consequently, the TRL/NAEI EM scaling factors were excluded during the statistical analysis to ensure like-for-like comparisons.

Post-analysis application of the scaling factors to EFs predicted by TRL/NAEI EM used in accuracy comparison (i.e. TRL/NAEI EM results in Table 6-20) resulted in MAF=1.00 (SD=0.27) and MAPE=21% (SD=17%). Hence, the performance of TRL/NAEI EM was improved to the point where prediction accuracy (in the case of MAFs) exceeded that of both PEMLA v.5 and v.7. However, because AIRE excludes the real-world effects addressed by the TRL/NAEI EM scaling factors, it could be argued that EFs predicted by AIRE (i.e. the outcome variable used for PEMLA calibration) should have similar scaling factors applied, which would then restore the difference in performance between PEMLA and TRL/NAEI EM seen in the original accuracy comparison analysis. It is therefore recommended that these scaling factors for real-world effects (LDVs=1.15, rigid HGVs=1.351 and articulated HGVs=1.023) also be applied to EFs predicted by PEMLA (and this recommendation was put into practice in the case study application of PEMLA detailed in Section 7.3.7).

7.2.3.6 Comparative advantages and disadvantages of PEMLA v.5 and v.7

In comparison to PEMLA v.5, the log transformation of the outcome variable prior to the MLR analysis in PEMLA v.7 has improved compliance with the MLR assumption of normally distributed residuals. Kolmogorov-Smirnov tests were applied to the standardised residuals for both PEMLA v.5 and v.7 to statistically test for normality, with results indicating the assumption had been violated in both versions of PEMLA (although the tests had to be treated with caution because with large sample sizes even small deviations from normality can produce significant results, refer to Section 5.5.3.3). Despite these results, visual inspection of the histogram and normal P-P plot of the standardised residuals for PEMLA v.7 (Figure 6-14), when compared to the same charts for PEMLA v.5 (Figure 6-12), showed that the extent of the violation of the normality assumption was less severe for PEMLA v.7 (i.e. for PEMLA v.7 the histogram was closer in shape to the normal distribution and the normal P-P plot was closer to the ideal straight line that represents a normal distribution).

Improving compliance with the normality assumption brings with it a disadvantage in terms of potential error magnification of PEMLA v.7 predictions (refer to Section 6.4.3.3). PEMLA v.7 is a good fit to the data used in calibration (Adj. R^2=.93 in the notes for Table 6-17), and to the data used in model comparison (LOO CV MAF=1.02 and MAPE=16% in Table 6-18). However, when generalised to make predictions from unseen data, residuals (i.e. model error) that would be acceptable in a model that predicted values for the natural log of EFs have the potential to be magnified to unacceptable proportions when converted back to EFs due to the exponential nature of the conversion to the final form of PEMLA v.7 (refer to Equation 23). Not using the log transformation method (i.e. as in calibration of PEMLA v.5) avoids this problem.

7.2.4 Recommended PEMLA version

The advantages associated with PEMLA v.7 of better performance in comparison of R^2 values (refer to Section 7.2.3.3), better performance in model comparison and partial validation (refer to Section 7.2.3.4), better performance in accuracy comparison (refer to Section 7.2.3.5) and better compliance with the MLR assumption of normally distributed residuals (refer to Section 7.2.3.6) were assessed as outweighing the disadvantage of potential error magnification (refer to Section 7.2.3.6). PEMLA v.7 was therefore selected over PEMLA v.5 as the recommended version for use by LGAs.

7.2.4.1 Detailed investigation of the performance of PEMLA v.7

Having been selected as the recommended version, the performance of PEMLA v.7 in comparison to that of TRL/NAEI EM was investigated in greater detail. The composite EF_T for the traffic (calculated as the sum of EFs for individual vehicle categories weighted by the NAEI national fleet model predictions for each category's fraction of total national VKMs on urban roads in England outside London in 2016) predicted by each EM was plotted against traffic average speed (the only variable input to TRL/NAEI EM), with the expectation that PEMLA v.7 predictions would follow a pattern similar to those of TRL/NAEI EM (as a widely accepted EM). Traffic average speed inputs to PEMLA v.7 also affected traffic average delay rate inputs (calculated as the difference between travel times at the traffic average speed and at the speed limit, normalized for distance, refer to Section 5.4.3). Access density inputs to PEMLA v.7 were held constant at the mean value of 8.43 intersections/km (Table 6-10). Four curves were generated for PEMLA v.7 representing the combination of values the Road Type and Time Period inputs could take: 30mph speed limit and peak period; 30mph speed limit and off-peak period; 40mph speed limit and peak period; and 40mph speed limit and off-peak period. Results are shown in Figure 7-2.

In general, a potential reason for the differences between the TRL/NAEI EM curve and the PEMLA v.7 curves shown in Figure 7-2 is that the TRL EFs 2009 average speed emission functions (the basis of the TRL/NAEI EM) were derived predominantly from laboratory emissions tests (refer to Section 2.5.5.1), whereas the PEMLA curves are derived from real-world data (GPS driving patterns and ILD data used to develop PEMLA). However, the slight 'humps' between approximately 8 to 28 km/h evident in the PEMLA v.7 curves were in contrast to the general u-shaped pattern of the TRL/NAEI EM curve. PEMLA v.7 predictions were therefore examined more closely by disaggregating the predicted EF_T curve for the 30mph speed limit and peak period situation (the situation producing the greatest predicted EF_T) to produce predicted EF curves for each individual vehicle category. Results are shown in Figure 7-3 to Figure 7-6.

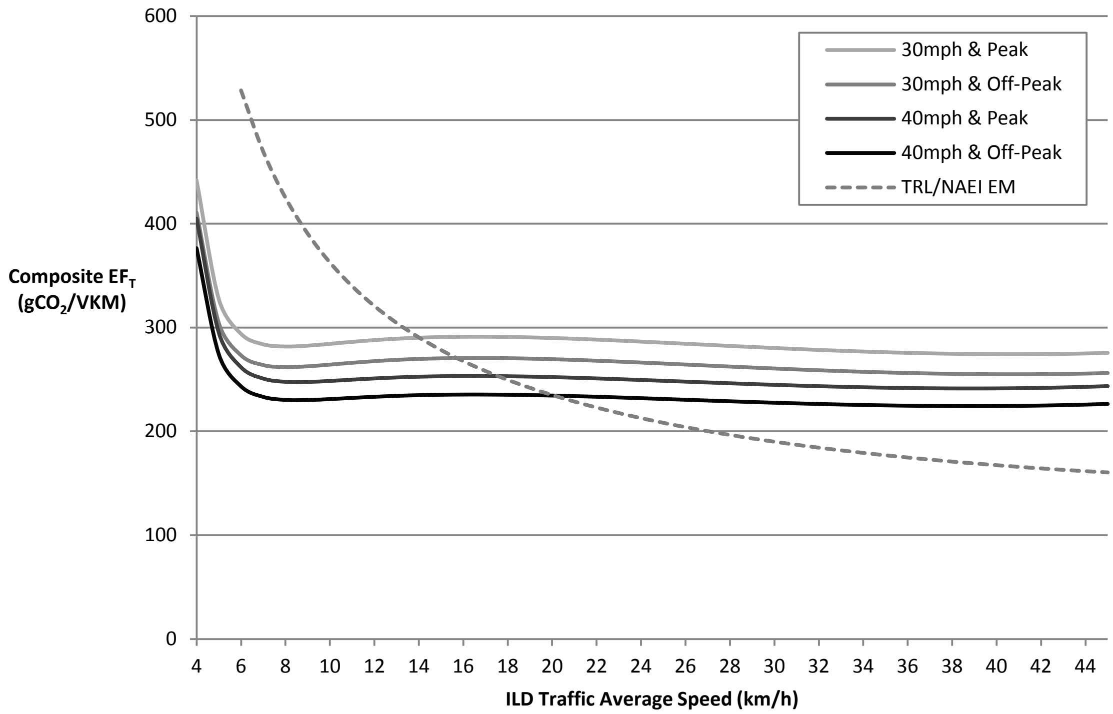

Figure 7-2: Composite EF_T predictions from PEMLA v.7 and TRL/NAEI EM plotted against traffic average speed.

- PEMLA v.7 predictions are shown by four curves representing the different combination of values the Road Type and Time Period predictor variables could take: 30mph speed limit and peak period; 30mph speed limit and off-peak period; 40mph speed limit and peak period; and 40mph speed limit and off-peak period.
- Access density was held constant for PEMLA v.7 predictions at the mean value of 8.43 intersections/km.
- The range of measured ILD traffic average speeds was 4 to 41 km/h.
- The minimum valid speed for TRL/NAEI EM predictions was 6 km/h.

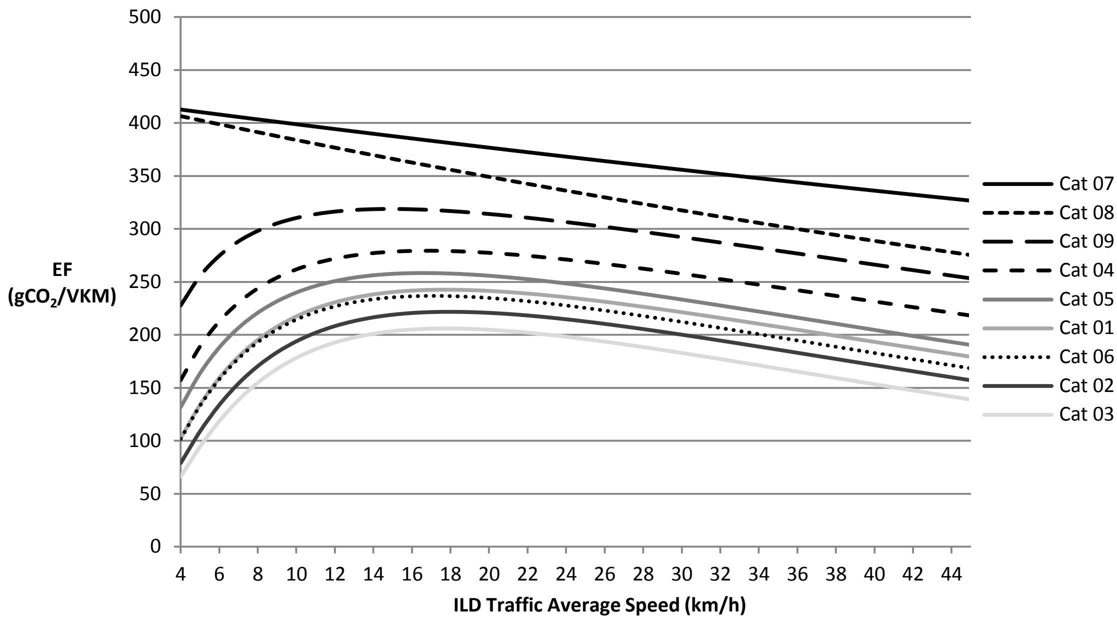

Figure 7-3: PEMLA v.7 predicted EFs for categories 01 to 09 (petrol cars) plotted against traffic average speed.

- Predictions are for access density = 8.43 intersections/km (mean value), 30mph speed limit and peak period.
- The range of measured ILD traffic average speeds was 4 to 41 km/h.

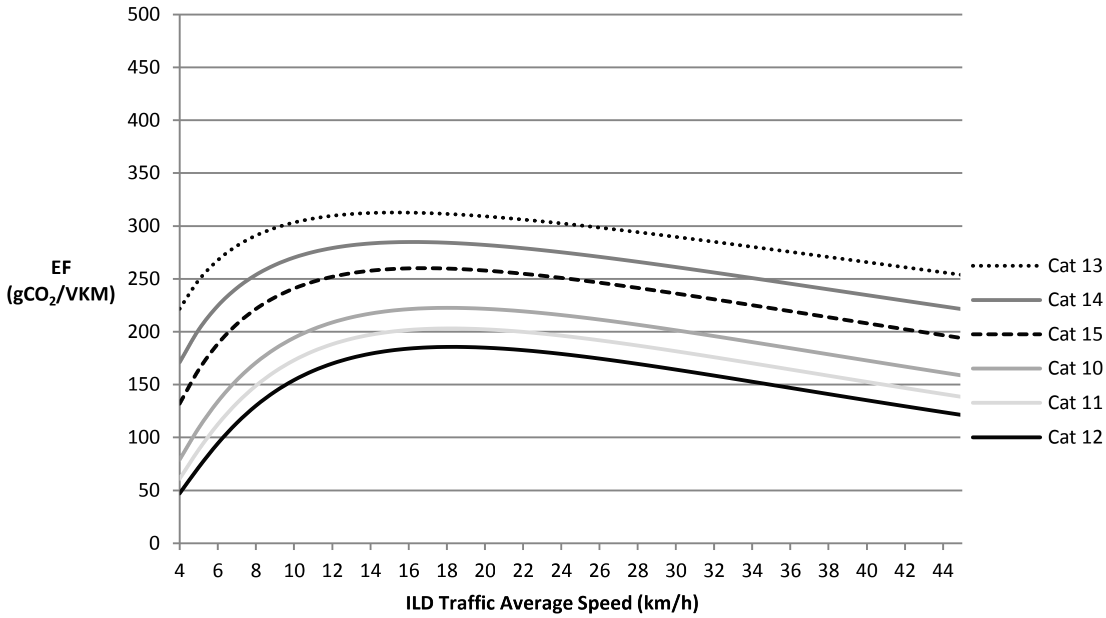

Figure 7-4: PEMLA v.7 predicted EFs for categories 10 to 15 (diesel cars) plotted against traffic average speed.

- Predictions are for access density = 8.43 intersections/km (mean value), 30mph speed limit and peak period.
- The range of measured ILD traffic average speeds was 4 to 41 km/h.

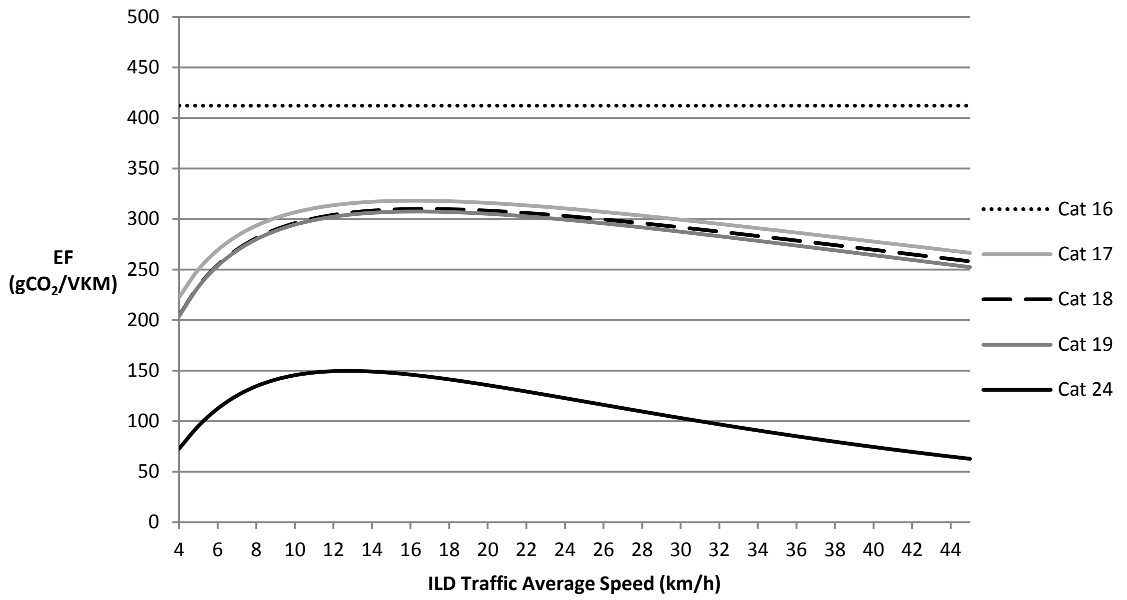

Figure 7-5: PEMLA v.7 predicted EFs for categories 16 to 19 and 24 (LGVs and two-wheel vehicles) plotted against traffic average speed.

- Predictions are for access density = 8.43 intersections/km (mean value), 30mph speed limit and peak period.
- The range of measured ILD traffic average speeds was 4 to 41 km/h.

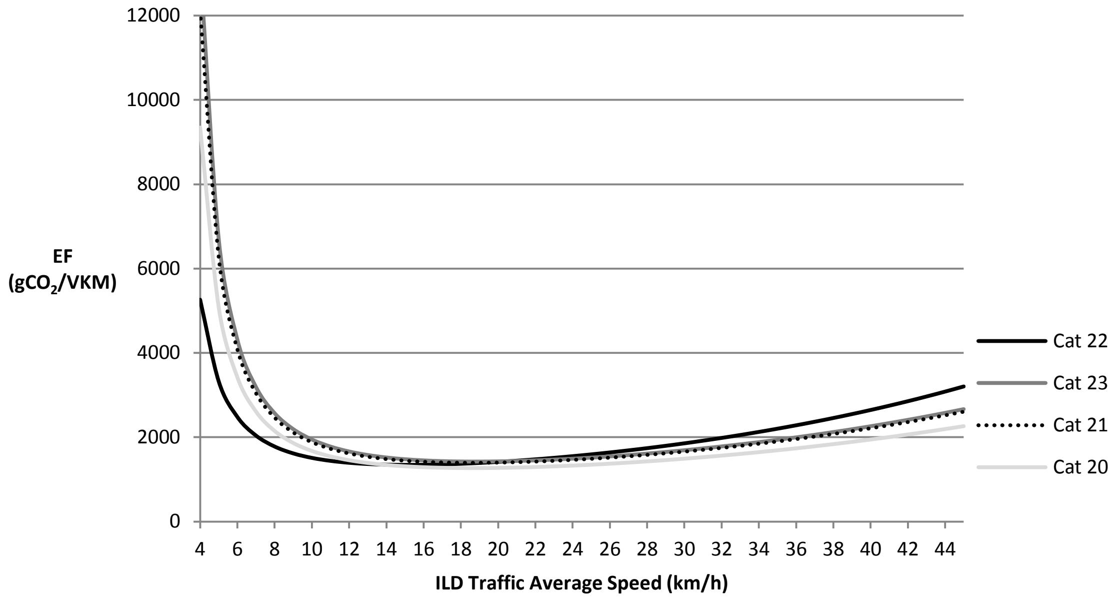

Figure 7-6: PEMLA v.7 predicted EFs for categories 20 to 23 (HDVs) plotted against traffic average speed.

- Predictions are for access density = 8.43 intersections/km (mean value), 30mph speed limit and peak period.
- The range of measured ILD traffic average speeds was 4 to 41 km/h.

Inspection of Figure 7-3 to Figure 7-6 suggested that the 'humps' in Figure 7-2 were due to the n-shaped curves for the predicted EFs of LDVs and two-wheel vehicles. These n-shaped curves were in contrast to the u-shaped curve for EF_T predicted by TRL/NAEI EM and were not the shape that was expected. The unexpected signs of the coefficients associated with the traffic average delay rate IV predictor variables for LDVs and two-wheel vehicles (i.e. negative coefficients indicating EF reduces as traffic average delay rate increases) were suspected of being the reason for the unexpected n-shaped curves, with the unexpected signs themselves being a consequence of the IV calibration method (refer to Section 7.2.3.2). This suspicion was supported by evidence from the curves for categories 07, 08 (Figure 7-3) and 16 (Figure 7-5), which were not n-shaped and were the three categories which did not have traffic average delay rate IVs as statistically significant predictor variables (refer to Table 6-17). In fact category 16 did not have any traffic variable IVs as predictor variables and therefore was a straight, horizontal line in Figure 7-5.

The traffic average delay rate IV predictor variable, when considered in isolation, produced curves of the shapes shown in Figure 7-7. The two curves were generated by calculating EFs using generic formulae including only the traffic average delay rate IV predictor variable and a representative value (0.001) for the associated coefficient. The formulae (Equation 26 and Equation 27) were of the same form as the final form of PEMLA v.7 (Equation 23 including the MLR analysis constant for PEMLA v.7 of 5.9485 from Table 6-17) and demonstrated the effect of changing the sign of the coefficient. Additionally, these curve shapes were replicated when a similar analysis was performed for PEMLA v.5, and so were not due to the exponential nature of the conversion to the final form of PEMLA v.7 (Equation 23).

When combined with other traffic variable IVs (typically traffic average speed IVs in PEMLA v.7), the effect of the traffic average delay rate IV dominated at low traffic average speeds because its value was much greater than the value of traffic average speed. For example, for a 30mph speed limit, as traffic average speed varied from 4 to 45 km/h, the associated traffic average delay rate varied from 825 to 5 s/veh.km[151]. This low speed dominance resulted in n-shaped curves for categories with (unexpected) negative coefficients for traffic average delay rate IVs

[151] Travel times of: 900 s/km at 4 km/h; 80 s/km at 45km/h; and 75 s/km at 48.28 km/h (i.e. at 30mph speed limit). These values give traffic average delay rates of: (900-75=) 825 s/vehicle.km at 4 km/h; and (80-75=) 5 s/vehicle.km at 45 km/h.

(LDVs and two-wheel) and u-shaped curves for categories with positive coefficients for traffic average delay rate IVs (HDVs).

Equation 26

$$EF\ (gCO_2/VKM) = e^{(5.9485\ +\ (0.001\ \text{x traffic average delay rate IV}))}$$

Equation 27

$$EF\ (gCO_2/VKM) = e^{(5.9485\ -\ (0.001\ \text{x traffic average delay rate IV}))}$$

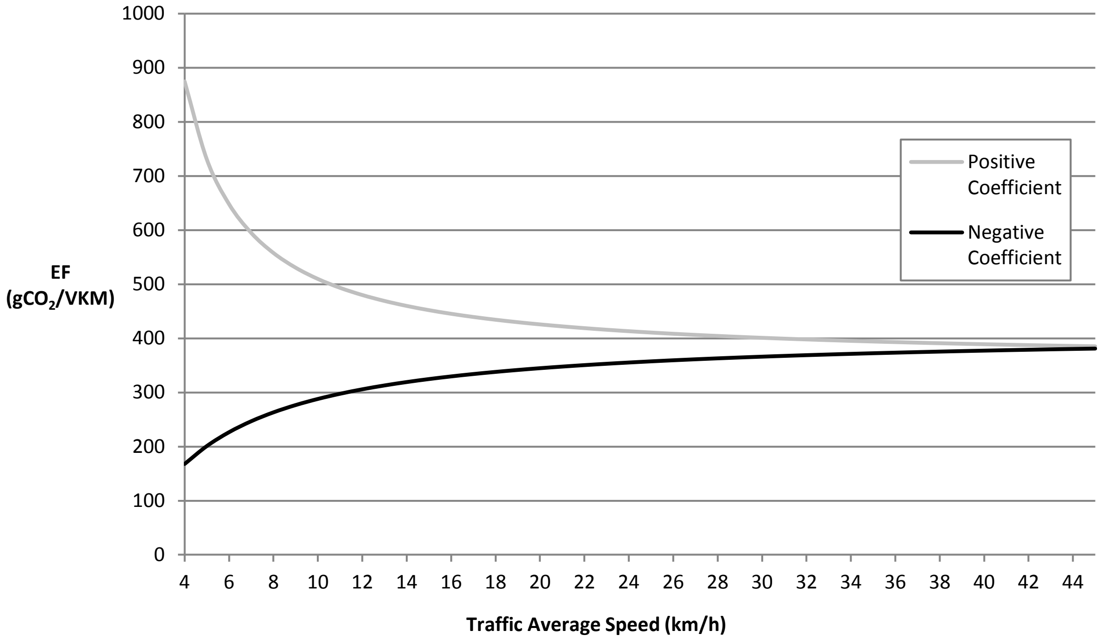

Figure 7-7: Generic EFs plotted against traffic average speed to demonstrate the isolated effect of the traffic average delay rate IV predictor variable.

- Positive coefficient curve shows the effect of a positive coefficient for the traffic average delay rate IV (Equation 26).
- Negative coefficient curve shows the effect of a negative coefficient for the traffic average delay rate IV (Equation 27).
- The range of measured ILD traffic average speeds was 4 to 41 km/h.
- Traffic average delay rate was calculated based on a 30mph speed limit.

The reason for the unexpected signs associated with traffic average delay rate IVs was because the effect of vehicle category outweighed the effect of traffic average delay rate such that vehicle categories with EFs below average (LDVs and two-wheel vehicles) always had (unexpected) negative coefficients and vehicle categories with EFs above average (HDVs) always had positive coefficients (refer to Section 7.2.3.2), where the average EF was represented by the constant from the MLR analysis (i.e. the constant in Table 6-17 gives PEMLA v.7 average EF = $e^{5.9485}$ = 383 gCO_2/VKM). To provide further evidence in support of the theory that these unexpected signs (coupled with the low speed dominance of traffic average delay rate) were the cause of the unexpected n-shaped curves, PEMLA v.9 (results in Table 7-2) was calibrated as a diagnostic tool using IV predictor variables, a log transformation of the outcome variable and OLS HCSE (i.e. by the same MLR analysis method as PEMLA v.7). However, PEMLA v.9 included only LDVs and two-wheel vehicles to investigate whether u- and n-shaped curves appeared for vehicle categories above and below the average EF in a similar fashion to PEMLA v.7, i.e. to move the average EF (which will be reduced in an EM including only LDVs and two-wheel vehicles) and investigate whether this affected the curve shape for a category that was below average in PEMLA v.7, but above average in PEMLA v.9.

In general, Figure 7-10 to Figure 7-12 showed a similar pattern to results from PEMLA v.7, in that vehicle categories with EFs above average and positive coefficients for traffic average delay rate IVs had u-shaped curves, and vehicle categories with EFs below average with negative coefficients for traffic average delay rate IVs had n-shaped curves, where the average EF was again represented by the constant from the MLR analysis (i.e. the constant in Table 7-2 gives PEMLA v.9 average EF = $e^{5.5512}$ = 258 gCO_2/VKM). Category 17 was selected as a particular example because it had a traffic average delay rate IV as a statistically significant predictor variable in both PEMLA v.7 and v.9. In PEMLA v.7, EFs for category 17 were below average (IV – Cat 17 & TraffAvDlyRt coefficient = -0.0007 in Table 6-17) and formed a n-shaped curve (Figure 7-5). However, in PEMLA v.9, EFs for category 17 were above average (IV – Cat 17 & TraffAvDlyRt coefficient = 0.0006 in Table 7-2) and became a u-shaped curve (Figure 7-12). This indicated the theory was correct, which, in summary, gave rise to two types of curve: (1) if a vehicle category's EFs were below average it will have a negative (unexpected) coefficient for the IV associated with traffic average delay rate, which will (in combination with the low speed dominance of traffic average delay rate) cause a n-shaped curve; and (2) if a vehicle category's EFs were above average it will have a positive (expected) coefficient for the IV associated with traffic average delay rate, which will (in combination with the low speed dominance of traffic average delay rate) cause a u-shaped curve.

Table 7-2: Statistics from the MLR Analysis to Calibrate PEMLA v.9.

Predictor Variable	B	Std. Error of B (HC)	Standardised Coefficient β	t-Statistic (HC)
(Constant)	5.5512	0.0121	-	458.76*
IV - Cat01 & TraffAvSpd	-0.0079	0.0007	-0.13	-11.15*
IV - Cat02 & TraffAvSpd	-0.0099	0.0008	-0.17	-11.70*
IV - Cat02 & TraffAvDlyRt	-0.0006	0.0002	-0.04	-3.42*
IV - Cat03 & TraffAvSpd	-0.0126	0.0009	-0.21	-13.88*
IV - Cat03 & TraffAvDlyRt	-0.0009	0.0002	-0.06	-4.40*
IV - Cat04 & TraffAvSpd	-0.0020	0.0007	-0.03	-2.76*
IV - Cat05 & TraffAvSpd	-0.0058	0.0008	-0.10	-7.59*

Table 7-2 continued.

Predictor Variable	B	Std. Error of B (HC)	Standardised Coefficient β	t-Statistic (HC)
IV - Cat06 & TraffAvSpd	-0.0093	0.0008	-0.16	-11.50*
IV - Cat07 & TraffAvSpd	0.0056	0.0009	0.09	6.27*
IV - Cat07 & TraffAvDlyRt	0.0012	0.0002	0.08	5.53*
IV - Cat07 & AccDensCubd	5×10^{-5}	0.0000	0.05	3.45*
IV - Cat08 & TraffAvSpd	0.0026	0.0010	0.04	2.70*
IV - Cat08 & TraffAvDlyRt	0.0009	0.0002	0.06	3.96*
IV - Cat08 & AccDensCubd	0.0001	0.0000	0.05	3.47*
IV - Cat09 & TraffAvDlyRt	0.0006	0.0002	0.04	2.63*
IV - Cat09 & AccDensCubd	0.0001	0.0000	0.05	3.56*
IV - Cat10 & TraffAvSpd	-0.0097	0.0008	-0.16	-11.87*
IV - Cat10 & TraffAvDlyRt	-0.0006	0.0002	-0.04	-3.97*
IV - Cat11 & TraffAvSpd	-0.0127	0.0009	-0.21	-14.47*
IV - Cat11 & TraffAvDlyRt	-0.0009	0.0002	-0.06	-5.12*
IV - Cat12 & TraffAvSpd	-0.0155	0.0009	-0.26	-16.41*
IV - Cat12 & TraffAvDlyRt	-0.0012	0.0002	-0.08	-5.89*
IV - Cat13 & TraffAvDlyRt	0.0004	0.0002	0.03	2.28*
IV - Cat13 & AccDensCubd	4×10^{-5}	0.0000	0.04	2.56*
IV - Cat14 & TraffAvSpd	-0.0031	0.0009	-0.05	-3.55*
IV - Cat14 & AccDensCubd	4×10^{-5}	0.0000	0.04	2.92*
IV - Cat15 & TraffAvSpd	-0.0068	0.0009	-0.11	-7.24*
IV - Cat15 & AccDensCubd	4×10^{-5}	0.0000	0.04	2.53*
IV - Cat16 & TraffAvSpd	0.0093	0.0008	0.16	11.12*
IV - Cat16 & TraffAvDlyRt	0.0015	0.0002	0.10	7.82*
IV - Cat16 & AccDensCubd	3×10^{-5}	0.0000	0.03	2.40*
IV - Cat17 & TraffAvSpd	0.0017	0.0007	0.03	2.38*
IV - Cat17 & TraffAvDlyRt	0.0006	0.0001	0.04	4.01*
IV - Cat18 & TraffAvDlyRt	0.0007	0.0001	0.05	4.68*
IV - Cat19 & TraffAvDlyRt	0.0005	0.0001	0.04	3.75*
IV - Cat24 & TraffAvSpd	-0.0254	0.0008	-0.35	-33.84*
IV - Cat24 & TraffAvDlyRt	-0.0010	0.0001	-0.12	-7.92*
IV - Cat24 & AccDensCubd	-0.0002	0.0000	-0.07	-5.23*
DV - Road Type by Speed Limit (1=40, 0=30)	-0.1350	0.0079	-0.20	-17.08*
DV - Time Period (1=Peak Period, 0=Off-Peak Period)	0.0649	0.0075	0.10	8.69*

- Outcome variable is the natural log of EF from AIRE (gCO_2/VKM).
- n = 2713.
- B and Std. Error of B are quoted to four decimal places because values are approximately two orders of magnitude smaller than in PEMLA v.1 to v.5. Some values are too small to register at four decimal places. In instances where this applies to B, the values are included (and expressed in scientific notation) because they are required for EM application.
- Adj. R^2 = .71.
- For comparison, equivalent MLP neural network analysis resulted in R^2 = .69.
- HC is Heteroscedastic-Consistent.
- Durbin-Watson statistic = 1.93 (i.e. close to 2), which indicates the assumption of independent residuals is tenable.

- Average VIF = 1.91 (i.e. not considerably greater than 1) and all individual predictor variable VIF values < 10, which indicates the MLR assumption of no strong multicollinearity is tenable.
- B, Standard Error of B, Standardized Coefficient β and t-statistic are detailed in notes for Table 6-11.
- * indicates t-statistic is significant ($p<0.05$).

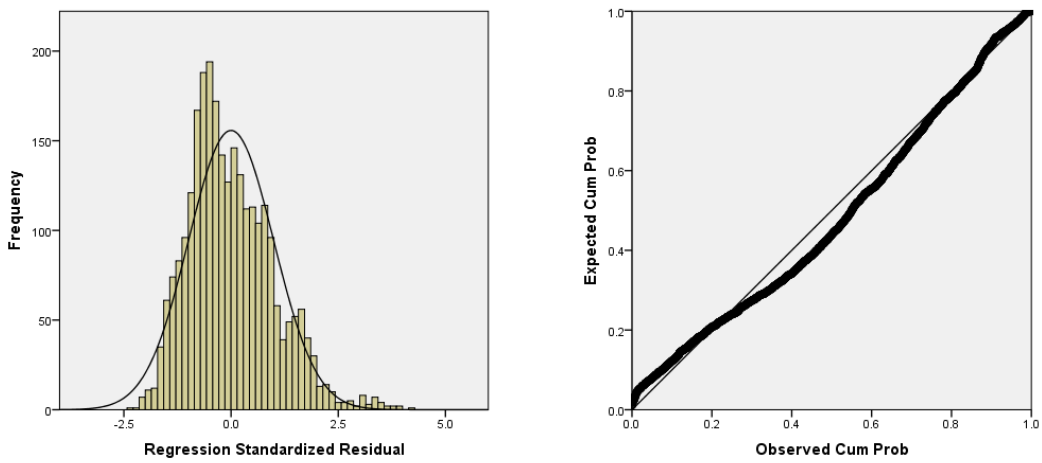

Figure 7-8: Histogram and normal P-P plot of standardised residuals from MLR analysis of PEMLA v.9.

- Positive kurtosis is evident in the plots (refer to notes for Figure 6-2).
- Skewness is evident in the plots (refer to notes for Figure 6-8).

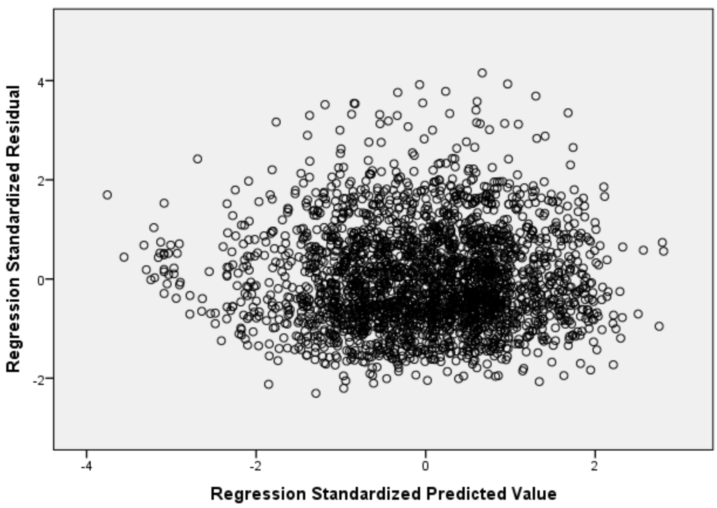

Figure 7-9: Scatter plot of standardised residuals against standardised predicted values from MLR analysis of PEMLA v.9.

- Funnelling-out pattern of the data points is characteristic of heteroscedasticity.

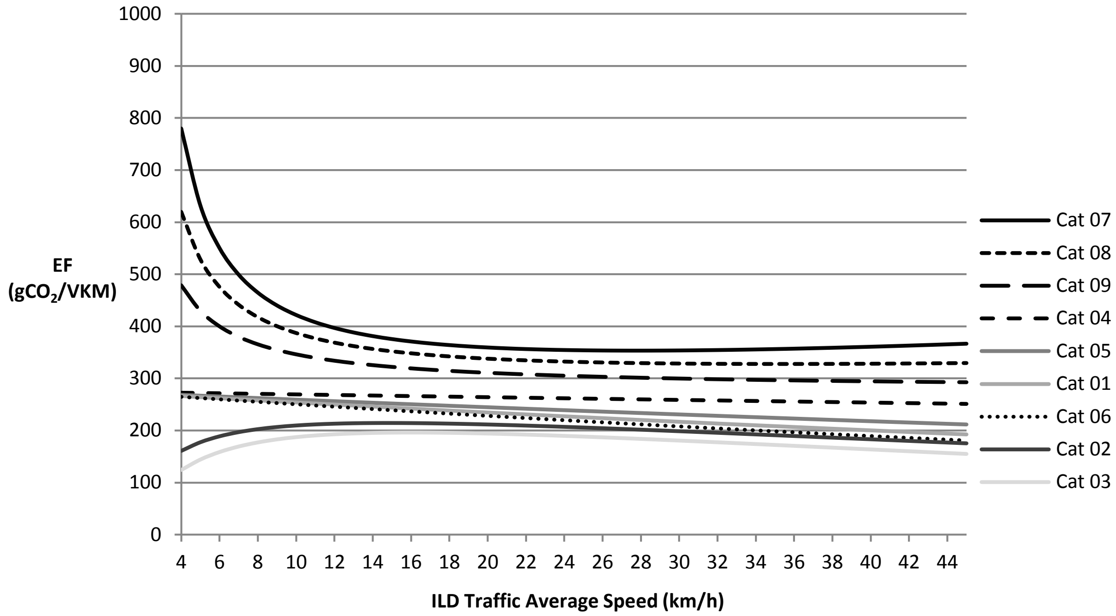

Figure 7-10: PEMLA v.9 predicted EFs for categories 01 to 09 (petrol cars) plotted against traffic average speed.

- Predictions are for access density = 8.43 intersections/km (mean value), 30mph speed limit and peak period.
- The range of measured ILD traffic average speeds was 4 to 41 km/h.

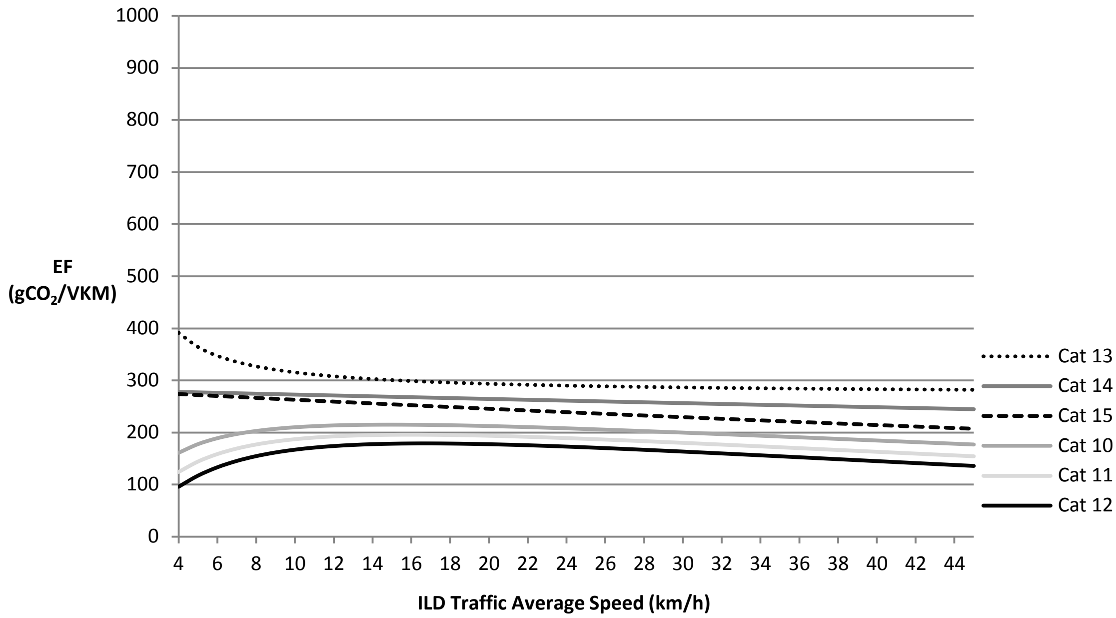

Figure 7-11: PEMLA v.9 predicted EFs for categories 10 to 15 (diesel cars) plotted against traffic average speed.

- Predictions are for access density = 8.43 intersections/km (mean value), 30mph speed limit and peak period.
- The range of measured ILD traffic average speeds was 4 to 41 km/h.

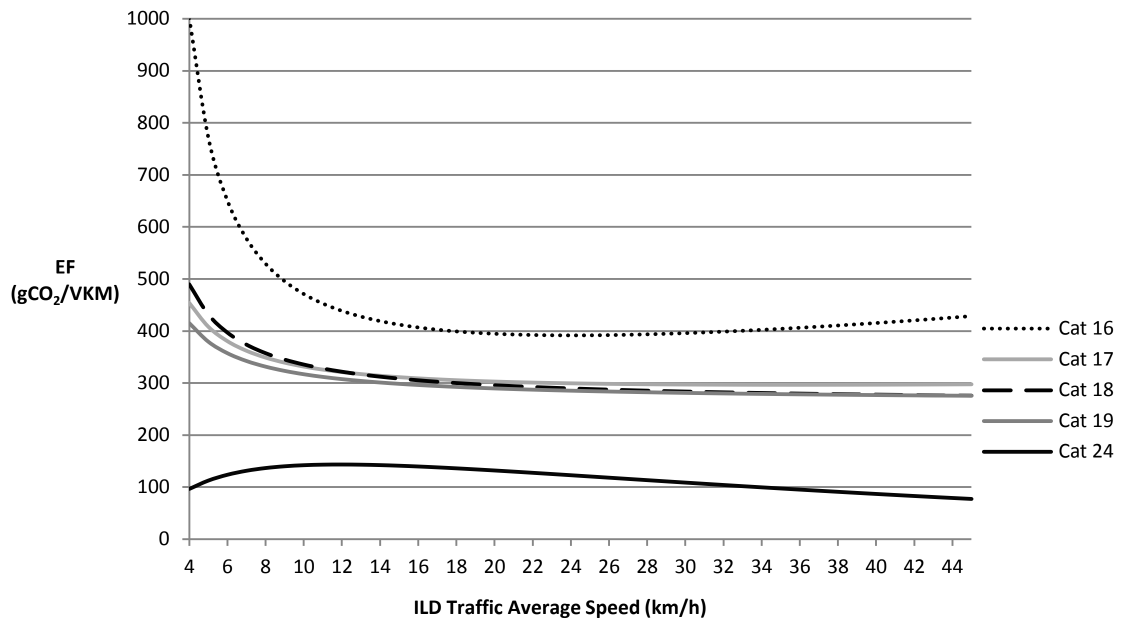

Figure 7-12: PEMLA v.9 predicted EFs for categories 16 to 19 and 24 (LGVs and two-wheel vehicles) plotted against traffic average speed.

- Predictions are for access density = 8.43 intersections/km (mean value), 30mph speed limit and peak period.
- The range of measured ILD traffic average speeds was 4 to 41 km/h.

Furthermore, the analysis of the effect of unexpected signs applied equally to the coefficients associated with traffic average speed IVs in PEMLA v.7. In other words, the (unexpected) positive coefficients associated with traffic average speed IVs caused the (unexpected) upward trends at higher speeds in HDV u-shaped curves; and the (expected) negative coefficients associated with traffic average speed IVs caused the (expected) downward trends at higher speeds in LDV and two-wheel vehicle n-shaped curves. The effects of traffic average speed IV coefficients began to dominate at higher speeds because as traffic average speed increased its value became much greater than that of traffic average delay rate (for a 30mph speed limit, as traffic average speed varied from 4 to 45 km/h, the associated traffic average delay rate varied from 825 to 5 s/veh.km, refer to Footnote 151 in Section 7.2.4.1).

7.2.4.2 Revisiting the decision to develop the IV calibration method

The problem with the characterisation of EFs predicted by PEMLA v.7 for individual vehicle categories (which also affected PEMLA v.5 because it too had similar unexpected signs associated with certain IV predictor variable coefficients, refer to Section 7.2.3.1) caused the earlier decision (refer to Section 7.2.2.4) to reject other methods for incorporating vehicle category (i.e. PEMLA v.1 and v.2) in favour of development of the IV method (i.e. PEMLA v.3) to be revisited. PEMLA v.1 did not include any traffic variables as statistically significant predictor variables. This remained a substantial disadvantage for the utility of the model to LGAs because, without the inclusion of traffic variable predictor variables, PEMLA v.1 cannot (for a given road type and time period) be used to assess interventions that do not alter the fleet mix of vehicle categories (refer to Section 7.2.2.4). The original decision to reject the method used to calibrate PEMLA v.1 was therefore still viewed as valid.

PEMLA v.2 was originally rejected because the model included a relationship between speed and EFs (from the WebTAG formulae) which was forced into the model and not actually present in the data collected, and because it resulted in further aggregation of the 24 PEMLA vehicle categories (refer to Section 7.2.2.4). In addition, examination of the predictor variable coefficients for PEMLA v.2 revealed a problem similar to PEMLA v.7, in that the coefficient associated with traffic average delay rate had an unexpected negative sign (-1.84 in Table 6-12) which (in combination with the low speed dominance of traffic average delay rate) led to unexpected n-shaped curves for EFs plotted against traffic average speed. With the addition of this n-shaped curve problem, the original decision to reject the method used to calibrate PEMLA v.2 was also still viewed as valid. PEMLA v.7 (as a product of development of the method used to calibrate PEMLA v.3) therefore remained the recommended version.

In accordance with the wider purpose of this project to provide a practical method for LGAs to estimate road traffic CO_2 emissions at network-level, PEMLA was not designed to be disaggregated into individual vehicle categories; but when such disaggregation was performed, characterisation of individual vehicle category EFs predicted by PEMLA v.7 produced counter-intuitive results (i.e. unexpected n-shaped curves for LDV and two-wheel vehicle categories). However, based on the results of model comparison (Table 6-18) and accuracy comparison (Table 6-20), overall predictions by PEMLA v.7 of total emissions from all vehicle categories at network-level were satisfactory and compared favourably with results for TRL/NAEI EM. PEMLA v.7 is therefore recommended as suitable for estimating emissions for an urban road network (or substantially large parts of a network) as a whole. This recommendation has some similarity with the findings from the validation of TRL EFs 2009 (refer to Section 2.5.5.1) which indicated that the EM probably provided "a reasonably accurate characterisation of total emissions from road transport", although some emission functions for individual vehicle categories had a high degree of uncertainty (Boulter *et al.* 2009c).

7.2.4.3 Suggested solutions to the problem of n-shaped EF curves

No straightforward method to overcome the problem of n-shaped EF curves in PEMLA v.7 could be found within the constraints of this project, and the search for a suitable solution is an area for future work. One potential solution that could be investigated is an alternative method for measuring traffic average delay rate (which was the traffic variable IV with the problematic coefficient sign). The method adopted in this project (refer to Section 5.4.3) was based on the difference between travel times at the traffic average speed (obtained from the ILD U07 message at the time of vehicle crossing) and at the free-flow speed (assumed to be the link speed limit), which tends to overestimate congestion by comparing measured travel times to travel times in idealised free-flow conditions that may not be achievable in practice (Goodwin 2004). An alternative method would be to compare travel time at the traffic average speed (obtained from the ILD U07 message at the time of vehicle crossing) with the short-run (i.e. no allowance for changes in road capacity) average travel time for the relevant ILD at that same time of day. A database of short-run average travel times for each ILD could be estimated from yearly averages (or monthly averages if finer-grained resolution was required) for traffic average speed from the U07 message for peak and off-peak periods (or hour-by-hour periods if finer-grained resolution was required) on each different day of the week. This method is more akin to that which is occasionally used for calculating Traffic Congestion Indices (TCIs, refer to Section 2.4.3), whereby the marginal cost of congestion (the cost of adding one extra VKM to the current level of congestion) is compared with the average cost of congestion (total cost divided by the total number of VKMs).

Measuring traffic average delay rate by this alternative method would mean the variable could take positive and negative values when current travel times were above and below the short-run average, respectively; and would reduce the dominance of traffic average delay rate over traffic average speed at very low values for traffic average speed (i.e. avoid the very large traffic average delay rates that occurred at very low traffic average speeds due to the large differences between traffic average speeds and the idealised free-flow speeds approximated by the speed limit). Hence, the alternative measurement method could provide a suitable solution to the problem, and its effect on the traffic average delay rate IV predictor variable coefficient signs and on the shape of EF curves for individual vehicle categories would be worth investigating.

A disadvantage of the alternative method for calculating traffic average delay rate would be the resources required to compile the database of short-run average travel times, which is a more onerous task than calculating free-flow travel times based on link speed limits; although, once compiled, the database should be valid for a reasonable length of time (e.g. several years) because road capacity and the underlying demand for road travel (i.e. average number of VKMs over longer periods, such as VKMs/year) are not subject to high rates of change.

Another potential solution that could be investigated would be the inclusion in PEMLA of vehicle category-specific constants that would allow category-specific adjustments to be applied to the global constant in the MLR analysis. In other words, in PEMLA v.7 the value of the constant (= 5.9485 in Table 6-17) would be adjusted by an appropriate value determined for each vehicle category. To achieve this, the Dummy Variables (DVs) encoding vehicle category (as used in the calibration of PEMLA v.1, refer to Section 5.5.3.1) would need to be included as predictor variables in the re-calibration of PEMLA v.7 alongside the IV predictor variables. The DVs have a value of 1 for a vehicle from the associated category, and a value of 0 for vehicles from all other categories. The coefficient associated with the DV for a given category would therefore be the category-specific constant for that category.

The ability to adjust the global constant by a category-specific amount may reduce the problem of IV predictor variable coefficients always having a particular sign due to the effect of vehicle category relative to the global constant ($e^{5.9485}$ = 383 gCO_2/VKM) always being in a particular direction (i.e. LDVs and two-wheel vehicles always downwards and HDVs always upwards, refer to Section 7.2.3.2) and outweighing the effect of the traffic variable. However, in essence, this suggested solution is equivalent to developing disaggregated, vehicle category-specific models; an approach which was not supported by the traffic variable data collected during the project. As highlighted during the preliminary statistical analysis, the traffic variables were found to possess only moderate performance as predictors of CO_2 emissions in the separate preliminary MLR analyses of the four representative vehicle categories (refer to Section 6.3.2). Hence, disaggregation of PEMLA into vehicle category-specific models is likely to encounter similar limitations, i.e. the DVs will represent the effect of vehicle category and will therefore be statistically significant predictor variables, whereas the IVs will be left to represent the effect of the traffic variables and are therefore likely to be no longer statistically significant predictor variables. This would result in a PEMLA version that was sensitive to changes in only vehicle category (i.e. the limitation associated with PEMLA v.1, refer to Section 7.2.2.4). For this reason, the first suggested solution (an alternative method for measuring traffic average delay rate) is the preferred option for investigation in future work.

7.2.5 General Issues with PEMLA Development

7.2.5.1 Model comparison

An important issue with PEMLA development was that throughout the model comparison and partial validation process and the accuracy comparison process the methods used have all constituted comparison of the predictions of different EMs with each other (except for the partial validation against PEMS data for buses). During the model comparison and partial validation process, PEMLA predictions were compared to AIRE predictions (LOOCV), and to TRL/NAEI EM predictions using GPS vehicle average speed as inputs. During the accuracy comparison process, PEMLA predictions and TRL/NAEI EM predictions using ILD traffic average speed as inputs were both compared to AIRE predictions. The use of model comparison was justified because of the inherent difficulty associated with obtaining real-world emissions measurements, which is a time consuming and costly process (refer to Section 2.5.2). However, whilst similarities in predictions between EMs improve confidence in their use, model comparison is not true model validation, and it is possible for results from two different EMs to be similar but still differ from reality (refer to Section 2.5.2).

7.2.5.2 AIRE EFs as a proxy for real-world EFs

The use of EFs predicted by AIRE to represent real-world EFs was justified because AIRE is an IEM whose outputs have been independently verified by TRL (refer to Section 2.5.9.4), and because AIRE represented the only practical method available to calculate the accurate vehicle EFs necessary for the calibration of all PEMLA vehicle categories (refer to Sections 5.3.1 and 5.3.5.1). However, in general, the poor performance of PEMLA when validated against bus PEMS data suggested that using AIRE outputs as a proxy for real-world EFs could be a major issue with PEMLA development. In the second reason suggested for PEMLA's poor performance during PEMS partial validation (reason (2) in Section 7.2.2.2) it was found that AIRE over-estimated EFs for buses by a factor of approximately two (MAF=2.08 and MAPE=108%) when compared to EFs calculated from PEMS data. This discrepancy between AIRE and PEMS EFs was a cause for concern, and indicated a problem with either AIRE predictions or measured PEMS data.

Predicted EFs from AIRE, PEMLA and TRL/NAEI EM were all broadly in agreement during model comparison and accuracy comparison, and it was EFs from PEMS that were substantially different. This may be evidence of a problem with the PEMS data; although it is important to note that similarities in the predictions of EMs can be indicative of the considerable amount of data that is shared between the calibrations of different EMs, rather than indicative of the accuracy of EM predictions (refer to Section 2.5.2). Conversely, the PEMS equipment was serviced and calibrated by the manufacturer (Horiba) prior to installation on the test bus, and the system performed self-calibration tests (by comparison to a reference gas containing known amounts of the different measured pollutants) both before and after each period of emissions measurement. Additionally, the experimental installation was validated by comparison of fuel flow (g/s) outputs from the PEMS with those from the engine control unit obtained via the Controller Area Network (CAN) bus. There was therefore no obvious reason to suspect PEMS outputs of being erroneous.

The discrepancy between predicted EFs from AIRE, PEMLA and TRL/NAEI EM and measured EFs from PEMS data needs to be investigated further and a satisfactory explanation sought. A potential method for this would be to use the GPS driving patterns collected from the PEMS-equipped bus as inputs to a more advanced IEM (e.g. PHEM), and to use the resulting outputs as evidence for which source of EFs (AIRE or PEMS) was most likely to be accurate. Also beneficial would be collection of further PEMS data from vehicle categories other than buses for comparison to predictions from AIRE, PEMLA and TRL/NAEI EM in order to ascertain whether similar discrepancies exist in other vehicle categories.

7.3 PEMLA APPLICATION

7.3.1 Optimal EM Complexity for LGAs

The research gap identified in this project constituted an investigation into whether a Traffic Variable EM represented optimal EM complexity for LGAs, improving on the ability of well-established Average Speed EMs to capture the influence on emissions of congestion, whilst remaining within resource constraints. Therefore, the advantages and disadvantages associated with the application of PEMLA by LGAs were compared to those associated with TRL/NAEI EM (as the next-best alternative) to assess the extent to which PEMLA (a Traffic Variable EM) represented a move towards optimal EM complexity relative to TRL/NAEI EM (a well-established Average Speed EM).

In accuracy comparison, PEMLA outperformed TRL/NAEI EM (refer to Section 7.2.3.5), which indicated that application of PEMLA to calculate network-level CO_2 emissions will produce estimates closer to real-world values than application of TRL/NAEI EM (2% over-estimation by PEMLA v.7 compared to 12% under-estimation by TRL/NAEI EM). PEMLA was purposefully designed to better account for the influence of congestion on emissions through the use as inputs of other traffic variables (in addition to traffic average speed). Therefore, when assessing the impact of transport interventions, PEMLA is sensitive to changes in fleet mix, traffic average speed, traffic average delay rate, access density, road type and time of day; whereas TRL/NAEI EM is sensitive to changes in only fleet mix and traffic average speed. The additional predictor variables in PEMLA allow it to offer greater utility to LGAs through better account of congestion and improved accuracy.

A point to note is that, during accuracy comparison, some of the inaccuracy in TRL/NAEI EM predictions may have been due to the use of ILD time-mean-speed as inputs (which was done to ensure comparison based on a like-for-like data source, refer to Section 5.5.5), whereas the inputs to an Average Speed EM should really be space-mean-speed (refer to Section 2.5.5). However, in the second of the three methods used in model comparison and partial validation, PEMLA predictions were compared to TRL/NAEI predictions using GPS vehicle average speed as inputs (i.e. average speed over longer distances as in the calculation of space-mean-speed), which resulted in PEMLA predictions 21% greater than those of TRL/NAEI EM (PEMLA v.7 MAF=1.21 in Table 6-18). This result is similar to the gap found in accuracy comparison, where PEMLA predictions were 16% greater than those of TRL/NAEI EM (PEMLA v.7 MAF=1.02 and TRL/NAEI EM MAF=0.88 in Table 6-20 giving (1.02-0.88)/0.88 x 100% = 16%). In fact, the smaller difference of 16% during accuracy comparison indicates TRL/NAEI EM performed better using ILD traffic average speed as inputs, which was an unexpected result.

PEMLA and TRL/NAEI EM both have similar requirements for vehicle category input data. Vehicle category data can be obtained from the NAEI national fleet model, with emissions for each vehicle category then weighted according to their fraction of VKMs[152]. For example, PEMLA vehicle categories can be weighted according to the percent of VKMs shown in Table 5-1, which represent NAEI national fleet model predictions for each category's fraction of total national VKMs on urban roads in England outside London in 2016. Alternatively, as a substitute for NAEI national fleet model data, a more accurate local fleet mix could be obtained, for example from ANPR data.

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[152] In fact, TRL/NAEI EM was defined in Section 5.2.2 as being TRL EFs 2009 average speed emission functions for each vehicle category weighted by the NAEI national fleet model predictions for each category's fraction of total national VKMs on urban roads in England outside London in 2016. However, this does not preclude the weighting of TRL EFs 2009 emission functions by other fleet mix data.

An important advantage of PEMLA is that required inputs are generated (mainly) from ILD data, which can be considered a free by-product of the UTC system, and were ranked highly by participants in the LGA survey as data that are easily obtainable, routinely collected and planned for future collection (refer to Section 4.4). Also, the fact that PEMLA uses data from point detectors (i.e. ILDs) as inputs provides a further advantage where data are collected in the real-world. This is because such data are typically easier to collect than data averaged over longer distances (e.g. space-mean-speed required as inputs to Average Speed EMs such as TRL/NAEI EM) as these require some method of estimating vehicle travel times over these distances (e.g. vehicle tracking), which is likely to be resource-intensive to achieve on a network-wide scale. However, in circumstances where data are collected from RTMs there is little difference in the ease with which simulated point detector data or data averaged over longer distances can be generated. In other words, when using RTMs as a road traffic data source, it is as easy to obtain traffic variables from simulated ILDs as it is to obtain traffic variables averaged over link length (or longer) in the modelled network. An easier data collection task in the real-world and a similar data collection task when using RTMs mean that the resources required to collect the input data for PEMLA are likely to be the same as, or arguably less than, those required to collect the space-mean-speed data necessary as inputs to TRL/NAEI EM.

A disadvantage of PEMLA is a limitation of only being valid for urban roads with 30mph or 40mph speed limits because these were the road types from which all trip segments were collected. However, the large majority of roads in UK urban areas are of these types; although extension through further data collection to include roads with other speed limits would make PEMLA more comprehensive. For example, extension to include the growing trend for urban roads with 20mph speed limits, or to include urban roads with 50mph speed limits (usually urban dual carriageway roads) which exist in some areas. In contrast, TRL/NAEI EM can be applied to any urban road regardless of speed limit, and is valid over a larger range of traffic average speeds – speed ranges equal to, or greater than, 6 to 75 km/h depending on vehicle category, compared to the 4 to 41 km/h range used in PEMLA's development (Table 6-10). That said, PEMLA was designed for application to urban roads, where (it could be argued) its speed range will be satisfactory because speeds were collected from real-world Southampton-specific data, and should therefore be a good characterisation of those typically found in cities. Also, PEMLA's traffic average speed range of 4 to 41 km/h is consistent with the most congested (<15 km/h) and least congested (30 to 45 km/h) driving cycles used to represent urban driving conditions in the study by Smit and McBroom (2010) (refer to Section 2.3.3).

On a related point, the ILD traffic average speeds (mean = 25 km/h; range = 4 to 41 km/h) and GPS vehicle average speeds (mean = 26 km/h; range = 5 to 57 km/h) measured during the project (Table 6-10) were lower than might be expected with reference to those provided in the DfT Basic Local Authority Carbon Tool[153] (DfT 2011a), which were obtained in 2008 from forecast results for 2010 from the National Transport Model (NTM, the DfT's strategic transport model). A possible reason for this discrepancy (other than the difference in year) is that the speeds from the Carbon Tool are an average for urban areas across the whole of the South-East region of England (except London), whereas the speeds measured in the project are Southampton-specific. This reason is plausible because, as a large city in the South-East region, Southampton is likely to have higher congestion and lower traffic average speeds than other, less densely populated, urban areas in the region. This may affect the transferability of PEMLA to other UK urban areas, which will require validation before it can be confidently applied (refer to Section 7.4.5).

The ranges of the other three traffic variables (excluding the square of traffic average speed whose range is related to that of traffic average speed) are: traffic density from 1 to 92 vehicles/km, traffic average delay rate from 15 to 825 s/vehicle.km, and access density from 0.97 to 20.34 intersections/km (Table 6-10). Similar to traffic average speed, having been collected from real-world data, it is likely these ranges were a good characterisation of those typically found in a city; and again using the Smit and McBroom (2010) study for comparison (refer to Section 2.3.3), the range of traffic density collected during this project (1 to 92 vehicles/km) is consistent with the least congested (0 to 35 vehicles/km) and most congested (70 to 125 vehicles/km) urban driving cycles.

A further disadvantage of PEMLA is that it is new and unfamiliar to LGAs. In contrast, TRL/NAEI EM is well-established, with TRL EFs 2009 being the officially recognised EM recommended for use in the UK, and therefore likely to be familiar to LGAs. For example, WebTAG and DfT Basic

[153] Average speeds on urban roads in the South-East region of England during peak period are: LDVs on major roads = 47.2 km/h; HDVs on major roads = 46.5 km/h; LDVs on minor roads = 32.6 km/h; and HDVs on minor roads = 32.5 km/h.
Average speeds on urban roads in the South-East region of England during inter-peak period are: LDVs on major roads = 53.7 km/h; HDVs on major roads = 52.2 km/h; LDVs on minor roads = 34.4 km/h; and HDVs on minor roads = 34.0 km/h.

Local Authority Carbon Tool (which are both based on TRL EFs 2009) were the EMs most used by LGA survey participants (refer to Figure 4-4). However, TRL EFs 2009 is being replaced as the official UK EM by COPERT during the course of 2016 (refer to Footnote 52 in Section 2.5.5.1), which means LGAs are likely to be faced with the challenge of applying an unfamiliar EM in the near future regardless.

Weighing the relative advantages and disadvantages associated with the application of PEMLA by LGAs, it was concluded that the investigations undertaken in this project have successfully produced an EM (PEMLA) that is closer to optimal complexity than the current, widely-used, next-best alternative (TRL/NAEI EM). The two key reasons for this conclusion were: (1) because PEMLA predictions were more accurate through better accounting for congestion; and (2) because PEMLA consumed the same (or potentially lower) resources to operate. It is also likely that comparison between PEMLA and the in-coming COPERT would produce similar results because (like TRL/NAEI EM) COPERT is an Average Speed EM. The move towards the point of optimal EM complexity and the minimisation of model prediction error represented by the use of PEMLA instead of TRL/NAEI EM is illustrated graphically in Figure 7-13, which is a version of Figure 2-1 with the y-axis modified to include a scale that quantifies EM prediction error in terms of the percentage deviation from unity of a model's MAF (PEMLA v.7 MAF=1.02 corresponds to 2% prediction error and TRL/NAEI EM MAF=0.88 corresponds to 12% prediction error, with MAFs extracted from accuracy comparison results shown in Table 6-20).

It is possible that PEMLA itself could still be improved upon, which is acknowledged in Figure 7-13 by PEMLA being positioned slightly to the left of the optimal position of minimum total model prediction error. Excluding Cycle Variable and Modal EMs from the analysis (because accurate input data are not readily available to LGAs and their complex operation is beyond LGA resources), exhaustive accuracy comparison of PEMLA predictions with predictions based on all other possible traffic variables (and combinations thereof) would be required to prove conclusively that PEMLA is positioned at the minimum. Providing such theoretical proof is therefore an impractical task, and is also unlikely to be of interest to LGAs. Instead, LGAs are likely to be concerned with PEMLA's position on the curve relative to the next-best alternative, which has been established.

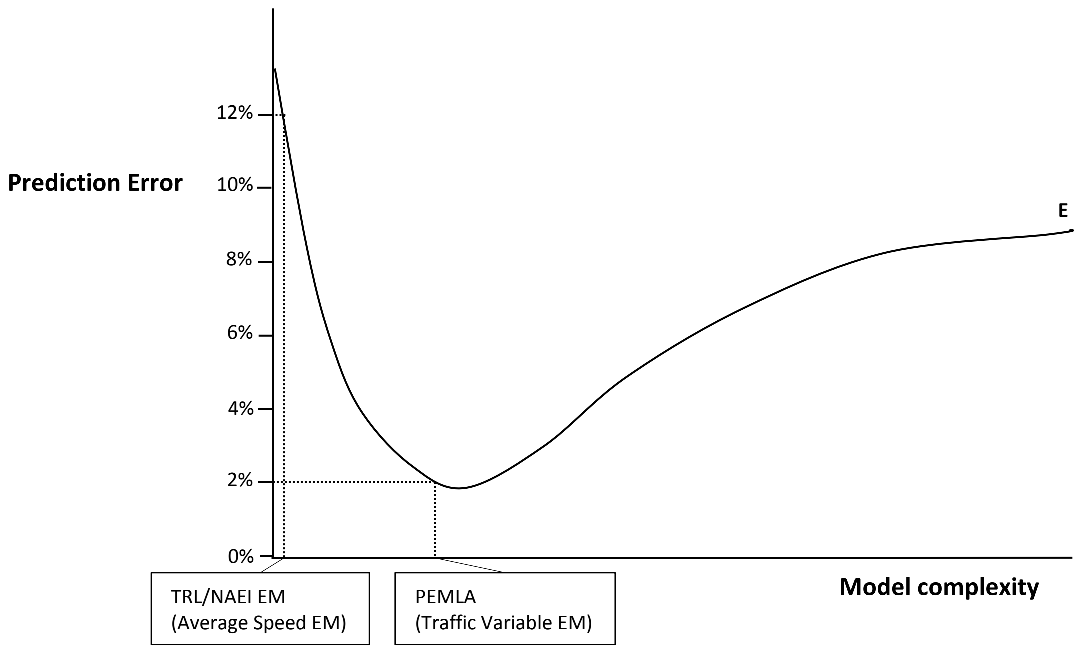

Figure 7-13: PEMLA and TRL/NAEI EM plotted on a graph of model complexity and model prediction error.

- E is total prediction error.
- Prediction error scale is the percentage deviation from unity of an EM's Mean Accuracy Factor (MAF).
- Source: adapted from Alonso (1968).

7.3.2 Minimum Spatial Resolution

In general, the minimal spatial resolution for application of Aggregate, Average Speed, Traffic Situation, Traffic Variable and Cycle Variable EMs is (at least) link level, and should ideally be trip segment level (i.e. a series of consecutive links). This is for two reasons: (1) calibration of these EMs is based on results from emissions tests for EFs averaged over the length of driving cycles (which are typically longer than link length, refer to Section 2.5.5); and (2) any underlying assumptions (e.g. zero gradient) made during calibration are more likely to be valid over longer distances (or even more so over substantially large parts of a network as a whole).

Accordingly, PEMLA (a Traffic Variable EM) was developed based on values of predictor (traffic variables) and outcome (EF) variables averaged over the distance of at least two links (i.e. as specified in the definition of a trip segment as the unit of observation, refer to Section 5.3.2.1). The minimum spatial resolution where application of PEMLA can be expected to generate accurate predictions is therefore at least link length, and ideally trip segment length. The accuracy of PEMLA predictions is less likely to be reliable over shorter distances, such as (for example) application to analyse CO_2 emissions associated with an isolated junction. This is an issue common to all EM types identified in the preceding paragraph (which, as an Average Speed EM, includes TRL/NAEI EM), i.e. common to all types except Modal EMs. Hence, PEMLA was specified as an EM designed to predict emissions for an urban road network (or substantially large parts of a network) as a whole.

7.3.3 Options for LGAs' Use of PEMLA

PEMLA can be utilised by LGAs in a number of ways. Due to being based on ILD-generated data, it can be readily integrated into UTC systems such as SCOOT. This integration would allow the impact on CO_2 emissions of different traffic management strategies to be estimated in near real-time, and provide the facility for traffic signal timings to be optimised so as to minimise network-level emissions rather than (the more typical) traffic delay or stops (Reynolds 1996). In essence, integration into UTC systems provides LGAs with a real-time road traffic CO_2 emissions monitor, which could also be used to visualise the impacts of traffic management strategies on emissions via a map display in a similar fashion to common visualisations of road traffic congestion (e.g. the congestion display function of Google Maps software).

Alternatively, PEMLA can be integrated into Road Traffic Models (RTMs), obtaining inputs from simulated ILDs installed across the modelled road network. For hypothetical scenarios, when a proposed intervention is still at the planning stage, a RTM is likely to be used to assess the traffic impacts of the intervention. If PEMLA was packaged with this RTM, the emissions impact of the intervention could be assessed at the same time. A barrier to integration into RTMs is the likely mismatch in vehicle categories between PEMLA and host RTMs, which typically only include highly aggregate vehicle categories in comparison to EMs (refer to Section 2.6.4).

However, the form for PEMLA offering LGAs the greatest versatility is as a stand-alone EM. The way in which EM outputs are used to inform policy making is subject to considerable variation between different LGAs (refer to Section 2.5.12). A stand-alone form of PEMLA that can take inputs obtained from either real-world ILDs in UTC systems or simulated ILDs in RTMs is therefore likely to offer the greatest utility to LGAs, leaving them free to apply PEMLA as their individual situations warranted. The simplest form this stand-alone PEMLA could take would be to encode the emission functions (i.e. model parameters for PEMLA v.7 shown in Table 6-17) in a spreadsheet model (this was accomplished for the case study application of PEMLA detailed in Section 7.3.7) similar to the way in which TRL EFs 2009 are encoded in the DfT Basic Local Authority Carbon Tool spreadsheet model. Based on the fact that the DfT goes to the effort of providing a stand-alone, purpose-built EM specifically for LGA use (i.e. the Basic

LA Carbon Tool), it seems reasonable to assume that outputs from the Carbon Tool are likely to be suitable for LGA policy making. If this assumption is accepted, then a stand-alone PEMLA, which would generate similar (more accurate) outputs, is also likely to provide suitable outputs for LGA policy making purposes.

A stand-alone PEMLA would also be consistent with an overarching recommended approach to estimating road traffic CO_2 emissions, i.e. a preferred method recommended by national government for use by all LGAs, which provides the benefit of comparability of results across assessment of different transport interventions. This is the approach adopted in the UK as evidenced by the DfT's engagement in producing TRL EFs 2009 and the Basic Local Authority Carbon Tool. A similar approach can be seen in the USA where the EPA recommends the use of MOVES (refer to Section 2.5.12). In contrast, an integrated PEMLA in either UTC systems or RTMs would be restricted to situations where the associated host was deployed.

Additionally, a stand-alone PEMLA would have the flexibility to be reusable in assessment of future, as yet undetermined, interventions, which was considered by participants in the LGA survey to be the most important factor affecting allocation of resources to the emissions modelling process (refer to Section 4.4). A stand-alone PEMLA would therefore bring the benefits associated with reusable EMs such as staff familiarity, goodness of fit with existing skills, shorter timescales required to use familiar software applications, avoidance of regular staff retraining, reliability of operation, trust in validity of results, comparability of results across different intervention assessments, and goodness of fit with road traffic data routinely collected. A series of focus groups to elicit the opinions of LGA emissions modelling experts (i.e. the intended end-users of PEMLA) would be an ideal way to advance understanding of how PEMLA may be best utilised by LGAs and is an area for future work (refer to Section 7.4.3).

Over recent years in the UK (e.g. project duration from 2012 to 2016), reduction of AQ emissions has (it could be argued) overtaken reduction of GHG emissions in importance to the local political agenda. Likely reasons for this shift in emphasis in LGA policy direction are three-fold: (1) the continuing environment of LGA budget cuts means selective resource focus is necessary; (2) potential fines from the EU for breaching concentration limits for AQ pollutants, the (full or partial) payment of which national government are threatening to pass on to LGAs (DEFRA 2014b) (although this threat will recede due to the UK's exit from the EU); and (3) the lack of any statutory requirement for LGAs to reduce emissions of GHGs (DECC

2014), i.e. GHG emissions reduction targets are set voluntarily, with little penalty for non-compliance (refer to Section 1.5.2.1). In July 2016, political changes in UK national government saw the abolition of the Department for Energy & Climate Change. Whilst its responsibilities have been merged into a new ministry called the Department of Business, Energy and Industrial Strategy, the abolition of DECC could be seen as a downgrading of the UK's actions to reduce GHG emissions, which is likely to filter down into LGA policy making. In Southampton, as part of the implementation of the Low Carbon City Strategy (LCCS), SCC produced the 'Low Carbon City Strategy and Delivery Plan – Year 1 Annual Progress Report (2011/2012)' (SCC 2012). However, subsequent annual progress reports have not been produced because such non-statutory activities could not be resourced as a consequence of staff cutbacks (Tuck 2014).

In contrast, for AQ emissions there exists a statutory requirement for LGAs to monitor and report on AQMAs (for which DEFRA provides the EFT Average Speed EM to assist LGAs in discharging their duty, refer to Section 2.5.5.5) (DEFRA 2009b; DEFRA 2016). This continuing statutory requirement, coupled with the threat of EU fines, has seen AQ pushed up the local political agenda. This is particularly so in Southampton because the city was identified as one of the five cities in England (outside London) that are projected to still be exceeding limits for NO_2 by 2020 (DEFRA 2015b). Now that the UK has voted to exit the EU and the threat of fines will recede, it will be interesting to see the influence this has on the relative political importance of GHG emissions compared to AQ emissions.

PEMLA only predicts CO_2 emissions. This is a disadvantage compared to the TRL/NAEI EM, which includes a full range of pollutant emissions (i.e. both CO_2 and AQ emissions). Extension of PEMLA to include AQ emissions is an area for future work (refer to Section 7.4.4). That said, despite the short-term fluctuations of political emphasis, the long-term threat of global warming due to anthropogenic GHG emissions has not receded, and facilitating mitigation of road traffic CO_2 emissions therefore remains an important task.

7.3.4 Alternative Road Traffic Data Sources

ILDs are old technology (it could be argued), having first been introduced in the early 1960s (FHWA 2006); although since that introduction ILDs have become the most utilised type of sensor in traffic control systems (FHWA 2006; Kim *et al.* 2013), and this long and wide history of use also brings the benefit of proven reliable operation. As old technology, ILDs may be superseded by other traffic sensors utilising alternative technologies. For example, the magnetometer sensor is an ILD-equivalent device that is a suitable alternative for use in UTC systems such as SCOOT. The sensor detects vehicles based on the associated disturbance to the Earth's magnetic field. The advantage of magnetometers over ILDs is that they require less disruption to the road surface for installation, and require less maintenance during operation (Siemens 2011; Siemens 2015). Another example is the Speed Detection Radar (SDR) sensor, which detects vehicles using microwave radar (refer to Section 2.4.1). The advantages of SDRs over ILDs are that they provide more accurate measures of vehicle speed (compared to estimates provided by single-loop ILDs), and installation and maintenance does not require any work to the road surface, therefore avoiding associated traffic disruption (Econolite 2012). A further example, which again avoids any work to the road surface, is the use of video analytics software to extract, *inter alia*, vehicle speed and count data from CCTV cameras monitoring the road network (Kim *et al.* 2013). Additionally, CCTV cameras can be used to provide vehicle category data in circumstances where the video analytics software also includes ANPR capability (Smart CCTV 2010).

However, any road traffic data source that can provide values for traffic average speed (time-mean-speed) and traffic count (the two pieces of data required to calculate the traffic variable inputs to PEMLA) of vehicles passing the sensor location is likely to be suitable for providing PEMLA inputs; although this would need to be verified through comparing PEMLA predicted EFs based on inputs from the alternative data source with observed EFs (calculated either from PEMS data or from GPS driving pattern inputs to AIRE). As a final point, the possibility that ILDs may be replaced with other traffic sensors was one reason why ALOTPV and ATGBV (two variables also included in the U07 SCOOT message, refer to Section 5.4.2.1) were not selected for investigation as predictor variables (another reason was that neither had been previously used in emissions predictions). These variables were developed based on ILD-specific data, and would not necessarily be readily available from other sensors such as magnetometers or SDR.

7.3.5 Alternative Drivetrains or Fuels

In general, vehicle categories using low carbon alternative drivetrains or fuels (BEVs, PHEVs, HEVs, FCVs, biofuels, CNG and LPG) have been excluded from this project for the reasons discussed in Section 2.3.12. If (when) a low carbon alternative successfully penetrates the mass market this decision would have to be revisited and PEMLA recalibrated to include the relevant alternative vehicle category. This would require GPS driving patterns to be collected from vehicles in the alternative category, which would then be used as inputs to an IEM that includes the alternative category to calculate accurate EFs (AIRE currently does not include any alternative vehicle categories).

That said, reference to the DfT Basic Local Authority Carbon Tool offers a number of simple ways in which some of these vehicle categories can be accounted for in PEMLA without needing the process of full recalibration (refer to Section 2.5.5.2). The DfT recommend that use of biofuel is incorporated through the assumption that biofuels produce zero CO_2 emissions when combusted. This approach is adopted in the Carbon Tool, with predicted emissions being discounted by the percentage of biofuel supplied, and is also adopted in PEMLA. Therefore, total emissions predicted by PEMLA should be reduced by 3.29% to reflect the percentage of biofuel supplied under the RTFO (refer to Section 2.3.12.1). For LDVs running on LPG and CNG fuels, the Carbon Tool applies a correction factor to the predicted emissions for the relevant petrol LDV of 0.9 and 0.8, respectively, and this approach can be easily applied to PEMLA predictions. For cars that are PHEVs or BEVs, the Carbon Tool adopts a simple approach using aggregate EFs of 97.3 gCO_2/VKM and 53.4 gCO_2/VKM, respectively. These aggregate EFs can be easily used alongside PEMLA.

7.3.6 Low Carbon Technologies

Separate from vehicle categories using low carbon alternative drivetrains or fuels, there are a number of low carbon technologies installed on conventionally fuelled (i.e. mineral petrol or diesel) ICE vehicles beginning to proliferate the mass market, such as: stop-start engine technology; light-weight structures; reduced aerodynamic drag; efficient heating, ventilation and air conditioning systems; and waste energy recovery systems. Typically, such technologies reduce emissions through reducing fuel consumption. Consequently they have a financial (as well as environmental) impetus driving their popularity, which means their penetration of the vehicle fleet is likely to go on increasing over the next 5-10 years and beyond.

TSAFs were used in PEMLA calibration when EFs from AIRE for Euro 4/V vehicle categories had to be adjusted to Euro 5/6/VI categories (because AIRE did not include later Euro Standards, refer to Section 5.3.5.3). TSAFs were calculated using TRL/NAEI EM. The emission functions in TRL EFs 2009 (i.e. those in TRL/NAEI EM) included assumptions to account for technologies that reduce fuel consumption and for the voluntary agreements between the ACEA and the EU to reduce CO_2 emissions that are now enacted into European Legislation (refer to Section 2.5.5.1). Therefore, PEMLA also includes these low carbon technologies via the assumptions used in TRL EFs 2009. A caveat to this is the analysis performed to examine the likely maximum size of over-estimation of EFs due to using a fleet-average bus category rather than the lightest-weight, most modern Euro VI bus category (refer to Section 7.2.2.2), which indicated that TRL EFs 2009 may have under-estimated the emissions reductions actually achieved by modern vehicles. In other words, TSAFs could have been an under-estimate of the reductions actually achieved between Euro 4/V and Euro 5/6/VI vehicles. A way to overcome this caveat would be to recalibrate PEMLA using an IEM that includes all Euro Standards (e.g. PHEM, which proved too expensive for this project) to calculate accurate EFs, thus avoiding the need for TSAFs.

PEMLA only includes the penetration of low carbon technologies up to and including the current Euro Standard (Euro 6/VI). However, it does not include technologies that will be installed on future vehicles compliant with the next Euro Standards (i.e. the penetration of low carbon technologies *circa* 2020 based on previous intervals between Euro Standards). There are two options for incorporation into PEMLA. The first option would be to recalibrate PEMLA using an IEM that includes Euro 7/VII vehicle categories to calculate accurate EFs[154]. This recalibration can only be done at a later date when such an IEM has been released. The second option would be to apply a percentage discount to the emissions predicted by PEMLA as it currently stands (i.e. similar to the percentage discount to account for biofuel use). Appropriate amounts for such discounts to account for different technologies could be taken from other research reported in the literature. For example, the ICT-Emissions project predicted reductions in total CO_2 emissions from cars on congested urban roads of between 6-12% if all cars have stop-start technology installed (i.e. 100% penetration), with the percentage reduction directly proportional to the percentage penetration (ICT-Emissions 2015).

7.3.7 Case Study Application

The results of PEMLA v.7 (the recommended version) were encoded into a spreadsheet format (i.e. similar to the DfT Basic Local Authority Carbon Tool format), which was then used to predict the emissions impact of a case study intervention to demonstrate the practical application of PEMLA. The hypothetical scenario for the intervention was a situation where an LGA is considering reducing the speed limit on a particular road from 40 to 30 mph (for example, this action could be in response to safety concerns for the road in question). The selected testbed was the section of Thomas Lewis Way in Southampton running between the

[154] This option essentially relates to the problem identified in Section 2.6.4 of an on-going need to update all EMs at regular intervals to accommodate vehicles compliant with the latest emission standards.

existing 30/40 speed limit change location and the intersection with Stoneham Way (refer to Figure 7-14). Emissions from both northbound and southbound traffic were predicted. The fleet mix was assumed to be as predicted by the NAEI national fleet model for urban roads in England outside London in 2016 (i.e. each category's percentage of total VKMs was as shown in Table 5-1) and to be unchanged by the intervention.

For the pre-intervention scenario, traffic average speed and average 5 minute vehicle count data were obtained from two ILDs situated in the existing 40 mph speed limit testbed section (one northbound and one southbound, N1 and S1, respectively, in Figure 7-14). For the post-intervention scenario, the assumption was made that traffic average speed data from two ILDs situated in the existing 30 mph speed limit section of Thomas Lewis Way (one northbound and one southbound, N2 and S2, respectively, in Figure 7-14) now applied to the testbed section. However, an assumption that average 5 minute vehicle count data from N2 and S2 now applied to the testbed section was assessed as unrealistic because of the multiple opportunities for vehicles to enter/exit Thomas Lewis Way at the three intersections between the locations of the ILDs (i.e. three intersections between the N1/S1 location and the N2/S2 location). Instead, pre-intervention flows (i.e. 5 minute vehicle count data from N1 and S1) were adjusted to post-intervention values in accordance with the changes in traffic average speeds due to the intervention, based on an approximate value for the elasticity of traffic flow with respect to traffic average speed[155] of 0.75. This method was seen as more likely to provide realistic post-intervention 5 minute vehicle count data.

[155] The elasticity of traffic flow with respect to traffic average speed was an elasticity of demand, i.e. the response of the demand for use of a road (traffic flow) to a change in traffic average speed. For example, if traffic average speed is reduced due to imposition of a lower speed limit, the response is less demand to travel on that road. An approximate value for the elasticity of traffic flow with respect to traffic average speed was based on: the long run elasticity of car-km (equivalent to flow over a fixed link length as in the case study application) with respect to car travel time of -0.74 reported by De Jong and Gunn (2001) and Graham and Glaister (2004), and the long run average elasticity of traffic volume with respect to travel time of up to -1.00 reported by Goodwin (1996); and on the fact that speed varies in inverse proportion to travel time, which reverses the sign of the elasticity (Blainey *et al.* 2012).

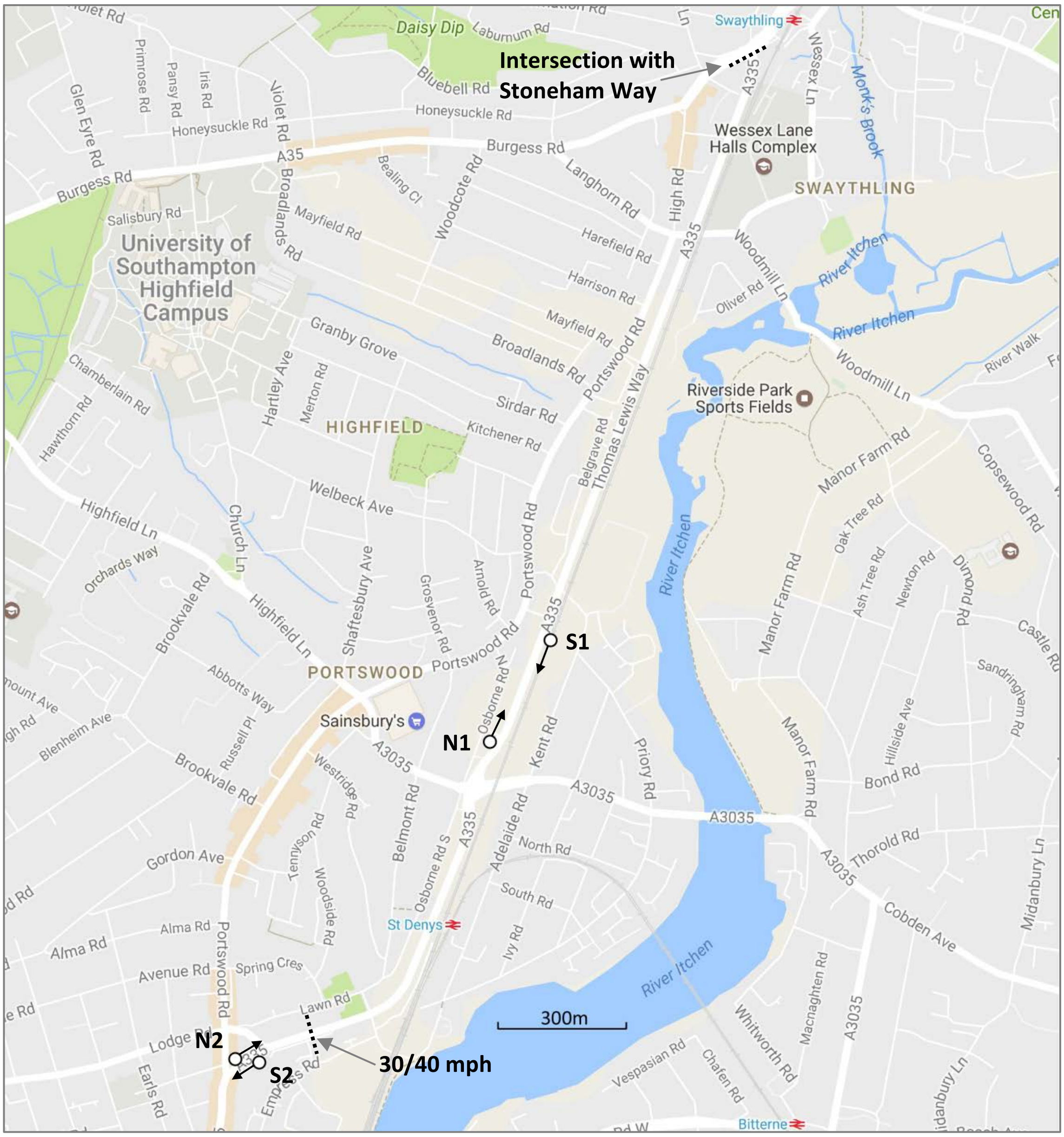

Figure 7-14: Map of Thomas Lewis Way for the case study application of PEMLA.

- 30/40 mph indicates the speed limit change location.
- The testbed section of Thomas Lewis Way between the 30/40 mph speed limit change location and the intersection with Stoneham Way is 2.56 km in length.
- N1 is the pre-intervention northbound ILD; S1 is the pre-intervention southbound ILD.
- N2 is the post-intervention northbound ILD; S2 is the post-intervention southbound ILD.
- Scale bar indicates a distance of 300 metres.
- Source: Base map obtained from Google Maps.

The analysis period was selected as the three-hour AM peak period (07:00 to 10:00) on Monday 7th to Friday 11th March 2016 (i.e. a typical weekday peak period with no special events or school holidays). Traffic average speed and average 5 minute vehicle count were calculated as the average over the 5 day period of the values in the U07 message returned by the ILDs for each 5 minute period between 07:00 and 10:00. Averaging over these time periods is consistent with the guidance provided by the DfT for application of the Basic Local Authority Carbon Tool. For example, all worked examples included in the Carbon Tool user guidance document involve traffic average speeds that are averaged over peak periods or inter-peak periods (i.e. a constant traffic average speed for the whole period) indicating this is the intention for typical applications (DfT 2011b), although this does not preclude shorter time periods being used by LGAs if desired. The ILD providing post-intervention, southbound traffic average speed data (S2 in Figure 7-14) failed to operate on Thursday 10th March. This intermittent failure of an ILD is likely to be typical of the sort of problem an LGA might encounter when applying PEMLA. The problem was overcome in the case study by taking an average of the data for the four other days when the ILD was operational. A screenshot of the PEMLA spreadsheet tool is shown in Figure 7-15.

INPUT				
Deduction due to biofuel use under RTFO	3.29	%		
Intervention ID	Thomas Lewis Way, N bnd, 40 to 30			
Date(s) of Assessment Period	Mon 07 Mar to Fri 11 Mar 2016			
Assessment Period Time of Day	07:00 to 10:00 (AM weekday peak)			
Length of Assessment Period	3	hours		
	Pre-Intervention		Post-Intervention	
Road Length	2.56	km	2.56	km
Fleet-Mix (Fraction of total VKMs)				
Category 01: Car, Petrol, <1400cc, Pre-Euro 5	8.0%		8.0%	
Category 02: Car, Petrol, <1400cc, Euro 5	6.5%		6.5%	
Category 03: Car, Petrol, <1400cc, Euro 6	3.6%		3.6%	
Category 04: Car, Petrol, 1400-2000cc, Pre-Euro 5	8.5%		8.5%	
Category 05: Car, Petrol, 1400-2000cc, Euro 5	6.9%		6.9%	
Category 06: Car, Petrol, 1400-2000cc, Euro 6	3.8%		3.8%	
Category 07: Car, Petrol, >2000cc, Pre-Euro 5	2.4%		2.4%	
Category 08: Car, Petrol, >2000cc, Euro 5	1.9%		1.9%	
Category 09: Car, Petrol, >2000cc, Euro 6	1.1%		1.1%	
Category 10: Car, Diesel, <2000cc, Pre-Euro 5	8.8%		8.8%	
Category 11: Car, Diesel, <2000cc, Euro 5	12.1%		12.1%	
Category 12: Car, Diesel, <2000cc, Euro 6	6.8%		6.8%	
Category 13: Car, Diesel, >2000cc, Pre-Euro 5	3.7%		3.7%	
Category 14: Car, Diesel, >2000cc, Euro 5	5.1%		5.1%	
Category 15: Car, Diesel, >2000cc, Euro 6	2.9%		2.9%	
Category 16: LGV, Petrol, All	0.3%		0.3%	
Category 17: LGV, Diesel, All Weights, Pre-Euro 5	3.3%		3.3%	
Category 18: LGV, Diesel, All Weights, Euro 5	7.4%		7.4%	
Category 19: LGV, Diesel, All Weights, Euro 6	2.3%		2.3%	
Category 20: HGV, Rigid, All	1.7%		1.7%	
Category 21: HGV, Artic, All	0.4%		0.4%	
Category 22: Bus, All	1.0%		1.0%	
Category 23: Coach, All	0.4%		0.4%	
Category 24: Two-Wheel, All	1.2%		1.2%	
Check Total	100.0%		100.0%	
ILD Traffic Average Speed	28	km/h	25	km/h
Average ILD 5 minute vehicle count	40	vehicles	37	vehicles
Access Density	1.56	int./km	1.56	int./km
Speed Limit	40	mph	30	mph
Time of Day (peak/off-peak)	Peak		Peak	

OUTPUT				
	Pre-Intervention		Post-Intervention	
Total VKMs	3686	km	3410	km
EF_T	283	gCO_2/VKM	328	gCO_2/VKM
Total Emissions	1042	$kgCO_2$	1117	$kgCO_2$
Total Emissions after biofuel deduction	1007	$kgCO_2$	1080	$kgCO_2$
Contribution to EF_T (gCO_2/VKM)				
	17.8		21.5	
	13.0		15.9	
	6.6		8.1	
	22.1		26.3	
	16.2		19.5	
	8.1		9.9	
	8.4		9.7	
	6.1		7.2	
	3.0		3.6	
	17.7		21.6	
	21.9		27.0	
	11.2		13.9	
	10.9		12.9	
	13.5		16.1	
	6.9		8.3	
	1.2		1.3	
	9.9		11.6	
	21.7		25.5	
	6.5		7.7	
	31.1		31.2	
	6.1		6.1	
	15.1		15.0	
	5.9		5.9	
	1.3		1.7	
Total	282.6		327.6	

Figure 7-15: Screenshot of the PEMLA spreadsheet tool.

For comparison, the TRL/NAEI EM was also applied to the case study intervention (using ILD traffic average speed as input). To ensure consistency in this comparison, for both EMs, the scaling factors for real-world effects (LDVs=1.15, rigid HGVs=1.351 and articulated HGVs=1.023) were applied during calculation of predicted EF_T and the 3.29% deduction due to biofuel use was applied to total predicted emissions.

Results of the application of PEMLA and TRL/NAEI EM to the case study intervention are shown in Table 7-3. Both EMs predicted an increase in EF_T due to the intervention in both northbound and southbound directions (northbound PEMLA 16% and TRL/NAEI 6% increase; southbound PEMLA 18% and TRL/NAEI 19% increase). However, both EMs predicted an overall decrease in total emissions for the three-hour AM peak period (PEMLA 2% and TRL/NAEI 7% decrease), which was due to the reduction in VKMs more than offsetting the increase in EF_T.

Table 7-3: Summary details from application of PEMLA and TRL/NAEI EM to a case study intervention.

	Pre-Intervention	**Post-Intervention**
Northbound:		
Road Length (km)	2.56	2.56
Traffic Average Speed (km/h)	28	25
Average 5 minute vehicle count (vehicles/5 minutes)	40	37
Access Density (intersections/km)	1.56	1.56
Speed Limit (mph)	40	30
Time of Day	Peak Period	Peak Period
Total VKMs in 3 Hour Period (km)	3686	3410
PEMLA Predicted EF_T (gCO_2/VKM)	283	328
PEMLA Predicted Change in EF_T (gCO_2/VKM)	-	45 (16%) increase
PEMLA Predicted Total Emissions in 3 Hour Period (kg CO_2) *Including 3.29% deduction for biofuel use under the RTFO*	1007	1080
TRL/NAEI EM Predicted EF_T (gCO_2/VKM)	226	239
TRL/NAEI EM Predicted Change in EF_T (gCO_2/VKM)	-	13 (6%) increase
TRL/NAEI EM Predicted Total Emissions in 3 Hour Period (kg CO_2) *Including 3.29% deduction for biofuel use under the RTFO*	805	789
Southbound:		
Road Length (km)	2.56	2.56
Traffic Average Speed (km/h)	36	25
Average 5 minute vehicle count (veh./5 mins.)	74	56
Access Density (int/km)	1.56	1.56
Speed Limit (mph)	40	30
Time of Day	Peak Period	Peak Period
Total VKMs in 3 Hour Period (km)	6820	5161
PEMLA predicted EF_T (gCO_2/VKM)	277	328
PEMLA Predicted Change in EF_T (gCO_2/VKM)	-	51 (18%) increase
PEMLA Predicted Total Emissions in 3 Hour Period (kg CO_2) *Including 3.29% deduction for biofuel use under the RTFO*	1826	1691
TRL/NAEI EM Predicted EF_T (gCO_2/VKM)	201	239
TRL/NAEI EM Predicted Change in EF_T (gCO_2/VKM)	-	38 (19%) increase
TRL/NAEI EM Predicted Total Emissions in 3 Hour Period (kg CO_2) *Including 3.29% deduction for biofuel use under the RTFO*	1326	1194

Table 7-3 continued.

	Pre-Intervention	Post-Intervention
Combined Northbound and Southbound Total:		
PEMLA Predicted Total Emissions in 3 Hour Period (kg CO_2) *Including 3.29% deduction for biofuel use under the RTFO*	2833	2771
PEMLA Predicted Change in Emissions in 3 Hour Period (kg CO_2)	-	62 (2%) decrease
TRL/NAEI EM Predicted Total Emissions in 3 Hour Period (kg CO_2) *Including 3.29% deduction for biofuel use under the RTFO*	2131	1983
TRL/NAEI EM Predicted Change in Emissions in 3 Hour Period (kg CO_2)	-	148 (7%) decrease

- Period analysed was the 3 hour AM peak period (07:00 to 10:00) for Monday 7th to Friday 11th March 2016.
- Scaling factors for real-world effects (LDVs=1.15, rigid HGVs=1.351 and articulated HGVs=1.023) were applied during calculation of predicted EF_T; and the 3.29% deduction due to biofuel use was applied to predicted total emissions.

It is acknowledged that this case study application of PEMLA covered only a single road section rather than a whole network (or substantially large part of a whole network) and involved some optimistic assumptions (particularly that ILD data from a 30 mph speed limit section could be transferred to a 40 mph speed limit section). However, the case study application served the purpose of illustrating how PEMLA can be applied in practice.

When assessing and comparing the emissions impact of transport interventions, it is (arguably) the change in emissions that is of most interest to LGAs. In other words, LGAs are interested in the difference in emissions due to an intervention, rather than the absolute values of pre- and post-intervention emissions. The accuracy comparison performed in this project (Table 6-20) represented how accurately PEMLA (MAF=1.02) and TRL/NAEI EM (MAF=0.88) predicted absolute values of emissions. In contrast, as well as demonstrating how PEMLA can be applied in practice, the case study application was the initial step in the process of quantifying the difference between the change in emissions due to interventions predicted by PEMLA and the TRL/NAEI EM (for the case study intervention, the figures were a 2% reduction predicted by PEMLA and a 7% reduction predicted by TRL/NAEI EM). To continue this process, both PEMLA and TRL/NAEI EM need to be applied to a range of further case study interventions. These further case studies should be based on actual rather than hypothetical interventions (i.e. based on real-world pre- and post-intervention data to reduce the need for assumptions) and be assessed on a wider, whole-network scale (i.e. to better align with PEMLA's intended scale of application). This is an area for future work (refer to Section 7.4.2). To then complete the process, opinions from LGA emissions modelling experts should be sought on the results from the range of case study applications to determine if the difference between changes in emissions predicted by the two EMs is large enough to have a material effect on LGA decision making (i.e. to determine if the use of PEMLA is likely to make a difference to LGA decision making compared to the use of TRL/NAEI EM). A potential method for collecting such opinions would be a series of focus groups of LGA emissions modelling experts, which (as already suggested in Section 7.3.3) are also an area for future work (refer to Section 7.4.3).

7.4 FUTURE WORK

7.4.1 Further Data Collection

In Section 7.2.4.3 a requirement was identified to investigate the problem of unexpected n-shaped curves when EFs predicted by PEMLA were plotted against traffic average speed for certain individual vehicle categories (i.e. LDVs and two-wheel vehicles). A possible solution was put forward that involved re-measuring traffic average delay rate using an alternative method. The suggested alternative method would require a database of short-run average travel times (e.g. monthly or yearly averages) for each ILD, during different periods of the day (e.g. peak and off-peak periods), on different days of the week, to be compiled. The difference between actual travel time (from the traffic average speed in the U07 message at time of vehicle crossing) and short-run average travel time (from the database) would then be used as the new measure of traffic average delay rate. To complete the investigation, PEMLA v.7 would then need to be re-calibrated based on the new values of traffic average delay rate IVs, and then the curves of predicted EFs against traffic average speed re-plotted for individual vehicle categories.

In Section 7.2.5.2 a requirement was identified to investigate the discrepancy between EFs predicted by AIRE and EFs calculated from PEMS measurements. A potential method to achieve this would be to use the GPS trip segment driving patterns collected from the PEMS-equipped bus as inputs to PHEM (i.e. a more detailed IEM than AIRE), and to use the resulting outputs as guidance as to which source of EFs (AIRE or PEMS) was most likely to be accurate. Additionally, it would be informative to ascertain whether similar discrepancies exist in other vehicle categories through collection of further PEMS data from vehicle categories other than buses for comparison to predictions from AIRE, PEMLA and TRL/NAEI EM. This further PEMS data collection would also allow the partial validation of PEMLA against PEMS data to expand beyond the bus category.

In general, it has been suggested that the real test of any model depends on the ability of that model to accurately predict outcome variable values from observations of predictor variable values not used in estimating the model's parameters (Haan 1977). Confidence in the application of PEMLA will therefore continue to increase through the process of further validation based on comparison of PEMLA predictions with PEMS data.

7.4.2 Wider Case Study Application

It was identified in Section 7.3.7 that the process of comparing the emissions impacts of interventions predicted by PEMLA and TRL/NAEI EM should be continued through further case study applications, and an outline method to achieve this is proposed based on using Southampton as the testbed urban area. The University of Southampton has archived U07 message data for the period between August 1999 and January 2009 (data were not stored after January 2009 until the download link from Southampton's City Depot traffic control centre was re-established in March 2015). Therefore, real-world interventions implemented within these dates (Aug 1999 to Jan 2009; and Mar 2015 to present) will have pre- and post-intervention ILD data available.

The proposed method involves analysing an intervention's impact during the different daily time periods likely to be of interest to LGAs: namely weekday (Monday to Friday) peak periods (07:00-10:00 and 16:00-19:00), weekday inter-peak period (10:00-16:00), and weekend daytimes (Saturday 09:00-20:00 and Sunday 10:00-20:00) as defined in DfT (2015b). The necessary traffic variable EM inputs (except access density) would be calculated from the historic U07 message data, with an average value for each variable calculated for each time period over the course of a week both pre- and post-intervention (i.e. similar to the averaging period used in the case study application detailed in Section 7.3.7).

Appropriate geographic boundaries of the area for analysis can be defined based on the expected extent of a given intervention's influence, and the road network contained therein divided into suitable segments (i.e. constituting at least two consecutive links consistent with the trip segment definition used in PEMLA calibration and the ideal minimum spatial resolution for PEMLA application) such that ILD data are available for each segment. As in the case study application in Section 7.3.7, based on the average traffic variable values for each segment, a segment-specific composite EF_T (gCO_2/VKM_T) for the traffic as an aggregate whole can be calculated for pre- and post-intervention scenarios using both PEMLA and TRL/NAEI EM. Depending on the intervention in question, these composite EFs can be calculated based on the assumption that the fleet mix is held constant (e.g. assuming fractions of VKMs for each vehicle category are in accordance with the NAEI national fleet model for both pre- and post-intervention scenarios) or that the fleet mix is altered by the intervention with intervention-specific fractions of VKMs used as EM inputs.

Again as in the case study application in Section 7.3.7, the total number of vehicles on a trip segment can be calculated based on the average value for a time period of traffic flow for the segment. Multiplying the number of vehicles by trip segment length gives total VKMs, which can then be multiplied by the segment-specific EF_T to calculate emissions for a segment. Finally, total emissions for a scenario are the sum of total emissions for each segment. Thus, the proposed method allows the emissions impact of the intervention to be predicted by both EMs, and these predictions can then be compared.

A potential issue with the proposed method is the selection of appropriate case study interventions in Southampton. Finding real-world interventions large enough to have had an influence on a substantial proportion of the surrounding road network in areas covered by suitable, operational ILDs (i.e. ILDs installed across one rather than two lanes) is likely to be hindered by the uneven distribution of such ILDs across Southampton's road network (although the number of operational ILDs tends to increase as the data goes back in time). For example, a substantial development between August 1999 and January 2009, located in Southampton city centre that would have had an influence on the city's road traffic was the opening of the WestQuay shopping centre (refer to Figure 7-16), which occurred on the 28th September 2000. This development appears suitable as a case study intervention. However, the roads in the immediate vicinity of WestQuay (arguably the most important roads to include in the analysis, where the intervention's influence is strongest) typically have single ILDs installed across two road lanes, meaning the associated U07 message data is not suitable for calculating EM inputs. If suitable data cannot be found for interventions that have already been implemented in Southampton, then it will be necessary to wait for an appropriate intervention to be implemented, or to investigate the possibility of obtaining U07 message data for interventions implemented in other urban areas; although this second option would first require PEMLA to be validated for the other urban area in question (refer to Section 7.4.5).

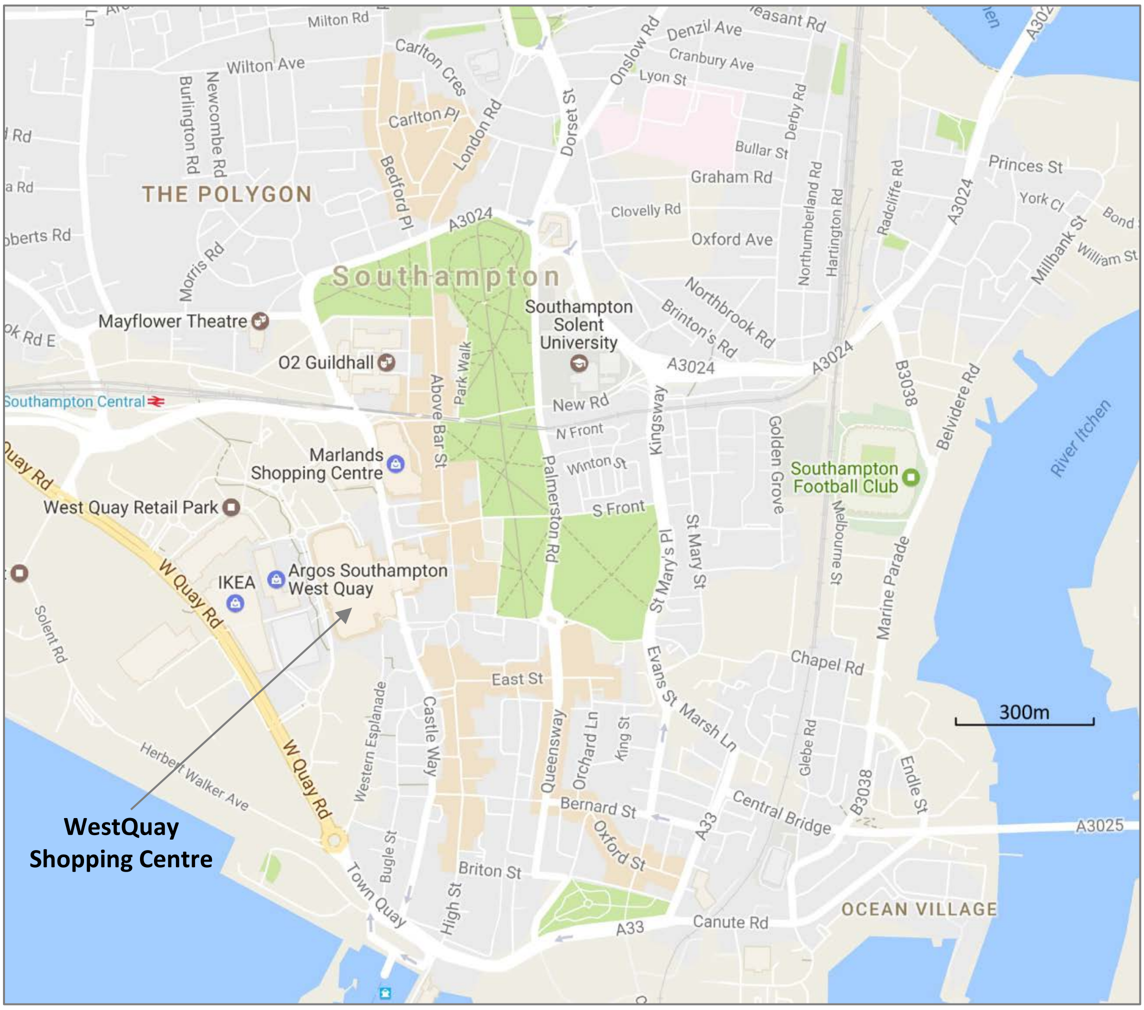

Figure 7-16: Map of the location of the WestQuay shopping centre in Southampton city centre.

- Scale bar indicates a distance of 300 metres.
- Source: Base map obtained from Google Maps.

7.4.3 LGA Focus Groups

A series of focus groups of LGA emissions modelling experts should be convened to establish how PEMLA can be best utilised by LGAs. This could be achieved through attending appropriate established events (e.g. Siemens UTC User Group meeting). Alternatively, when responding to the LGA survey, 13 participants indicated they would be interested in receiving a report detailing the results, and these 13 participants could be invited to take part in a focus group. The focus groups would also be an ideal opportunity to present results from case study applications of PEMLA and gather opinions on whether the magnitude of any difference between the change in emissions due to an intervention as predicted by each EM (i.e. PEMLA and TRL/NAEI EM) is likely to materially affect LGA decision making.

7.4.4 Extension to Other Pollutant Emissions

The methodology used to develop PEMLA can be readily adapted to develop versions for predicting other pollutant emissions. For example, alongside calculating emissions of total carbon (mg), AIRE also calculates emissions of NO_X (mg) and PM_{10} (mg) for each driving pattern input. If a version of PEMLA was to be developed for any other pollutants (e.g. CO or HC), then AIRE would have to be replaced in the methodology by an alternative IEM that included the pollutants of interest.

However, minimum spatial resolution is a potential barrier to the application of a PEMLA version developed for predicting AQ emissions. Using EFs that are averaged over distances of a link (or longer) to calculate area-wide total emissions is a suitable approach for CO_2 because it is the overall amount of CO_2 emitted that is important due to the global nature of this pollutant's detrimental effect (i.e. climate change). Area-wide prediction of AQ emissions is also an important indicator when assessing the impact of transport interventions. However, a localised assessment is arguably more important for AQ emissions because the location of emissions in relation to the human population is far more important than for CO_2. For example, high vehicle acceleration events associated with a particular localised network characteristic (e.g. intersection, speed hump or pedestrian crossing), which cause high emissions in the vicinity of a sensitive receptor (e.g. school or hospital) may be very important for local air quality.

This barrier applies not only to PEMLA but also to any EM type with a minimum spatial resolution of (at least) link length (refer to Section 7.3.2). In other words the barrier applies to Aggregate, Average Speed, Traffic Situation, Traffic Variable and Cycle Variable EMs, all of which calculate average EFs over longer distances, and will therefore not have the ability to accurately predict localised spikes in emissions. In this situation, application of a Modal EM may be the only suitable solution.

7.4.5 Extension to Other Urban Areas

PEMLA was calibrated based on real-world data (GPS driving patterns and ILD data) collected from Southampton's road network. Due to the Southampton-specific nature of this data, the transferability of PEMLA requires validation before it can be confidently applied in other UK urban areas. This validation would involve comparing PEMLA predicted EFs based on inputs calculated from ILD data collected in the new urban area of interest with observed EFs, calculated either from PEMS data (which would be true validation) or from GPS driving pattern inputs to AIRE (which would be model comparison), also collected in the new urban area.

Validation of the transferability of PEMLA would also provide a method to test the robustness of the assumption underlying PEMLA development that the ILD data were collected from a typical UTC system layout, which embodied the usual range of ILD positions across the network (refer to Section 5.4.4), i.e. to test that PEMLA is robust to application on a different network likely to have ILDs positioned in (slightly) different locations relative to intersections.

PEMLA is less likely to be transferrable to urban areas outside the UK due to differences in factors such as network characteristics (e.g. intersection types and layouts, pedestrian crossing types, speed limits), traffic management strategies (e.g. traffic signal control, rerouting, dynamic speed limits, bus priority) or vehicle fleet compositions (e.g. Euro Standards are of limited relevance outside Europe). This means validation of PEMLA in other countries is less likely to succeed. However, the methodology used to develop PEMLA is readily transferrable, and could easily be applied to enable other country-specific versions to be calibrated.

Chapter 8 CONCLUSIONS

8.1 INTRODUCTION

The presentation of conclusions that have been drawn from the investigations conducted during the course of this research has been divided into five main sections. Section 8.2 details the general conclusions of the research. Section 8.3 describes conclusions relating to the limitations of the research and Section 8.4 describes conclusions relating to suggested further work. The main contributions made by the research are summarised in Section 8.5, including a set of guidelines provided to assist LGAs in using PEMLA. Finally, Section 8.6 considers the extent to which the original research questions that constituted the framework for this project have been answered.

8.2 GENERAL CONCLUSIONS

A conclusion drawn from the qualitative evidence available in the literature relevant to the emissions modelling process was that, as the situation currently stands, LGAs do not necessarily have the right options to include accurately the effects of congestion on emissions of CO_2 (or other pollutants) from traffic on urban road networks. After consideration of the road traffic data likely to be readily available, a hypothesis was formed that the optimal model complexity for LGAs was represented by a Traffic Variable EM (refer to Section 2.7). Cycle Variable and Modal EMs are more complex EMs that calculate emissions for individual vehicles, but were discounted because they require driving patterns as inputs, which are difficult to collect, rarely used in traffic engineering to describe road network performance, and simulated with questionable accuracy in micro-scale Road Traffic Models (micro-RTMs). In contrast, traffic variables are used to describe network performance and are more readily available to LGAs. Aggregate, Average Speed and Traffic Situation EMs all use traffic variables as inputs, but they are less complex than Traffic Variable EMs and may not fully realise the explanatory power of all traffic variables available to LGAs, which could be used to explicitly include congestion influence and improve emissions prediction accuracy. However, a further conclusion drawn from the relevant literature was that, if the hypothesis was correct and LGAs are best-served by Traffic Variable EMs, the existing models of this type typically have limitations which prevent such use (refer to Section 2.6.4).

A conclusion drawn from the results of the survey of LGA emissions modelling experts was that scarcity of resources was the paramount issue for LGAs when conducting road traffic emissions modelling (refer to Section 4.5). Survey participants placed particular importance on EMs having the flexibility to be reusable for assessment of future transport interventions, and on a requirement for input data to be easily available. Of the road traffic data sources that can provide EM inputs, UTC systems and RTMs were found to be the most convenient options for LGAs because they were ranked highly by participants as easily obtainable data likely to be included in future collection plans, and because they can both provide traffic variables on a link-by-link basis for all (or mostly all) links in a network. The large majority of LGA emissions modelling is currently achieved using Average Speed EMs, with more detailed EM types being used rarely (if at all). However, both UTC systems and RTMs can generate other traffic variables (in addition to traffic average speed) whose incorporation as inputs could improve the accuracy of EMs for LGAs. Therefore, similar to the conclusions of the literature review, a Traffic Variable EM based on inputs generated by UTC systems or RTMs was seen as the most appropriate option for LGAs. A further important conclusion drawn from the survey results was that any development of a Traffic Variable EM that seeks to improve on the accuracy of Average Speed EMs must come at minimal additional cost to LGAs because they indicated a reluctance to commit extra resources for improved accuracy; although this barrier may prove to be less consequential where a transport intervention is of high significance to the local political agenda.

The two key conclusions of the literature review and LGA survey can be summarised as follows: (1) Traffic Variable EMs were identified as potentially offering an improved ability to capture congestion impacts compared to the widely used alternative of Average Speed EMs, through including other traffic variables (in addition to traffic average speed) as quantifiable measures of congestion, with little associated increase in complexity; and (2) ILDs were identified as a readily available source of these traffic variables, where collection does not entail additional expenditure of resources by LGAs.

The main experimental investigation of this project was built on these two conclusions and sought to develop a Traffic Variable EM based on input data generated by ILDs in UTC systems (or by simulated ILDs in RTMs), and then to compare the performance of this new EM (PEMLA) to the next-best alternative available to UK LGAs (TRL/NAEI EM). This was achieved through collection of GPS driving patterns from vehicles using Southampton's road network for use as inputs to an IEM (AIRE) to generate accurate vehicle EFs, alongside collection of data from Southampton's SCOOT UTC system from the ILDs crossed by vehicles during their journeys for calculation of associated traffic variables (except access density, which was calculated by map inspection). Statistical analysis of the traffic variables (predictor variables) and accurate EFs (outcome variable) led to the conclusion that, if vehicle category was also incorporated as a predictor variable, it was possible to develop a Traffic Variable EM for use by LGAs (PEMLA), designed to predict network-level road traffic CO_2 emissions.

PEMLA out-performed TRL/NAEI EM in accuracy comparison (Table 6-20) through using as inputs other traffic variable congestion indicators (in addition to traffic average speed), which provided an improved ability to capture the influence of congestion on emissions. Traffic variable inputs to PEMLA (except access density) are calculated from ILD data that are considered a by-product of UTC systems, which means they are readily available to LGAs and their re-purposing as EM inputs is an efficient use of resources. Operation of PEMLA therefore will be within LGAs' limited resources and no more expensive than that of the existing TRL/NAEI EM. The combination of these two factors (i.e. improved accuracy without increased resource consumption) led to the conclusion that PEMLA represented an EM closer to optimal complexity for LGAs than TRL/NAEI EM (refer to Section 7.3.1).

A stand-alone form of PEMLA, able to accept inputs obtained from either real-world ILDs in UTC systems or simulated ILDs in RTMs, offered the greatest utility to LGAs, leaving them free to apply PEMLA as their individual situations warranted, which accommodated the fact that the way in which EM outputs are used to inform policy making can be subject to considerable variation between different LGAs (refer to Section 7.3.3). A stand-alone version of PEMLA in a spreadsheet format provides outputs similar to the Basic Local Authority Carbon Tool (a stand-alone spreadsheet EM based on the TRL EFs 2009 emission functions, refer to Section 2.5.5.2), which will be appropriate for use in LGA policy making considering that the DfT specifically designed the Carbon Tool for this purpose. A stand-alone PEMLA also brings flexibility for re-use in assessment of many different (as yet undetermined) transport interventions, which was considered by LGA survey participants to be the most important factor affecting allocation of resources to emissions modelling (refer to Section 4.4), rather than PEMLA being integrated into a UTC system or RTM software application where PEMLA's use would then be restricted to only those occasions when the host system was deployed.

8.3 RESEARCH LIMITATIONS

The wider purpose of this project was to provide a practical method for LGAs to more accurately estimate road traffic CO_2 emissions in urban areas at network-level. In accordance with this purpose, PEMLA was not designed to be disaggregated into individual vehicle categories; but when such disaggregation was performed, analysis of EFs plotted against traffic average speed for certain individual vehicle categories produced counter-intuitive results, particularly at very low traffic average speeds (i.e. unexpected n-shaped curves for LDV and two-wheel vehicle categories, refer to Section 7.2.4.1). These results indicated the presence of an ecological fallacy within PEMLA whereby a model based on analysis at a higher level of data aggregation (e.g. all vehicle categories combined) is only valid for application at that level, and cannot be used to describe behaviour at lower levels of data aggregation (e.g. separate vehicle categories) where the relationships from the higher level are not necessarily demonstrated with the same strength (Robinson 1950; Lichtman 1974; Clark and Avery 1976).

The preferred solution to overcome the counter-intuitive results for certain individual vehicle categories proposed for investigation in future work was an alternative method for measuring traffic average delay rate based on comparing travel time at the current traffic average speed with travel time at the short-run traffic average speed (refer to Section 7.2.4.3). However, whilst re-measurement of traffic average delay rate could be a suitable solution to the problem of counter-intuitive n-shaped EF curves (for the reasons explained in Section 7.2.4.3), it is unlikely to provide substantial improvement upon the general situation for the traffic variables, which possessed only moderate performance as predictors of CO_2 emissions (refer to Section 6.3.2). Therefore, PEMLA will again have to be calibrated by MLR analysis of a combined dataset including vehicle category as an additional predictor variable, which will mean the potential for ecological fallacy remains. It may be the case that the only solution to establishing a model with the ability to accurately describe within-category relationships between the traffic variables and emissions is collection of a bigger dataset with more variation in traffic variable values allowing the full relationship between traffic variables and emissions to be captured (i.e. overcoming the problem of the relatively small ranges of values for the traffic variables measured during this project, refer to Section 7.2.1); although, as experience from this project has demonstrated, it is difficult to obtain this wider variation from data collection in a real-world situation.

Despite the limitations of PEMLA predictions for individual vehicle categories imposed by the likely presence of an ecological fallacy, based on the results of model comparison (Table 6-18) and accuracy comparison (Table 6-20), overall predictions by PEMLA of total emissions from all vehicle categories at network-level (i.e. the aggregation level at which PEMLA was calibrated and the purpose for which it was designed) were satisfactory and compared favourably with results for TRL/NAEI EM. PEMLA is therefore recommended as suitable for estimating emissions for an urban road network (or substantially large parts of a network) as a whole.

Introduction of PEMLA would represent a new EM unfamiliar to LGA staff, which would bring initial disadvantages such as a requirement for staff training, longer timescales to use unfamiliar software applications, and lack of comparability of results with previous intervention assessments conducted with different EMs; although LGAs are likely to encounter these challenges regardless due to the imminent introduction of COPERT (refer to Footnote 52 in Section 2.5.5.1). Additionally, PEMLA is only applicable to urban roads with 30 or 40 mph speed limits since all the data used for PEMLA's development were collected from these road types. This means PEMLA is suitable for the large majority of urban roads, but would benefit from extension to include the remaining urban road types with 20 or 50 mph speed limits.

PEMLA is only applicable to CO_2 emissions; although this is a criticism that could also be levelled at the DfT Basic Local Authority Carbon Tool. If LGAs want to assess the impact of an intervention on other pollutant emissions, an alternative EM would be required (e.g. the TRL/NAEI EM, which includes a wider range of pollutants). This limitation is important in light of the recent shift in political emphasis towards AQ emissions, although it is equally important to remember that the long-term issue of global warming has not receded. A related point is that PEMLA's minimum spatial resolution is (at least) link length (a limitation common to all EM types except Modal EMs, refer to Section 7.3.2), which is appropriate for CO_2 whose emissions are important on a global scale, but would be less appropriate for air quality whose emissions are likely to be important on a local (sub-link length) scale.

PEMLA is applicable over a narrower range of traffic average speeds than TRL/NAEI EM, having been calibrated for speeds between 4 to 41 km/h (Table 6-10). However, because speeds were collected from real-world Southampton-specific data, this range will be a good characterisation of that typically found in cities, and is likely to be sufficient for application to urban roads. In contrast, TRL/NAEI EM is valid for traffic average speed ranges equal to, or greater than, 6 to 75 km/h depending on vehicle category; although speeds at the higher end of this range are likely to be redundant for application to urban roads.

Vehicle categories using low carbon alternative drivetrains or fuels were excluded from PEMLA (apart from use of biofuel, which was discounted at a constant rate in accordance with the RTFO) due to their small fraction of total national VKMs, and associated small contribution to CO_2 emissions (refer to Section 2.3.12). However, a time when the majority of the global road vehicle fleet is alternatively fuelled (e.g. electric, natural gas or hydrogen) still appears to be some years, possibly decades, away. In the meantime modelling emissions from conventionally fuelled ICE vehicles remains an important task, and PEMLA is a practical option to fulfil this requirement.

Low carbon technologies installed on conventionally fuelled ICE vehicles were included in PEMLA via TSAFs (because TSAFs were calculated using TRL/NAEI EM, which includes assumptions to account for these low carbon technologies, refer to Sections 5.3.5.3 and 7.3.6). However, the market penetration of low carbon technologies was only included up to and including vehicles compliant with the current Euro Standards (Euro 6/VI which are the latest standards available in TRL/NAEI EM). Inclusion of the low carbon technologies that will be installed on future vehicles compliant with the next round of Euro Standards would require recalibration of PEMLA to include Euro 7/VII vehicle categories, or application of a percentage discount to PEMLA predictions to account for the impact of such technologies on emissions. In general, the requirement for on-going re-calibration to accommodate newer vehicle categories entering the fleet is an issue that affects all EMs (refer to Section 2.6.4).

A matter which arose during the development of PEMLA was the lack of comprehensive coverage of Southampton's road network by operational ILDs (refer to Section 5.4.2.2) suitable for generating the required input data for PEMLA (i.e. ILDs covering a single road lane, refer to Section 5.4.4). The passage of time coupled with increasingly restricted LGA budgets (i.e. limited funds available for UTC system maintenance) has led to a reduced number of operational and suitable ILDs in Southampton, meaning there are areas of the city where application of PEMLA (based on real-world ILD data) would not be possible due to a lack of input data. This was particularly highlighted as a problem in the wider case study application of PEMLA proposed for future work in Section 7.4.2. Assuming the example of Southampton is typical, a lack of input data may hamper the widespread application of PEMLA in other urban areas as well; although it is important to emphasise that, as an alternative, missing real-world ILD data can be supplied by simulated ILDs in a RTM of an urban area's road network instead.

That said, if PEMLA can be demonstrated to LGAs as a cost-effective method for assessing the impact of transport interventions on network-level CO_2 emissions, this would provide an incentive for LGAs to install and maintain the ILDs necessary to provide area-wide input data to PEMLA. This would also have the twin benefit of providing more comprehensive vehicle detection for use by the UTC system. Hence, the costs of installing and maintaining additional ILDs could be offset against both the saving from cost-effective emissions predictions using PEMLA and the benefits to the UTC system (in terms of improved progression for vehicles through the road network).

8.4 FUTURE WORK

A number of conclusions were drawn concerning potential future work in developing PEMLA. Investigating the unexpected n-shaped curves for EFs predicted by PEMLA plotted against traffic average speed for certain individual vehicle categories (refer to Section 7.2.4.3), and investigating the discrepancy between EFs predicted by AIRE and EFs calculated from PEMS data (refer to Section 7.2.5.2) both require further data collection and analysis. Additional case study applications of both PEMLA and TRL/NAEI EM to wide-scale real-world transport interventions would provide further quantification of the difference between the changes in emissions due to an intervention predicted by each EM. This quantification is important because it is (arguably) the magnitude of the change in emissions due to an intervention that is of most interest to LGAs (refer to Section 7.3.7). Focus groups of LGA emissions modelling experts could then be convened to collect opinions on case study results, and on the wider question of how PEMLA might best be utilised (refer to Section 7.4.3).

PEMLA would benefit from extension to include roads with 20 mph and 50 mph speed limits, which would then provide comprehensive cover of all roads found in UK urban areas (refer to Section 7.3.1). Due to the Southampton-specific nature of its development, the transferability of PEMLA requires validation before it can be confidently applied in other UK urban areas. Additionally, transferability of the PEMLA development methodology requires investigation to enable calibration of PEMLA for urban areas outside the UK (refer to Section 7.4.5). Given the current political emphasis on the reduction of AQ emissions, it would also be beneficial to investigate the transferability of the PEMLA development methodology to prediction of other pollutant emissions (refer to Section 7.4.4).

8.5 CONTRIBUTIONS OF THE RESEARCH

The research conducted during this project has made a number of contributions to the process of modelling CO_2 emissions from road traffic at network-level. Insight into the general situation regarding the attitudes and practices of British LGAs concerning the emissions modelling process was provided by the survey of LGA emissions modelling experts.

Investigation of the ability of ILD data to generate traffic variables capable of predicting CO_2 emissions was an important contribution for four reasons: (1) ILDs are widely installed traffic detectors; (2) ILDs can be easily simulated in RTMs; (3) ILD data can be considered a free by-product of UTC systems; and (4) ILD data have the potential for like-for-like replacement by data from other point detector systems (e.g. SDR, magnetometer or CCTV sensors).

As a result of investigating the prediction of CO_2 emissions based on ILD data, a new Traffic Variable EM (PEMLA) for use by LGAs was developed. The contribution of PEMLA is that, when assessing the impact of transport interventions, it allows LGAs to predict network-level emissions more accurately than the next-best alternative EM (TRL/NAEI EM) through being better able to account for congestion, whilst also remaining within LGAs' limited resources. Additionally, the quantitative comparison of the accuracy of a Traffic Variable EM (PEMLA) with an Average Speed EM (TRL/NAEI EM) has made a contribution to addressing the general lack of research dealing with quantification of prediction errors in road traffic EMs.

The title of the journal article providing an abridged version of Chapter 2 of this thesis (Grote *et al.* 2016a) posed the question "Including congestion effects in urban road traffic CO_2 emissions modelling: Do Local Government Authorities have the right options?" and concluded that, whilst a Traffic Variable EM was likely to represent the right option, existing methodologies for estimating network emissions based on traffic variables typically had limitations. The evidence for this finding was shown in the Traffic Variable EM section of Table 2-4 and discussed in Section 2.6.4, where the limitations of each Traffic Variable EM available to LGAs were summarised. PEMLA's contribution to the LGA emissions modelling process is to provide a suitable option by addressing these limitations. In other words, PEMLA contributes the following attributes: account for congestion is quantitative and explicit through the use of traffic variable inputs; it includes current vehicle categories (i.e. current Euro Standards); it includes all vehicle types in 24 different vehicle categories; it has been developed into a format easily useable by LGAs (i.e. encoded into a spreadsheet format); it is suitable for assessment of any type of transport intervention affecting road traffic; it is based on easily available input data generated by ILDs, either as a by-product of UTC systems or simulated in RTMs, with ILDs being the most widely installed type of traffic sensor (Kim *et al.* 2013); it does not rely on the installation of any specialist sensors; and, importantly from the perspective of UK LGAs, is a UK-specific development.

8.5.1 Guidelines for Use of PEMLA by LGAs

A set of guidelines has been compiled to provide practical assistance to LGAs in using PEMLA for the assessment of transport interventions. The guidelines summarise the main requirements for the use of PEMLA and are set out in a convenient list format below.

Staff Training Requirements

Staff training requirements are minimal because PEMLA is a spreadsheet EM based on the widely used Microsoft Excel software. With reference to the guidelines set out in this section (Section 8.5.1), in conjunction with a familiarity with the input data required and the SCOOT UTC system U07 message, collecting and entering the necessary PEMLA inputs should be relatively straightforward to anyone with a basic knowledge of Microsoft Excel. Interpretation of results is also relatively straightforward, with PEMLA outputs consisting of total emissions (kgCO_2) for each segment (defined as a series of at least two consecutive links) of the road network in a specified study area, over the duration of a specified study period. Total emissions at the network-level for the whole of a study area are then calculated as the sum of the emissions for each segment.

Input Data Requirements

For both pre- and post-intervention scenarios, the PEMLA input data required for each segment in a specified study area, averaged over the duration of a specified study period, are:

- Duration of the specified study period (hours).
- Segment length (km).
- Vehicle fleet mix consisting of the fraction of total VKMs performed by each PEMLA vehicle category, with the default being the NAEI national fleet model for urban roads in England outside London in 2016.
- Average value for: 5 minute traffic average speed (km/h) for the ILD(s) installed on a segment, extracted from the SCOOT U07 message.
- Average value for: 5 minute traffic flow (vehicles/5 minutes) for the ILD(s) installed on a segment, extracted from the SCOOT U07 message.

- Access density (intersections/km).
- Speed limit (mph).
- Peak or off-peak period.
- Percentage deduction to be applied to total CO_2 emissions due to biofuel use under the Renewable Transport Fuel Obligation (RTFO).

Obtaining the SCOOT U07 Message

The U07 message is a specialist SCOOT message developed at the University of Southampton. Although the message does not feature in SCOOT user manuals, it is available for download from any SCOOT system through contacting the local SCOOT operator. For example, in Southampton the message was readily available from Balfour Beatty Living Places Limited (the operator of Southampton's City Depot traffic control centre). The U07 message is generated daily (i.e. each message contains data for a particular day), and is downloaded in a dBase III format (an early database file format), which can be opened with Microsoft Excel software, and then saved in an Excel file format for convenient manipulation.

Data Extraction from the SCOOT U07 Message

A U07 message for a particular day contains data for each five minute period of the day. The following fields are relevant when extracting the data required for input to PEMLA: the SCN field contains the unique ILD loop identifier; the VALUE01 field contains the estimate of traffic average speed in km/h for the vehicles crossing an ILD in the last five minutes, i.e. 5 minute traffic average speed (km/h); the VALUE02 field contains the number of vehicles crossing an ILD in the last five minutes, i.e. 5 minute traffic flow (vehicles/5 minutes). The other fields (VALUE00, VALUE03, VALUE04, VALUE05 and VALUE06) are not relevant for use of PEMLA.

Data Extraction from Simulated ILDs

In situations where there are no real-world ILDs from which to collect the desired PEMLA input data, if a Road Traffic Model (RTM) of a specified study area has been developed as part of the transport intervention assessment process, then simulated ILDs installed in the RTM can be used as an alternative source of data. The data extracted from the simulated ILDs must be equivalent to that extracted from a U07 message. In other words, the required data are: an average value for the spot speeds (i.e. time-mean-speed) of vehicles crossing a simulated ILD, which is equivalent to 5 minute traffic average speed (km/h); and an average value for the number of vehicles crossing a simulated ILD in five minutes, which is equivalent to 5 minute traffic flow (vehicles/5 minutes).

Data Extraction from Other Types of Traffic Sensors

Where there is a desire to collect PEMLA input data from other types of traffic sensors (i.e. other than real-world or simulated ILDs), then any road traffic data source that can provide values for traffic average speed (time-mean-speed) and traffic count of vehicles passing the sensor location is likely to be suitable for providing PEMLA inputs. In other words, any sensor that acts as a point detector (i.e. a detector providing a snap-shot of vehicle activity at a point location in a road network) is likely to be suitable. For example, sensors such as magnetometer sensors (ILD-equivalent devices that are suitable for use in UTC systems), Speed Detection Radar sensors (which detect vehicles using microwave radar), or CCTV cameras (which use video analytics software to extract data from CCTV pictures). However, a caveat to the use of other types of traffic sensors is that the accuracy of PEMLA predictions based on data from such sources has not been verified. Verification would need to be accomplished before PEMLA could be used in this way with confidence.

Scaling Factors for Real-World Effects

Scaling factors are used in PEMLA to account for the effect on emissions of operating vehicles in the real-world (as opposed to emissions tests performed on vehicles under laboratory conditions); for example, the effect of the use of vehicle auxiliary systems such as air conditioning, or the effect of levels of vehicle maintenance. The scaling factors (LDVs=1.15, rigid HGVs=1.351 and articulated HGVs=1.023) are applied automatically during calculation of the predicted composite Emission Factor for the traffic (EF_T in gCO_2/VKM).

Vehicles with Alternative Drivetrains or Fuels

The use of biofuel under the RTFO is included in PEMLA through the percentage deduction applied to total CO_2 emissions (the magnitude of this deduction is a PEMLA input which can be adjusted in accordance with the current RTFO figure). Other than the use of biofuel, vehicles utilising alternative drivetrains or fuels, such as Battery Electric Vehicles (BEVs), Plug-in Hybrid Electric Vehicles (PHEVs), Hybrid Electric Vehicles (HEVs), Fuel Cell Vehicles (FCVs), and vehicles running on Compressed Natural Gas (CNG) or Liquefied Petroleum Gas (LPG), are excluded from PEMLA because they represent only a small fraction of total fleet VKMs. However, where necessary, the methods suggested in the DfT Basic Local Authority Carbon Tool EM to calculate

CO_2 emissions for some of these vehicle types can also be used with PEMLA. For LDVs running on LPG and CNG fuels, a correction factor should be applied to the predicted emissions for the relevant petrol LDV of 0.9 and 0.8, respectively. For cars that are PHEVs or BEVs, constant EFs should be used of 97.3 gCO_2/VKM and 53.4 gCO_2/VKM, respectively.

Vehicles with Low Carbon Technologies

The effect on emissions of low carbon technologies installed on conventionally fuelled (i.e. mineral petrol or diesel) internal combustion engine vehicles (e.g. stop-start engine technology; light-weight structures; reduced aerodynamic drag; efficient heating, ventilation and air conditioning systems; and waste energy recovery systems) are included in PEMLA.

Transferability to Other Urban Areas

PEMLA is likely to be transferable to other urban areas within the UK (i.e. other than Southampton). However, a caveat to this transferability is that the accuracy of PEMLA predictions in other urban areas has not been verified. Due to the Southampton-specific nature of the data used to develop PEMLA, this verification needs to be accomplished before PEMLA can be transferred with confidence. PEMLA is less likely to be transferrable to urban areas outside the UK due to differences in factors such as network characteristics, traffic management strategies, or vehicle fleet compositions. However, PEMLA's development methodology is readily transferrable, and could be used to develop other country-specific versions.

Traffic Average Speed Range

The data used to develop PEMLA had a range of 4 to 41 km/h for ILD traffic average speed. Therefore, the traffic average speed range specified for PEMLA application is from 4 to 45 km/h. Outside this range, the accuracy of PEMLA predictions may begin to degrade. However, because the data used to develop PEMLA were collected from ILDs in the real-world, the specified application range is likely to be sufficient to encompass the range of speeds typically found in UK urban areas.

Road Types

The data used to develop PEMLA were all collected from urban roads with 30 or 40 mph speed limits. Therefore, PEMLA is suitable only for application to roads of these types, which constitute the large majority of roads in UK urban areas.

Minimum spatial resolution

The minimum spatial resolution over which PEMLA will produce accurate emissions predictions is at least link length (and ideally segment length). In general, this constraint is true of all types of EMs except highly detailed Modal EMs. If an assessment of emissions is desired over a shorter spatial resolution (i.e. sub-link length), then a Modal EM is likely to be the only suitable option.

Network-level Emissions Calculation

PEMLA is designed to provide a practical method for LGAs to estimate total CO_2 emissions from road traffic in urban areas at the network-level, calculated as the sum of emissions from the traffic on the segments forming the road network of a particular study area. However, because PEMLA was calibrated at this level of aggregation, it can only produce reliable emissions estimates at the same level of aggregation, i.e. total emissions for the traffic at a minimum spatial resolution of at least link length (ideally segment length), in accordance with PEMLA's design purpose. Therefore, PEMLA emissions estimates will become less reliable if they are disaggregated according to individual vehicle categories (known as an ecological fallacy), and such disaggregation should be avoided.

8.6 ANSWERS TO RESEARCH QUESTIONS

The three research questions that constituted the framework for this project (refer to Section 2.6.5) are repeated here, followed by an assessment of the extent to which they have been answered.

1. *What data and models are currently used by LGAs for road traffic CO_2 emissions modelling, and what are their attitudes to the issues of resource use and prediction accuracy?*

The answer to Research Question 1 was provided by a combination of the literature review and the survey of LGA emissions modelling experts. In accordance with the objectives of this project to investigate methods for predicting CO_2 emissions useable by all (or the majority of) LGAs (refer to Section 1.1), the answer sought was of a general nature, i.e. an indication of the general situation rather than the nuances which are likely to vary from LGA to LGA.

2. *Is it possible to identify traffic variables as indicators of congestion that have a consistent relationship with CO_2 emissions from road traffic, and that are readily available to LGAs?*

The answer to Research Question 2 was provided by statistical analysis of the data collected from Southampton's road network, i.e. analysis of the ability of the selected traffic variables, which were all indicators of congestion, to act as predictor variables in predicting the outcome variable, which was accurate EF based on GPS driving pattern input to an IEM (AIRE). An important caveat to the answer is that the statistical relationship established between traffic variables and EF relied on the inclusion of vehicle category as an additional predictor variable. The traffic variables are readily available to LGAs because they were based on data from ILDs (except access density), which can be regarded as a by-product of UTC systems or can be simulated in RTMs, with UTC systems and RTMs both being identified as readily available by participants in the LGA survey. Access density is a network characteristic easily calculated with reference to a map and, once measured, subject to very little change.

3. *By virtue of being readily available, is it possible to use such traffic variables, in addition to traffic average speed, to explicitly include congestion influence and improve the accuracy of urban network CO_2 emissions predictions compared to predictions from EMs based solely on average speeds, whilst avoiding a substantial increase in model complexity and remaining a tractable tool for use by LGAs in transport intervention assessments?*

The answer to Research Question 3 was provided by the development of PEMLA, a Traffic Variable EM with the ability to explicitly include the influence of congestion on emissions, for use by LGAs in assessing transport interventions. Accuracy comparison revealed that PEMLA's prediction accuracy (based on traffic variable inputs) was superior to that of TRL/NAEI EM (based solely on average speed inputs). PEMLA remained a tractable tool useable within LGAs' limited resources by being a Traffic Variable EM (i.e. avoiding the complexity of Cycle Variable or Modal EMs with their associated requirement for driving pattern inputs), and by using readily available inputs generated from ILD data (which are a UTC system by-product or easily simulated in RTMs). The final conclusion therefore is that the investigations conducted during this project have provided suitable answers to the three research questions initially posed.

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Appendix A

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Including congestion effects in urban road traffic CO_2 emissions modelling: Do Local Government Authorities have the right options?

Matt Grote *, Ian Williams, John Preston, Simon Kemp

Faculty of Engineering and the Environment, University of Southampton, Highfield Campus, Southampton SO17 1BJ, United Kingdom

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ABSTRACT

Tailpipe emissions from vehicles on urban road networks have damaging impacts, with the problem exacerbated by the common occurrence of congestion. This article focuses on carbon dioxide because it is the largest constituent of road traffic greenhouse gas emissions. Local Government Authorities (LGAs) are typically responsible for facilitating mitigation of these emissions, and critical to this task is the ability to assess the impact of transport interventions on road traffic emissions for a whole network.

This article presents a contemporary review of literature concerning road traffic data and its use by LGAs in emissions models (EMs). Emphasis on the practicalities of using data readily available to LGAs to estimate network level emissions and inform effective policy is a relatively new research area, and this article summarises achievements so far. Results of the literature review indicate that readily available data are aggregated at traffic level rather than disaggregated at individual vehicle level. Hence, a hypothesis is put forward that optimal EM complexity is one using traffic variables as inputs, allowing LGAs to capture the influence of congestion whilst avoiding the complexity of detailed EMs that estimate emissions at vehicle level.

Existing methodologies for estimating network emissions based on traffic variables typically have limitations. Conclusions are that LGAs do not necessarily have the right options, and that more research in this domain is required, both to quantify accuracy and to further develop EMs that explicitly include congestion, whilst remaining within LGA resource constraints.

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Introduction

More than half the world's population now live in urban areas (UNFPA, 2007), where concentrated travel requirements can often overwhelm transport systems during peak periods, leading to congestion. For urban road networks, carrying increasingly large numbers of vehicles results in increasingly large amounts of tailpipe emissions, including both greenhouse gases (GHGs) and pollutants detrimental to air quality (AQ), with the problem exacerbated by the stop-and-go nature of congestion increasing emissions yet further. This problem is particularly relevant in developing countries because towns and cities in the developing world are projected to constitute 80% of urban humanity by 2030 (UNFPA, 2007). Consequently,

* Corresponding author. Tel.: +44 2380 598755; fax: +44 2380 667519.
E-mail addresses: mjg1g12@soton.ac.uk (M. Grote), I.D.Williams@soton.ac.uk (I. Williams), j.m.preston@soton.ac.uk (J. Preston), S.Kemp@soton.ac.uk (S. Kemp).

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urban areas produce a disproportionate amount of road traffic emissions compared to their geographic size, and should be a focus for efforts to mitigate such emissions.

In large part, responsibility for facilitating mitigation of these emissions falls to those Local Government Authorities (LGAs) which have urban road networks situated within their areas of administration. Hence, this research sets out to investigate whether (or not) LGAs have available the emissions modelling options they require to enable them to properly discharge this responsibility. The method employed for the investigation is an extensive and contemporary review of literature concerning road traffic data and its use by LGAs in emissions models (EMs). During the review, an absence was found of research specifically investigating the practicalities of LGAs engaging in the emissions modelling process. Strategies for mitigating climate change must tackle increasing urbanisation and its associated problems, and LGAs in all countries play a key role. Therefore, this is an important area for current research.

This article's scope is limited to GHG emissions, in particular carbon dioxide (CO_2) because it is, by far, the largest constituent of transport's GHG emissions, e.g. 99% on a CO_2e[1] basis in the UK (DECC, 2014). Globally, the transport sector's contribution to total CO_2 emitted from fuel combustion is 23%, of which road traffic is responsible for almost three-quarters (IEA, 2014). Although article scope is limited to CO_2, it is generally acknowledged that integrated strategies to reduce GHG emissions and AQ emissions will often result in significant co-benefits (DEFRA, 2009; EEA, 2009; King et al., 2010; Tiwary et al., 2013). The harmful nature of CO_2 manifests as a global phenomenon. Hence, it is the overall effect of a transport intervention (or combined effect of many small diffuse interventions) on emissions of CO_2 which is more important than any localised effects. Therefore, this article is concerned with estimation of emissions for an urban road network (or substantially large parts of a network) as a whole.

Requirement for emissions models

When instigating transport interventions, critical to the decision making process is the ability to assess environmental impacts, including the impact on road traffic emissions. To analyse this impact, it is necessary to quantify an intervention's effect on emissions. However, it is impractical to measure real-world emissions at road network level due to the large number of vehicles and traffic conditions involved (Smit, 2006; Smit et al., 2010); and measurement is impossible when hypothetical scenarios are considered. Consequently, there is a requirement for EMs, which can offer a practical (and cheaper) alternative to real-world measurements.

Ultimately governments (typically LGAs in urban areas) are responsible for providing road infrastructure, and for maintaining local air quality to within established limits and achieving agreed GHG emission reduction targets. Therefore, LGAs must find the necessary resources for modelling the emissions impact of transport decisions. However, in most cases, public funds are limited. The global financial crisis of 2008 and subsequent austerity measures have increased the constraints on public funds, with many governments forced to make budget cuts (Lowndes and McCaughie, 2013). Hence, LGA resources are under pressure, meaning funds for modelling are scarce.

Models used by LGAs must strike a difficult balance. On the one hand, EMs must not be so simplistic that they fail to capture the majority of the emissions impact of potential interventions. On the other hand, there is a need to avoid model complexity. More complexity entails more time and expertise in building and running models and collecting the necessarily detailed input data. Such time and expertise is generally expensive, and beyond LGA budgets and decision making timescales.

Another factor in the accuracy/complexity trade-off is that, although more complex models are generally more accurate than less complex models, they also require more detailed input data (Smit et al., 2006). Finely detailed input data are more susceptible to errors in estimation, measurement, or assumptions. Therefore, a lack of quality input data may offset any accuracy gained through increased model complexity (Smit et al., 2010; Ramos et al., 2011; Zhu and Ferreira, 2013). This is illustrated by Alonso (1968) who distinguished between two error sources. Firstly, specification error which arises due to models being simplified representations of real-world phenomena; and secondly, measurement errors in input data. Total model error is the sum of these two sources. Fig. 1 shows there is an optimal model complexity where total prediction error is minimised.

Major factors influencing emissions

Distance, speed and vehicle category

Tailpipe emissions (i.e. from fuel combusted in-vehicle) are typically estimated through multiplying activity data by emission factors (EFs) (Smit et al., 2010). Hence, distance travelled by a vehicle (vehicle-kilometres, VKMs) has a large influence on emissions (i.e. greater activity gives greater emissions). Vehicle speed is another important influence on emissions, because road traffic EFs are strongly dependent on speed (Smit et al., 2008b; Abou-Senna and Radwan, 2013). Vehicle

[1] CO_2-equivalent: amount of CO_2 emitted that would cause the same time-integrated radiative forcing, over a given time horizon, as an emitted amount of another GHG.

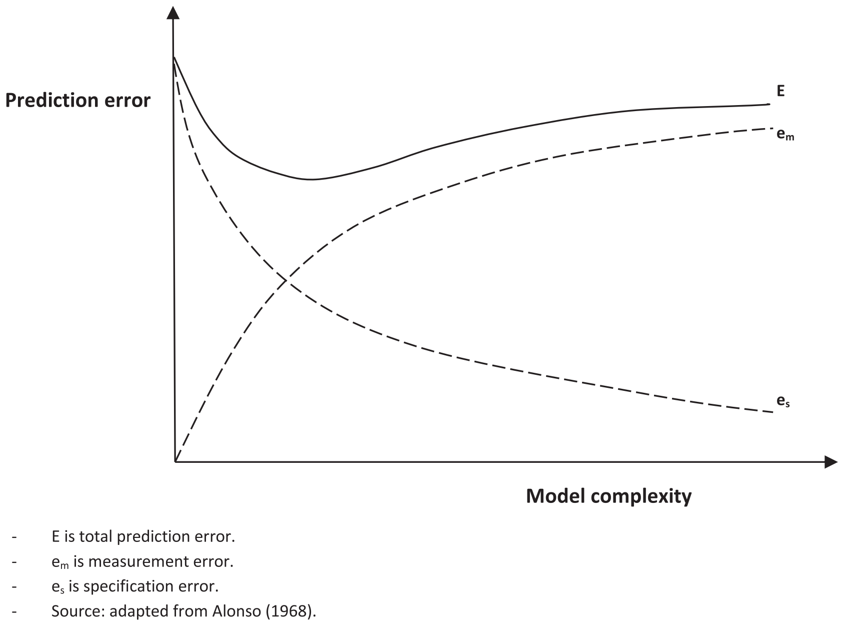

Fig. 1. Model complexity and prediction error.

category also has a considerable influence on emissions. Different vehicle categories have different EFs due to factors such as vehicle mass, fuel specification, engine size, aerodynamics, and emissions control technology.

Importance of congestion

Congestion is the deterioration of smooth, free-flowing traffic conditions due to increased travel demand and/or reduced traffic movement capacity (Smit et al., 2008a). It is commonly accepted that under the stop-and-go traffic conditions associated with congestion there is an increase in the number of acceleration and deceleration events experienced by vehicles, which results in increased emissions (Chen and Yu, 2007; Barth and Boriboonsomsin, 2008; Smit et al., 2008a; Madireddy et al., 2011). Congestion has been repeatedly identified as a major factor when estimating road traffic emissions (Smit et al., 2008a), and ranks alongside VKMs, vehicle speed and vehicle category, as one of the most important influences (De Haan and Keller, 2000; Int Panis et al., 2006; Smit et al., 2008a,b).

Barth and Boriboonsomsin (2008) compared CO_2 emissions from cars during steady-state activity (i.e. constant speed) to emissions during real-world activity (i.e. including dynamics due to congestion) having the same average speed. According to results, the increase in emissions at 45 km/h (a typical average speed on urban roads[2]) due to congestion was approximately 40%. This study assumes that all the dynamics of real-world driving patterns[3] are due to congestion. This is a reasonable assumption because the important issue is to capture as much as possible (within resource constraints) of the influence of vehicle dynamics, regardless of whether or not they are labelled as congestion. In effect, the term congestion is used as a proxy for vehicle dynamics, regardless of source.

Congestion can be considered at multiple scales, for example around a single intersection, along a certain corridor (series of links[4] and intersections), or for a network as a whole. Assessment of the emissions impact of transport interventions at these different scales may require LGAs to use different types of road traffic data and EMs. However, the scope of this article is predicting the impact of interventions on CO_2 emissions at the network level and, consequently, it is LGA options for inclusion of congestion at this scale that formed the focus of research.

Other factors

There are many other factors which influence emissions including: driver behaviour and gear-shift strategies; road gradient; payload; cold starts; ambient temperature; increasing vehicle age or lack of maintenance; use of auxiliaries; and vehicles using alternative drivetrains or fuels. The justification for this article's focus on congestion, rather than other factors, is

[2] According to the UK Government's Department for Transport, the average speed on major urban roads in the South-East region of the UK during the peak hour is approximately 47 km/h.
[3] Fine grained time series (e.g. 1 Hz) of speed points for an individual vehicle.
[4] Uni-directional road section between two intersections.

that congestion (arguably) ranks alongside VKMs, vehicle category, and vehicle speed as one of the most important influences on CO_2 emissions; and, therefore, should also be explicitly[5] included in EMs. In general, the influences of other factors are smaller than that of congestion. However, it is acknowledged that all factors should be included in EMs where possible. Indeed, the influences of most other factors are usually included to some extent, typically through assumptions, either of a constant value (e.g. zero road gradient), or that emissions tests, the data from which are used as the basis for EM construction, cover the real-world distribution of values these factors can take (e.g. vehicle age).

This article is concerned with estimation of emissions at network level (or substantially large parts of a network, e.g. >1 km^2). Therefore, the validity of assumptions used to include other factors is strengthened because random errors introduced by not fully accounting for vehicle-specific values should (to a certain extent) average out (Smit et al., 2008b). For example, negative gradients will offset positive gradients, and lighter than average vehicle loads will offset heavier than average vehicle loads. A final point is that, in general, LGAs have more influence over congestion than for example gradient, vehicle loading, ambient weather, use of auxiliaries, etc., and it is interventions affecting congestion in which LGAs are interested.

Road traffic data

Road traffic data required as inputs to EMs are available from numerous sources. Traffic counts (manual or automatic) record the number of vehicles passing a location, and can also include vehicle category data. Automatic Number Plate Recognition (ANPR) cameras read vehicle licence plates allowing vehicle category to be determined, and journey time data to be produced from the time taken for vehicles to travel between different camera locations. The long-established Moving Car Observer (MCO) method uses observers in a test vehicle to derive average journey time and traffic flow data. Queue length surveys manually record the number of queueing vehicles or queue length in metres, and often include associated delay times. The utility of these sources for predicting emissions can be limited, either because their availability is restricted to only a few locations (i.e. they lack link-by-link resolution), or because they involve resource-intensive data acquisition, or both. However, they can be a useful addition to the emissions modelling process, either in combination with other data or through providing data for the calibration and validation of models.

Vehicle category data for a given nation (or sub-national region) are usually available from fleet models, which are typically provided by a country's government (or other delegated authority). Measurements of the characteristics of the road network itself (e.g. link length, number of lanes, link curvature, intersection layouts, number of intersections per kilometre, speed limits, signal timings or roadside land use) provide another useful source of road traffic data.

Intelligent transport systems technologies

Intelligent Transport Systems (ITS) are defined as any application of information and communication technology to transport, which includes several technologies that can serve as sources of road traffic data. Floating car data (probe vehicles) can be provided by a number of different in-vehicle devices, such as Bluetooth, GPS, mobile telephony and Wi-Fi. These devices can provide information on traffic flow, average speeds, delays, travel times, and driving patterns. A drawback of floating car data is privacy. Gathering identifiable data requires driver permission, which may not be forthcoming from private citizens. Installing devices on captive fleets could be more practical, but resistance may still be encountered from reluctant workforces or business owners. Another problem is penetration, i.e. the number of vehicles from which data can be gathered compared to the total number of vehicles. A small sample size decreases the likelihood that the samples will be representative of the traffic conditions on all parts of a network (De Kievit et al., 2014b). An example of the use of floating car data can be found in the compilation of the 2010 London Atmospheric Emissions Inventory[6] where traffic average speeds for approximately 62% of major road links were available from GPS data provided by Trafficmaster[7] (GLA, 2014).

Automatic Vehicle Identification using Radio Frequency Identification Devices (RFID) provides similar data to ANPR cameras. Vehicles are fitted with RFID tags (sometimes called transponders), typically in the form of labels attached to the windscreen or licence plate, which pass the vehicle's details to a roadside tag reading unit. However, vehicle identification is limited to those carrying transponders (De Kievit et al., 2014b).

Based on the vehicle telematics data available from ITS, Traffic Congestion Indices (TCIs) (also known as Traffic Performance Indices, TPIs) can be produced using methods such as comparison of measured travel times with free-flow measured travel times or, less commonly, comparison of the marginal cost of congestion with the average cost of congestion. For example, TomTom produce a Traffic Index for 218 cities worldwide based on GPS data. INRIX also produce global congestion data for urban areas (e.g. the Urban Mobility Scorecard Annual Report), and the Texas A&M Transportation Institute produce similar data for the USA. In the UK, Mott MacDonald produce Strat-e-gis Congestion which provides historic congestion data based on GPS.

[5] Explicit: within model-user control, with values specified for use as EM inputs. Implicit: outside model-user control, but may be included through underlying EM assumptions.

[6] Inventory of all atmospheric emissions sources in Greater London.

[7] Trafficmaster is a division of Teletrac, one of the largest fleet companies in the UK and USA.

Road traffic models

Road Traffic Models (RTMs) are often used as a source of EM input data. RTMs represent how travel demand is satisfied by the road network, with demand generally expressed in the form of an origin–destination (O–D) demand matrix, populated by the number of trips between each pair of defined origin and destination zones. RTMs are usually classified according to scale. Macro-RTMs typically consider road traffic as an aggregated flow, with the flow of traffic through links and intersections described by relationships between variables such as: traffic density (vehicles/km), traffic average speed (km/h) and traffic flow (vehicles/h) (Lighthill and Whitham, 1955; Kotsialos et al., 2002). Demand is assigned to the network iteratively, aimed at finding an equilibrium solution that replicates route choice through the network. Demand, and the resulting values for each link's density, speed and flow, are assumed to be constant for the entire modelled period which is not a very realistic assumption for congested networks (Ortúzar and Willumsen, 2011), particularly over longer time periods (e.g. a peak hour).

Micro-RTMs consider the motions and interactions of individual vehicles based on combining detailed network characteristics with detailed driver behaviour sub-models (car following, lane choice, and gap acceptance) (Papacostas and Prevedouros, 2005; Ortúzar and Willumsen, 2011; Ramos et al., 2011). Hence, driving patterns for each vehicle are available as outputs. However, micro-RTMs are typically calibrated and validated for aggregate traffic measures (e.g. traffic flow, average speed, average delay and queue length), rather than for driving patterns of individual vehicles (Hirschmann et al., 2010; Song et al., 2012, 2013; Toffolo et al., 2013). Therefore, driving pattern outputs from micro-RTMs are rarely validated properly, and do not necessarily accurately represent real-world driving patterns (Song et al., 2012, 2013).

Meso-RTMs are a third classification often distinguished between micro-RTMs and macro-RTMs. Vehicle motions and interactions are considered, but in less detail than in micro-RTMs. For example, SATURN[8] groups vehicles into platoons, and uses a platoon-dispersion module to simulate the movement of vehicles over the network accounting for interaction of vehicles at intersections and different drivers' preferred speeds (Papacostas and Prevedouros, 2005; Ortúzar and Willumsen, 2011). When functioning at meso-scale (it also functions at micro and macro-scales), AIMSUN[9] considers the motions of individual vehicles (using less detailed driver behaviour sub-models than at micro-scale), but only calculates entry and exit times for each link, rather than calculating full driving patterns.

The resources (costs, labour, and computer runtimes) demanded by RTMs increase with network size. Hence, for a given resource constraint, as the size of network to be modelled increases, the detail of traffic data generated is effectively reduced. For large urban road networks, the outputs of RTMs are usually limited to data for the traffic on each link, rather than for individual vehicles (Smit et al., 2008b). In other words, micro-RTMs are limited to micro-scale geographic areas (e.g. several links and intersections). As network scale increases, meso-RTMs and macro-RTMs are used instead, providing less detailed output data.

Urban traffic control data

Urban Traffic Control (UTC) systems coordinate traffic signals to achieve good progression for vehicles through urban networks. An example of a widely used system is SCOOT,[10] which operates in over 250 cities and towns worldwide (Bretherton et al., 2011). The data used to control the signals are generated by inductive loop detectors (ILDs) installed under the road surface, which send updates of vehicle presence every 250 ms in the form of 1s and 0s (denoting occupied or unoccupied respectively).

An advantage of UTC data is that it can be considered a by-product of the traffic signal control system (Marsden et al., 2001), allowing EM input data to be collected without using additional resources (Reynolds and Broderick, 2000). Another advantage is that UTC data provide an 'on the ground' picture of the real-world situation, in contrast to RTM outputs which are a modelled representation of the real-world. However, a disadvantage is that data availability is limited to certain point locations on the network, i.e. data are only available where ILDs are installed. Another disadvantage is that, where traffic average speed is required as an EM input, this is typically space-mean-speed (i.e. based on average travel time over longer distances, e.g. link length or longer), whereas ILDs provide estimates of time-mean-speed (i.e. average of vehicle spot speeds). Also, because UTC data are real-world measurements, the data are not available for assessment of hypothetical scenarios.

Alongside their primary function of detecting vehicle presence, some enhanced ILDs also provide vehicle category data. Enhanced ILDs rely on the resulting change in inductance due to the passage of a vehicle over the detector being distinct for different vehicle categories. To further assist with vehicle category classification, enhanced ILD data can be supplemented with axel count data (from pneumatic tubes or piezoelectric sensors). However, whilst enhanced ILDs can typically distinguish between two-wheel vehicles, LDVs, rigid HGVs, articulated HGVs and buses/coaches, they cannot further disaggregate vehicle categories (e.g. by fuel type, mass, compliance with different emissions standards, or vehicle age). Additionally, enhanced ILDs are not universally installed, and upgrading existing, conventional ILDs would involve expense and time.

Emissions models

In this review, types of EM are broadly dealt with in order of complexity, moving from simpler EMs to the more complex, as depicted in Fig. 2. The system of EM classification selected to provide a framework for the review is that published in Smit

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[8] Simulation and Assignment of Traffic to Urban Road Networks – developed at the Institute for Transport Studies, University of Leeds and distributed by Atkins Limited.

[9] Advanced Interactive Microscopic Simulator for Urban and Non-Urban Networks – distributed by Transport Simulation Systems.

[10] Split, Cycle and Offset Optimisation Technique – distributed by Siemens.

et al. (2010). However, it is acknowledged that there is no definitive, universally agreed classification system; and that under any given system some examples of EMs may defy easy classification.

Average speed emissions models

Average Speed EMs calculate EFs for each vehicle category as a function of traffic average speed (space-mean-speed). Most road traffic EMs are currently based on average speed (Boulter et al., 2012). A suggested reason for this prevalence is that, particularly for larger urban networks, readily available data are often restricted to estimates of traffic average speed for each link (Smit et al., 2008b). A limitation of Average Speed EMs is that they cannot account for the fact that trips with differing vehicle operation characteristics will all have differing emissions, but could all result in the same average speed (Int Panis et al., 2006; Toffolo et al., 2013). This is a particular problem at low average speeds, such as those in congested urban areas where the possible range of operational characteristics for a given average speed is large (Boulter et al., 2012, 2009; Ramos et al., 2011). However, when applied to a whole network (or substantially large parts of a network) this inaccuracy should be subject to a certain amount of averaging out, i.e. the increase in emissions due to stop-and-go conditions at particular network locations (model under-estimating) is offset by the decrease in emissions from free-flowing conditions at other locations (model over-estimating).

Average Speed EMs do implicitly account for some congestion influence because the driving cycles[11] used in vehicle emissions tests that generate the data from which EMs are developed will have a dynamic speed–time profile. However, the driving cycles used during model development cannot be varied by the model user so as to reflect the particular congested situation of interest (Smit et al., 2008a). Common examples of Average Speed EMs include COPERT[12] in Europe, MOBILE[13] and EMFAC[14] in the USA, TRL EFs 2009[15] in the UK, and the EM built-in to the SCOOT UTC system. Although all these EMs perform emissions calculations using average speed, specific methods for calculations can vary between EMs. For example, calculations based on an average speed for each link, or a single average speed for an entire network, or weighting average speeds by VKMs travelled at each speed. In addition to variation with average speed, EFs in MOBILE and EMFAC are also road type-specific, and so could arguably be classified as Traffic Variable EMs.

Traffic situation emissions models

In Traffic Situation EMs the parameters of emissions tests, and their associated average EFs, are correlated to specific traffic situations. This results in each traffic situation being referenced to an average EF. Different traffic situations are characterised by road type (e.g. motorway with 120 km/h limit, or main road outside built-up area) and a qualitative description of congestion (e.g. free flowing, or stop-and-go). The user specifies a traffic situation, and then appropriate average EFs for different vehicle categories are weighted according to traffic composition (Smit et al., 2010; Boulter et al., 2012). Explicit account for congestion influence is achieved through the user-defined qualitative description of traffic conditions. An example of a Traffic Situation EM is HBEFA,[16] which is widely used within Europe. However, a disadvantage of HBEFA is that it is designed specifically for use in Germany, Austria, Switzerland, Sweden, Norway and France, with traffic situations representative of conditions in those countries, which means its application elsewhere is questionable (Boulter et al., 2012; De Kievit et al., 2014a).

Traffic variable emissions models

Traffic Variable EMs predict EFs based on variables aggregated for the traffic as a whole (Smit et al., 2010). The inclusion of other traffic variables (in addition to traffic average speed) as indicators of congestion allows congestion influence to be accounted for explicitly and quantitatively. The definition of 'traffic variable' is extended here to encompass network characteristics because of their influence on traffic movement capacity. Whilst this EM category is somewhat lacking in examples of fully developed, commercially available EMs, the following paragraph details examples of research in this domain.

An early example of a Traffic Variable EM is provided by the Traffic Energy and Emissions-Kinematic Correction Factor (TEE-KCF), which attempted to overcome the limited ability of Average Speed EMs to account for congestion through use of a KCF. Its application initially involves calculating emissions using traffic average speed and COPERT. Then link-specific KCFs are calculated based on values for traffic average speed, traffic density, effective green-time ratio,[17] and link length. Finally, COPERT emissions are multiplied by the KCF (Smit, 2006; Boulter et al., 2012). Research by Reynolds (1996) investigated the use of SCOOT UTC data to predict roadside concentrations of AQ pollutants. An attempt was made to produce a Traffic Variable Concentration

[11] Standardised driving pattern over which a vehicle's emissions are measured.

[12] COPERT is coordinated by the European Environment Agency.

[13] MOBILE has now been replaced by MOVES as the United States Environmental Protection Agency's (EPA's) official model for estimating road traffic emissions.

[14] EMission FACtors (EMFAC) is used by the California Air Resources Board for estimating emissions from road vehicles.

[15] In 2009, the Transport Research Laboratory (TRL), commissioned by the Department for Transport, produced a set of average speed emission functions for UK road vehicles.

[16] Handbook of Emission Factors for Road Transport.

[17] Ratio of effective green-time (displayed green-time adjusted for time loss due to vehicles accelerating up to speed, and time gain due to vehicles crossing a yellow signal) to signal cycle time (the time required to complete one complete sequence of signal phases).

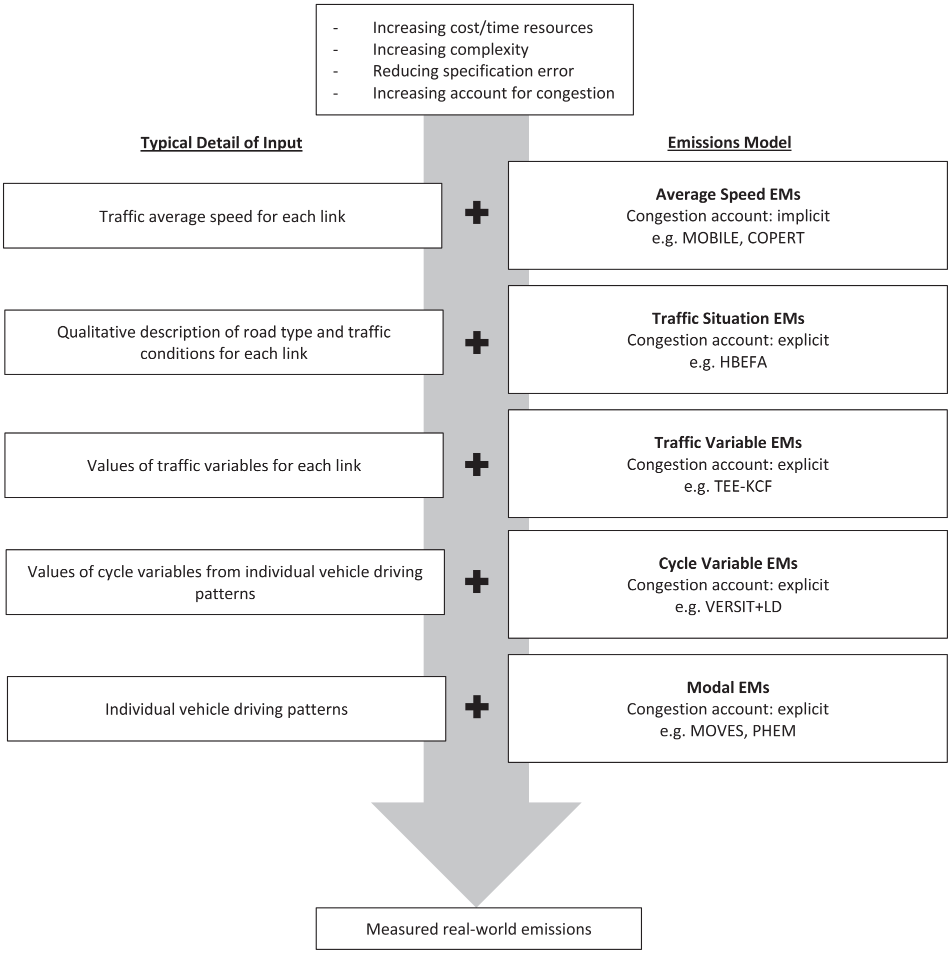

Fig. 2. Emissions model classification on a scale of resource consumption, complexity, accuracy, and account for congestion. Further details of the specific examples shown for each EM type are included in the sections 'Average speed emissions models' to 'Modal emissions models'.

Model that predicted roadside concentration of carbon monoxide (CO) based on SCOOT values for traffic delay and flow. A study by Smit et al. (2008b) investigated improving the accuracy of emissions predictions through application of a link-specific average speed distribution, rather than a single traffic average speed. In other words, supplementing traffic average speed with data on how the average speeds of individual vehicles are distributed around the average for the traffic as a whole. This method was seen as being a closer approximation to reality, and so was expected to improve on the accuracy of emissions predictions based solely on traffic average speed. Jeng et al. (2013) investigated enhanced ILDs that went beyond vehicle category classification, and worked on the principle that the resulting change in inductance due to vehicle passage is unique to that vehicle. The study used 'raw' ILD data (rather than UTC system outputs) to provide improved estimates of traffic average speed and vehicle category mix, which could then be used as inputs to existing EMs. Song et al. (2015) developed the Delay Correction Model (DCM) to predict emissions from buses traversing intersections based on traffic variables commonly used to describe intersection performance. The DCM is applied using intersection delay (seconds), number of stops (during intersection crossing), and intersection type (arterial/arterial or arterial/collector) as inputs, from which a Delay Correction Factor (DCF) is calculated. A baseline EF, which represents the case where a bus encounters no delay during intersection crossing, is then multiplied by the DCF to find the EF particular to the situation of interest.

Cycle variable emissions models

Cycle Variable EMs calculate EFs for individual vehicles as a function of variables derived from a vehicle's driving cycle, for example: number of stops per km, average speed, maximum acceleration, idle time, etc. A vehicle's driving pattern is typically required as input, which means congestion influence is explicitly included. However, the necessary driving patterns for each vehicle can only be acquired from a micro-RTM or vehicles equipped with a GPS device (Smit et al., 2010).

VERSIT+ LD[18] (for Light Duty Vehicles) was originally developed as a Cycle Variable EM. It consisted of statistical models that were constructed using multiple linear regression analysis of emissions test data to find an empirical relationship between EF and driving cycle variables for each vehicle category (Smit et al., 2007). However, major changes were made to VERSIT+ LD in 2009, and it is now better described as a Modal EM (Ligterink and De Lange, 2009). The Network Emissions Model (NEMO) was developed during ARTEMIS.[19] Emissions for individual vehicles are calculated based on values of cycle variables (Smit, 2006; Palmer, 2007). However, rather than using driving patterns for each vehicle as inputs, NEMO is designed to calculate cycle variables from a single driving pattern representative of all traffic. This simplification was introduced to avoid difficulties associated with collecting driving patterns for every vehicle and to reduce computing time. In this respect, NEMO could arguably be classified as a Traffic Variable EM because a single driving pattern is used to represent all traffic on a link.

Modal emissions models

Modal EMs calculate EFs for individual vehicles as a function of vehicle or engine operating modes (Smit et al., 2010). A vehicle's driving pattern is typically required as input, which means congestion influence is explicitly included. The latest generation of Modal EMs predict EFs for operating modes at high temporal resolutions (e.g. 1 Hz), i.e. a vehicle's mode, and associated EF, is calculated on a second-by-second basis. At this temporal resolution, Modal EMs are typically termed Instantaneous EMs (IEMs).

Motor Vehicle Emission Simulator (MOVES) is the EPA's official EM. Operating modes in MOVES are characterised by a combination of vehicle speed and Vehicle Specific Power[20] (VSP), and are divided into bins, with each speed–VSP bin having an associated EF. From a driving pattern, a link's operating mode distribution (amount of time vehicles spend in each speed–VSP bin) is calculated (Zhao and Sadek, 2013). Hence, similar to NEMO, MOVES could arguably be classified as a Traffic Variable EM because a single operating mode distribution is used to represent all traffic on a link. The Passenger car and Heavy duty Emissions Model[21] (PHEM) uses a vehicle's driving pattern, vehicle characteristics data, and a model of gear shift behaviour, to compute instantaneous values of engine power and engine speed. These values are then used to determine the associated EF (Boulter et al., 2012; Hausberger et al., 2009).

Emissions models to assess ITS

This section does not constitute a separate class of EM. Instead, because ITS assessment has generated substantial research into predicting urban network emissions (using various EM types), this work is grouped together here for convenient review. AMITRAN[22] and ECOSTAND were concerned with developing standard methodologies for evaluating the effects of ITS on CO_2 emissions. Both projects concluded that network geographic scale has a major bearing on the appropriate type of EM for assessment. For localised interventions, a detailed EM is required that predicts emissions for individual vehicles. However, when assessing ITS interventions on larger scales, a less detailed EM is acceptable and may be the only practical option (De Kievit et al., 2014a; Jonkers et al., 2014).

CARBOTRAF produced a Traffic Variable EM that predicts real-time network CO_2 emissions based on ILD data supplemented by data from specialist roadside sensors called smart eye Traffic Data Sensors[23] (TDS) which determine the proportion of accelerating vehicles in the traffic. Alternative traffic management options that satisfy traffic demand with reduced network CO_2 emissions are then offered to the traffic control centre operator (Litzenberger et al., 2012; North and Hu, 2012).

The ICT-Emissions approach was to model in detail the local effect of an ITS intervention, and then extrapolate the effect across the network. Two methods were proposed to integrate between detailed, local-scale modelling and less detailed, larger-scale modelling. The first used a local-scale micro-RTM to determine local changes to traffic's speed–flow–density relationships, which were then used to adjust a network-scale macro-RTM, the average speed outputs of which were used as inputs to COPERT. The second method involved constructing an extended Average Speed EM. Driving cycles were selected to represent conditions with and without the ITS intervention in place, and an IEM used to calculate associated emissions. In this way, two average speed emission functions are generated for each vehicle category, one with the ITS intervention and one without. A macro-RTM is then used to generate average speed inputs to the extended Average Speed EM (Toffolo et al., 2013).

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18 VERkeers SITuatie – distributed by the Netherlands Organisation for Applied Scientific Research (TNO).

19 Assessment and Reliability of Transport Emission Models and Inventory Systems – a European Commission 5th Framework project.

20 VSP (kW/tonne) is calculated from a vehicle's instantaneous speed and acceleration, and represents the power demand placed on a vehicle (by rolling resistance, aerodynamic resistance, acceleration resistance, and road gradient resistance) divided by vehicle mass.

21 Developed during the ARTEMIS project.

22 AMITRAN, ECOSTAND, CARBOTRAF & ICT-Emissions are all European Commission 7th Framework projects.

23 A proprietary sensor produced by the Austrian Institute of Technology.

Discussion

Readily available road traffic data

The results of the literature review indicate that the detail level of road traffic data readily available for collection by LGAs within their resource constraints is data aggregated at traffic level rather than data disaggregated at individual vehicle level; i.e. traffic variables rather than driving patterns. In general, driving patterns lack availability because they are difficult to collect, rarely used in traffic engineering to describe road network performance (Song et al., 2015), and their simulation in micro-RTMs is of questionable accuracy.

Two sources of traffic variables readily available on a link-by-link basis are UTC data and RTM output data. UTC data are particularly appealing because they are a by-product of the traffic signal control system. RTM data are required for instances when UTC data are not available, such as for assessment of hypothetical situations or for areas of the road network where ILDs are not installed. Reliance on other road traffic data sources to provide EM input data is likely to incur additional costs for collection and processing on a link-by-link basis, and/or involve sources that are not widely used by LGAs.

UTC data are more appropriate for the assessment of smaller, tactical interventions because their real-world nature means assessment can only be achieved post-intervention through comparing before and after emissions estimates. Examples of smaller interventions include altering traffic signal timings, re-routing particular vehicles (e.g. HGVs or buses), restricting vehicle loading/unloading to certain times, or prohibiting on-street parking at certain locations (Reynolds, 1996; Reynolds and Broderick, 2000). When assessing these interventions, it should be emissions for the whole network (or substantially large parts of the network) that are analysed, rather than local scale emissions, because assumptions about random errors averaging out become less valid for localised assessments (Smit et al., 2008b).

The impact of large, strategic interventions typically requires assessment prior to implementation, when there will be no real-world UTC data available for hypothetical post-intervention scenarios. Therefore, an RTM is required to simulate the effect of an intervention on traffic, and can be used as a source of traffic data for emissions modelling. Examples of large interventions include substantial alterations to the road infrastructure, variation of area-wide speed limits, or provision of large car parking facilities or park-and-ride schemes.

Network characteristics are an additional source of traffic variables readily available to LGAs. Data on these characteristics have the advantage of being fairly easily measured by LGAs (or on their behalf); and having been measured once, are not subject to change very often. The rise in vehicle telematics is also a potential source of traffic variables that could come to satisfy LGA traffic data requirements, and investigation of relationships between TCIs and CO_2 emissions is an area for future work.

Optimal EM complexity

Resulting from the literature review and based on the ready availability to LGAs of traffic variables, a hypothesis has been formed that optimal model complexity for LGAs is represented by Traffic Variable EMs. This is because using less complex models (i.e. Average Speed or Traffic Situation EMs) does not fully utilise all traffic variables readily available to LGAs, which offer potential to improve accuracy through explicitly including congestion influence. It has been suggested that including only the influence of vehicle category and speed, and ignoring other influences, could be a simplification that distorts the information supporting policy making (Ligterink et al., 2012).

Using more complex models (i.e. Cycle Variable or Modal EMs) requires LGAs to collect and process accurate driving patterns for each vehicle on the network, which is impractical within existing and likely future resource constraints. Even when LGAs invest in micro-RTMs, because they are typically calibrated for aggregate traffic measures rather than for individual vehicle driving patterns, there is uncertainty about whether simulated driving pattern outputs are accurately representative of the real-world. A case study by Vieira da Rocha et al. (2015) found some evidence that the effect of inaccuracies in simulated driving patterns causing inaccuracies in predicted emissions tends to average out when lots of driving patterns are used to predict emissions from groups of vehicles. However, even if these findings apply universally, the significant data processing requirements of collecting (accurate or inaccurate) driving patterns for every vehicle in a network, and then inputting them to Cycle Variable or Modal EMs are likely to be off-putting for LGAs.

EM options for LGAs

A reason for the prevalence of Average Speed EMs in network emissions modelling is the common availability of traffic average speed data for use as inputs (which should be space-mean-speed, but does not mean attempts aren't made in practice to use time-mean-speed). However, other traffic variables that can be used as indicators of congestion are also readily available to LGAs. Hence, a Traffic Variable EM that includes the influence of congestion is a practical option for LGAs. A further point worthy of reiteration is the advantage of Traffic Variable EMs over Average Speed EMs whereby a Traffic Variable EM can distinguish between different traffic conditions that happen to result in the same average speed. It is also worth noting the possibility that a Traffic Situation EM, which includes the influence of congestion qualitatively, may be able to compete with a Traffic Variable EM in terms of accuracy and resource consumption.

If LGAs want to use Traffic Variable EMs (or Traffic Situation EMs), what options do they have? The examples detailed here are typical of the options available, and serve to illustrate some of the obstacles that LGAs face. TEE-KCF was a fully developed example of a Traffic Variable EM, but the emissions data on which it is based are now over 10 years out-of-date. The application of average speed distributions by Smit et al. (2008b) was a case study investigation, which has not been developed into a format useable by LGAs as an EM. Development of the DCM by Song et al. (2015) was accomplished for buses traversing intersections in Beijing, China. Therefore, it would need extension to cover other vehicle categories, traversing links as well as intersections, in other global regions, before it can have wider application. NEMO has not achieved traction as a widely used EM, and has not replaced the wide-spread use across Europe of COPERT and HBEFA.

Both HBEFA (in Europe) and MOVES (in the USA) are fully developed, up-to-date EMs that are currently used by LGAs. However, both would require extension to be useable in other global regions. In general, transferability is an obstacle to be overcome when considering an EM developed in one global region for application in another. This is because vehicle category classifications can be markedly different between regions and there is often no easy way to map between them. Even within a given global region (e.g. Europe) where the system of vehicle category classification is standardised, transferability between sub-regional areas (e.g. European countries) may not be straightforward. The reason for this being differences in factors such as network characteristics or vehicle fleet compositions.

Reynolds (1996) attempted to predict roadside CO concentrations based on traffic variables output from SCOOT. Unfortunately, no relationship could be established, and no model was produced. Whilst this work concerned a different pollutant, and concentrations rather than emissions, the results suggest it may prove difficult to develop a Traffic Variable EM for CO_2 based solely on outputs from a UTC system. Rather than UTC system outputs, Jeng et al. (2013) investigated the use of 'raw' enhanced ILD data. However, this study was not aimed at developing an EM itself, but was a method to provide more accurate road traffic input data to existing EMs, and additionally requires LGAs to invest in upgrading conventional ILDs to enhanced versions.

CARBOTRAF is a Traffic Variable EM predicting network CO_2 emissions. However, CARBOTRAF is pre-loaded with a database of network CO_2 emissions for each alternative intervention (in CARBOTRAF these are alternative traffic management options), which have been pre-calculated using driving patterns from a micro-RTM as inputs to an IEM. CARBOTRAF works because the range of alternative traffic management options is limited, allowing their emissions to be pre-calculated. Extending CARBOTRAF to assess an open-ended range of interventions would entail assessing each alternative with a micro-RTM and an IEM, which is just the kind of resource-intensive process likely to be beyond LGA budgets. Also, CARBOTRAF is reliant on the specialist TDS, which would require LGAs to meet associated installation costs. ICT-emissions proposes two methods for including changes to vehicle dynamics in network level emissions modelling, both based on Average Speed EMs. However, as both methods extrapolate a micro-scale effect across a network as a whole, they are more appropriate for blanket interventions that affect all links at once in a similar fashion (e.g. area-wide promotion of eco-driving) rather than for interventions that affect different links in different ways (e.g. altering signal timings on certain links). Additionally, the first method relies on localised changes to speed–flow–density relationships due to an ITS intervention being replicated across an entire network, which may not be valid; and the second method requires the resource-intensive process of constructing an extended Average Speed EM to be repeated for each alternative intervention.

It could be argued that if an LGA has invested in building an RTM, then an efficient way to calculate emissions would be using the RTM's built-in EM (if it has one). However, built-in EMs come with problems. For example, the distributors of SATURN suggest that the built-in Traffic Variable EM is extremely crude, and that emissions predictions would be best handled using a stand-alone EM (Atkins Limited, 2014). The AIMSUN built-in IEM highlights another problem, which is the mismatch in vehicle category disaggregation between RTMs and EMs (Toffolo et al., 2013). RTMs are typically only concerned with highly aggregate vehicle categories; whereas, to accurately predict emissions, EMs are typically concerned with highly disaggregate vehicle categories. The AIMSUN IEM provides emission functions for only five aggregate vehicle categories, which is consistent with the vehicle category aggregation one might expect in RTMs (TSS, 2013). It is possible to define many more vehicle categories in AIMSUN, each with different emission functions. However, acquiring the data to define all the emissions-related characteristics of each new vehicle category would be a substantial task. Additionally, a large increase in the number of vehicle categories would entail a large increase in complexity of O–D demand matrices in order to accurately represent the proportion of vehicles in each category travelling between each origin–destination pair. A further problem that affects micro-RTMs with built-in Modal EMs is the aforementioned issue of micro-RTM calibration for aggregate traffic variables rather than for accurate driving patterns, leading to uncertainty about the simulated driving patterns used as inputs to the built-in Modal EM.

The examples discussed in this section demonstrate that extant methodologies in the domain of predicting network emissions based on traffic variables typically have (to a greater or lesser extent) limitations. These must be addressed if an EM that explicitly includes congestion, whilst remaining within LGA resource constraints, is to be widely established.

Requirement for further research

The hypothesis that a Traffic Variable EM is the optimal model complexity for LGAs is based on qualitative literature review results. It has not been possible to quantitatively validate this hypothesis because there is only limited literature concerning EM validation and quantification of prediction errors (Smit et al., 2010; Kousoulidou et al., 2013). In general, it is not possible to validate an EM at network level in the strict scientific sense because it is not possible to measure true emissions for a network due to the large number of vehicles and traffic conditions involved. Instead, only partial validation is possible for specific localised situations over relatively short time periods (Smit, 2006). A meta-analysis of EM validation studies by Smit et al. (2010) concluded that "there is inadequate understanding of the uncertainties in traffic emission models and the main factors affecting prediction errors". Another, interesting finding of this meta-analysis was that there was no conclusive evidence for more complex EMs systematically being more accurate than less complex EMs. Part of the explanation for this could be that more complex EMs are being used with input data at less than ideal accuracy, i.e. accuracy gains from decreasing specification error (e_s) are offset by increasing measurement error (e_m).

Additional research is required comparing the predictions of Average Speed, Traffic Situation and Traffic Variable EMs (EMs likely to be useable within LGA resource constraints) with real-world emissions before the hypothesis can be assessed quantitatively. Maybe Average Speed or Traffic Situation EMs will prove equivalent to Traffic Variable EMs in terms of accuracy; although, interestingly, the EPA felt that MOBILE (Average Speed EM) needed replacing with MOVES. If results show that Traffic Variable EMs do out-perform their rivals, then further research would be required to develop existing or new methodologies into a widely available EM for LGAs.

Conclusions

Returning to the question posed in this article's title, the conclusion is that the qualitative evidence indicates that LGAs do not necessarily have the right options to accurately include the effects of congestion on emissions of CO_2 (or other pollutants) from traffic on urban road networks. Based on readily available road traffic data, the hypothesis is put forward that the optimal model complexity for LGAs is a Traffic Variable EM. More complex models, that calculate emissions for individual vehicles, are discounted as an option because they require driving patterns as inputs, which are difficult to collect, rarely used in traffic engineering to describe road network performance, and simulated with questionable accuracy in micro-RTMs.

In contrast, traffic variables are used to describe network performance and are more readily available to LGAs. Average Speed and Traffic Situation EMs are both viable options because they use traffic variables as inputs, are well established, and are less complex than Traffic Variable EMs. However, they may not fully realise the explanatory power of all traffic variables available to LGAs, which could be used to explicitly include congestion influence and improve emissions prediction accuracy.

Whilst the superiority of Traffic Variable EMs over Average Speed and Traffic Situation EMs in terms of accuracy has not been established quantitatively, there is enough qualitative evidence in the literature to conclude that this subject warrants further research. Co-benefits of such research would be in addressing any limitations of existing methodologies in the domain of predicting network emissions based on traffic variables and further developing EMs that explicitly include congestion whilst remaining within LGA resource constraints.

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Appendix B

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Local government authority attitudes to road traffic CO_2 emissions modelling: a British case study

Matt Grote, Ian Williams, John Preston and Simon Kemp

Faculty of Engineering and the Environment, University of Southampton, Southampton, UK

ABSTRACT
Local government authorities (LGAs) play a key role in facilitating mitigation of road traffic CO_2 emissions and must engage in emissions modelling to quantify the impact of transport interventions. Existing Emissions Model (EM) methodologies range from aggregate to disaggregate approaches, with more detail normally entailing more resources. However, it is not clear which approaches LGAs actually utilise. This article reports results of a survey designed to discover the level of detail considered practical by British LGAs ($n = 34$). Results show that resource scarcity is important, with particular importance attached to EM reusability and convenient input data sources. Most LGA EMs use traffic variable inputs (predominantly traffic flow and traffic average speed), with this approach being the best-fit for LGA resources. Link-by-link sources of data rated highly for convenience are Road Traffic Models and Urban traffic control systems.

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Local government; questionnaire survey; road traffic model; emissions model; greenhouse gas; air quality

1. Introduction

Ultimately, governments are responsible for providing road infrastructure and for achieving agreed greenhouse gas (GHG) emissions reduction targets. Typically, motorways and major trunk roads (the strategic road network, SRN) are administered by central government agencies (e.g. Highways England and Transport Scotland), whilst responsibility for all other adopted[1] roads is devolved to local government authorities (LGAs). For comparison, the national total of 417 billion vehicle-kilometres travelled (VKT) in England in 2012 was split between 33% (136.3 billion VKT) carried by SRN roads and 67% (280.7 billion VKT) carried by non-SRN roads (DfT 2013). Those British[2] LGAs responsible for non-SRN roads are known as local highways authorities (LHAs).[3] Under the complex system of local government in Britain, not all LGAs are LHAs. Only first tier LGAs (County Councils) and single tier LGAs (Unitary Authorities, London Borough Councils and Metropolitan District Councils) are LHAs. Second tier LGAs (District Councils, Borough Councils and those City Councils that are not Unitary Authorities) are not responsible for the roads in their region, with the appropriate first tier LGA being

CONTACT Matt Grote mjg1g12@soton.ac.uk

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responsible instead. The result of this system is that approximately half of British LGAs (206 out of a total of 407) are also LHAs (DECC 2014b; DCLG 2015).

Road traffic has damaging environmental impacts. One cause of such impacts is vehicle tailpipe emissions, including both GHGs and pollutants detrimental to air quality (AQ). In their capacity as LHAs, much of the responsibility for facilitating mitigation of these emissions is borne by LGAs. When considering transport interventions, it is necessary to quantify an intervention's effect on road traffic emissions. However, it is impractical to measure real-world emissions at road network level due to the large number of vehicles and traffic conditions involved (Smit 2006; Smit, Ntziachristos, and Boulter 2010), and impossible to measure real-world emissions when considering hypothetical scenarios. Emissions Models (EMs) can offer a practical (and less expensive) alternative (Grote et al. 2016). LGAs have limited resources with which to engage in the emissions modelling process. Constraints on public funds are increasing due to the global financial crisis of 2008 and subsequent austerity measures, with many governments imposing dramatic budget cuts (Lowndes and McCaughie 2013), meaning funds for emissions modelling are scarce.

Existing EMs are based on various methodologies, ranging from less detailed, aggregate approaches (e.g. traffic considered as a whole at a constant average speed) to highly detailed, disaggregate approaches (e.g. individual vehicle operating modes sampled at 1 Hz). An absence of research specifically investigating the practicalities of LGAs engaging in emissions modelling has been noted (Grote et al. 2016), and it is not clear which of the available methodologies LGAs can afford to utilise and which they ignore. This research contributes to addressing this gap, with a focus on investigating the emissions modelling process that is best-fit for all (or the substantial majority of) LGAs. The methodology used was a survey of LGA emissions modelling experts. Strategies for mitigating climate change must tackle the problem of road traffic GHG emissions, with LGAs in all countries having an important role, and understanding their requirements is essential if practical options for estimating emissions are to be developed and gain traction.

The study's scope was limited to carbon dioxide (CO_2) because this is the largest constituent of transport's GHG emissions, constituting 99% of CO_2e[4] in the UK (DECC 2014a). Globally, transport's contribution to total CO_2 emitted from fuel combustion is 23%, of which road traffic is responsible for approximately three-quarters (IEA 2014). Additionally, it is acknowledged that other actors may influence the framework within which LGAs make transport decisions, for example, regional partnerships (between LGAs and other interested parties) and the use by LGAs of external consultants. However, ultimately LGAs are the highways authorities responsible for the non-SRN roads within their areas, and are also responsible for assessing any requirement to expend resources on engaging external consultants. The study's scope was therefore limited to LGAs' attitudes to CO_2 emissions modelling.

It was not possible within the constraints of this research to provide a full analysis of the transferability of the results from the case study survey of Britain. However, previous research into the governance of transport and climate change by Marsden and Rye (2010) concluded that, although decision-making structures may be different in other countries, issues concerning delivery of strategies to tackle climate change were not solely dependent on the formal institutional structures in a country and so 'the cases of England and Scotland will have some parallels to other locations'.[5]

The rest of this article is divided into sections. In Section 2 the method adopted for the research is described. Results are presented in Section 3, followed by a discussion of those results in Section 4. Section 5 is the final section and details the conclusions of the research. Additionally, abbreviations used in this article are included in an appendix.

2. Method

LGA personnel constitute a combination of councillors who are elected to decide policy on behalf of the electorate, and officers who have the expertise to translate policy into practice (Meek, Ison, and Enoch 2010). Prerequisites for meaningful survey responses were that participants had expertise, experience and detailed familiarity with road traffic data and emissions modelling. As elected councillors were unlikely to meet such requirements, a decision was made to survey only officers. After consultation with the Local Government Association,[6] a UK public sector database specialist (Oscar Research Ltd) was employed to provide at least one named, senior highways officer contact for each of the 206 LHAs in Britain, giving a total of 376 potential participants. An online questionnaire survey compiled in the iSurvey format (a University of Southampton research tool for distributing online questionnaires) was selected as the most effective method to reach this number of potential participants in the time available, with a cross-sectional survey design being appropriate for gathering data on current LGA attitudes to CO_2 emissions modelling. The data gathered by the questionnaire were intended to be statistically analysed and reported. Therefore, closed rather than open questions were used (i.e. including response choices, which produced either categorical or ordinal variables). However, a free-text 'Further Details' box was offered at the end of some questions (Oppenheim 1992; Fink 2003a, 2003b). It is accepted that this survey design was unlikely to capture the full nuanced picture of LGAs' attitudes. However, the aim of the research was to provide an indication of the general situation for all (or the majority of) LGAs, rather than the nuances which are likely to vary from LGA to LGA. The automated iSurvey reminder email facility, followed by three further reminder emails sent manually, were used to maximise rates of response. Finally, those that had shown any interest (by opening the URL link to the survey) but not completed the questionnaire were contacted by telephone in an attempt to encourage participation.

The relative importance of factors affecting allocation of resources to emissions modelling was established by asking participants to indicate the extent of their agreement with nine different statements, each asserting that a particular factor was important. An ordinal five-point Likert scale was used for responses (Strongly disagree, Disagree, Neither agree nor disagree, Agree, Strongly agree). Scores were assigned from Strongly disagree = 0, through to Strongly agree = 4.

EMs require road traffic data as inputs, and resources must be expended on collection of these data. In general, using convenient sources of such data minimises expenditure. Brief details of the numerous different sources of road traffic data about which participants were questioned are provided in the following paragraphs. Traffic counts (manual or automatic) record numbers of vehicles passing a location, and can include vehicle category data (i.e. car, light goods vehicle, heavy goods vehicle, bus, etc.). Automatic number plate recognition (ANPR) cameras read vehicle licence plates allowing vehicle category to be established, and journey times between cameras to be calculated. Queue length surveys record the details of traffic queues (e.g. length, number of vehicles and delay times). Roadside interview (RSI) surveys involve stopping a sample of vehicles passing a survey site and interviewing the occupants. Vehicle tracking data can be collected from in-vehicle devices using Bluetooth, GPS, mobile telephony or Wi-Fi technologies (e.g. Strat-e-gis Congestion[7] provides historic congestion data based on GPS technology). In the UK, there was a requirement (abolished in 2010) for National indicators (NIs) to be reported annually by LGAs to central government. However, LGAs are still encouraged by central government to collect NIs beneficial for monitoring and evaluation purposes (SCC 2011a), and some are measures of road network performance (e.g. average journey time per mile along key routes), with data from Strat-e-gis Congestion often used by LGAs to monitor performance against NIs.

Road traffic models (RTMs) are frequently used as sources of road traffic data, and represent how travel demand is satisfied by the road network (Grote et al. 2016). RTMs are typically classified by scale. Macro-RTMs model traffic as an aggregated flow described by relationships between traffic density (vehicles/km), traffic average speed (km/h) and traffic flow (vehicles/h) (Lighthill and Whitham 1955; Kotsialos et al. 2002), and produce equilibrium solutions with demand assumed to be constant over an entire modelled period. Micro-RTMs simulate the movements of individual vehicles through combining detailed network characteristics with detailed driver behaviour sub-models (Papacostas and Prevedouros 2005; Ortúzar and Willumsen 2011; Ramos, Vasconcelos Ferreira, and Barceló 2011), and can produce driving patterns for each vehicle as outputs. Meso-RTMs are a third classification often distinguished between micro-RTMs and macro-RTMs. Vehicle movements and interactions are modelled, but in less detail than in micro-RTMs. For example, SATURN[8] uses a platoon-dispersion module[9] to simulate the movement of vehicles between signal-controlled intersections accounting for interaction with vehicles entering/exiting the road and different drivers' preferred speeds (Papacostas and Prevedouros 2005; Ortúzar and Willumsen 2011).

Urban traffic control (UTC) systems coordinate traffic signals to achieve good vehicle progression through urban road networks. Signal control data are generated by inductive loop detectors (ILDs) installed beneath the road surface, which send vehicle presence information (ILD occupied or unoccupied) every 250 ms. Also, enhanced ILDs (as distinct from standard ILDs) can provide vehicle category data based on the inductance change due to vehicle passage measured by the detector being distinct for different categories (Grote et al. 2016).

Three questions in the study were concerned with road traffic data sources. The first established the perceived convenience of data sources by asking participants to select one categorical response that best described their opinion of the availability of data from each source. In the second, participants were asked to indicate all time periods when (if ever) data from each source had been routinely collected by (or on behalf) of their organisation. An additional time period response category was added to this question of 'Planned for future collection' because road traffic data to which LGAs have access 'going forward' are the most convenient for use in future emissions modelling. The third question examined in more detail LGAs' use of RTMs. This was for three reasons: (1) where LGAs have invested in RTMs, the outputs are likely to be a convenient source of EM input data; (2) the type of RTM used (macro/meso/micro) affects the detail of data available as EM inputs and (3) some RTMs incorporate their own built-in EM. Participants were asked whether or not they had used different RTM software applications. If an RTM had been used, participants were asked to select from categorical responses to indicate when it was last used by (or on behalf) of their organisation.

LGA use of EMs was examined by asking participants whether or not they had used different EM software applications, with EM types classified according to the system set out by Smit, Ntziachristos, and Boulter (2010) and briefly detailed here in order of increasing complexity. Aggregate EMs typically use a single, fixed emission factor (EF) for a given vehicle category travelling on a given road type, with the usual distinction being urban, rural or motorway. Average Speed EMs calculate EFs for each vehicle category as a function of traffic average speed. In Traffic Situation EMs a range of traffic situations are specified, with each traffic situation being correlated with EFs for a range of different vehicle categories. Different traffic situations are characterised by road type (e.g. motorway with 120 km/h limit) and a qualitative description of traffic conditions (e.g. free flowing). Traffic Variable EMs calculate EFs for each vehicle category as a function of variables describing the traffic as an aggregate whole (e.g. traffic average speed, traffic density, average delay rate, etc.). Cycle Variable EMs calculate EFs for individual vehicles as a function of variables derived from a vehicle's driving pattern (e.g. number of stops/km, vehicle average speed, maximum acceleration, etc.). Modal EMs calculate EFs for individual vehicles as a function of vehicle or engine operating modes. The latest generation of Modal EMs predict EFs for operating modes at temporal resolutions of 1 Hz, and are typically termed Instantaneous EMs. Where an EM had been used, participants were asked to indicate when it had last been used by (or on behalf) of their organisation.

Two questions were developed to investigate LGAs' willingness to commit resources to the emissions modelling process. To permit the extent of resource commitment to be quantifiably evaluated, the questions were designed so that results could be expressed as an implied monetary value placed on CO_2 emissions reductions (£/tonne), which would then allow comparison with official UK central government CO_2 valuations. Two questions were used, each with a different transport intervention scenario, to assess whether (or not) CO_2 valuations remained consistent.

In the scenarios for both questions it was assumed that there was a true amount of CO_2 emissions reduction resulting from an intervention. Participants were asked to compare the use of two different EMs (EM1 and EM2) for predicting this reduction. The less expensive, less complex and less accurate model (EM1) under-estimates the reduction. The more expensive, more complex and more accurate model (EM2) gets closer to the true reduction, and ultimately (in the series of response options offered to participants) replicates the true reduction exactly without ever over-shooting. In essence EM2 is assumed to have (near) optimal complexity. The difference between the predictions leads to EM2 predicting a greater emissions reduction than EM1. For both scenarios, this difference ranged from 100 tonnes up to 1000 tonnes (Table 1), with the latter occurring when the EM2 prediction exactly matched the true reduction.

Of course, both EM1 and EM2 could over-estimate the true emissions reduction. However, if this was the case, EM1 would appear to predict a greater reduction than EM2. A less expensive EM predicting a greater emissions reduction would be appealing to LGAs (regardless of the true emission reduction which would be unknowable in the real-world), and would have undermined the purpose of the two questions. This is why

Table 1. Response categories for both survey questions investigating LGAs' willingness to commit resources to emissions modelling.

Increased CO_2 reduction predicted by EM2 compared to EM1 (tonnes)	100	200	300	400	500	600	700	800	900	1,000	No switch to EM2
	○	○	○	○	○	○	○	○	○	○	○

in this hypothetical experiment EM2 needed to be posited as an optimal model and EM1 as a sub-optimal model in a particular direction (i.e. under-estimation). Additionally, for simplicity, any issues about precision or statistical variability in model predictions were deliberately omitted.

Information presented to the participants in the two scenarios (pre- and post-intervention annual road traffic CO_2 emissions, intervention cost, EM cost and population size) was based on real-world data from an abstraction of a Southampton (city in southern England) case study (SCC 2011b) and an email to the authors from Theo Genis[10] (personal communication, October 14, 2014). This is why the measurements used in the question are absolute (£s and tonnes of CO_2) rather than percentages.

Participants were asked, for a given cost increase, what improvement in accuracy from EM2 would justify its extra cost. For both questions, this sub-question was repeated five times, with the cost of EM2 increasing in £10,000 steps from £60,000 to £100,000. For example, participants were asked 'If EM1 costs £50,000 and EM2 costs £60,000, moving from left to right, select the button that best indicates the point at which the improvement in accuracy offered by EM2 becomes large enough to justify the extra cost of using EM2' and offered response categories as shown in Table 1. Considering only the extra cost of using EM2, and the associated extra predicted CO_2 saving, the choices available to participants in both questions placed valuations on CO_2 as shown in Table 2.

3. Results

Thirty-four surveys were returned with at least one question completed, and rates of response to individual questions ranged from a maximum of 9% ($n = 34$) to a minimum of 6% ($n = 23$). It is acknowledged that these sample sizes are relatively small, but other surveys of a similar type exist with sample sizes of a comparable order of magnitude (e.g. Xenias and Whitmarsh (2013) used a sample of 53 experts). Best efforts were made to maximise the number of participants, and low response rates may be symptomatic of pressure on LGAs' resources leading to a lack of available time/manpower to complete the survey. Whilst low response rates are not necessarily indicative of non-response bias (Lineback and Thompson 2010), they do increase the need for a non-response bias analysis to provide confidence in the data quality. Of the 206 LHAs, responses were received from at least 27 (13%) different authorities (7 of the 34 participants elected to remain anonymous). The group of known respondents was compared to the group of non-respondents (which also included the seven anonymous respondents) to identify any statistically significant differences. Variables for comparison were resident population (2011 census data), geographical area (hectares), an indicator of urbanisation

Table 2. CO_2 valuations associated with response categories for both survey questions investigating LGAs' willingness to commit resources to emissions modelling.

Increased CO_2 reduction predicted by EM2 compared to EM1 (tonnes)	100	200	300	400	500	600	700	800	900	1000	No switch to EM2
£10,000 extra cost for EM2	100	50	33	25	20	17	14	13	11	10	0
£20,000 extra cost for EM2	200	100	67	50	40	33	29	25	22	20	0
£30,000 extra cost for EM2	300	150	100	75	60	50	43	38	33	30	0
£40,000 extra cost for EM2	400	200	133	100	80	67	57	50	44	40	0
£50,000 extra cost for EM2	500	250	167	125	100	83	71	63	56	50	0

Note: Figures in the body of the Table are resultant CO_2 valuations (£/tonne).

(population density in residents/ha), and an indicator of spending (LGA net[11] revenue expenditure per capita in £s for 2013/2014). Non-parametric Mann–Whitney tests (Mann and Whitney 1947; Field 2009) showed that levels of the four variables in the sample of respondents did not differ significantly from those found in the non-respondents. The distribution of regional response rates was as follows (i.e. the number of LHAs that responded as a percentage of LHAs in each region): Scotland 16%; Wales 14%; SE England 11%; SW England 25%; London 3%; East of England 9%; East Midlands 22%; West Midlands 29%; Yorkshire and the Humber 13%; NE England 17% and NW England 4%.

Results from statistical analysis of response scores from the question asking participants their opinion on the importance of factors affecting allocation of resources are shown in Table 3, with a higher mean importance score (range 0–4) indicating a factor is perceived as more important. A score of 2 corresponds to the neutral statement: Neither agree nor disagree. Mean importance scores are all greater than 2, indicating that, on average, every factor is regarded as important to some extent. A non-parametric Friedman test (1937) and post-hoc pairwise Dunn tests (1964) were conducted to determine if the observed differences in responses to the different factors were statistically significant. The four pairwise comparisons having statistically significant differences were: 'Ability to re-use model in future projects' and 'Avoiding staff training'; 'Ability to re-use model in future projects' and 'Quick completion'; 'Ability to re-use model in future projects' and 'Avoiding employing external consultants'; and 'Easy availability of input data' and 'Avoiding employing external consultants'. The Friedman test results indicate that, in general, statistically significant differences only exist between responses to factors at the extremes of the rankings (i.e. between the top two and bottom three factors). Friedman test mean

Table 3. Mean importance scores and Friedman test mean rankings for factors affecting emissions modelling resource allocation.

Factor	Friedman mean rank	Mean importance score
Ability to re-use model in future projects	6.77	3.27
Easy availability of input data	5.93	2.93
Project significant to local political agenda	5.32	2.77
Avoiding high manpower resources	5.28	2.77
High accuracy	4.92	2.57
Inexpensive	4.80	2.60
Avoiding staff training	4.43	2.33
Quick completion	3.93	2.20
Avoiding employing external consultants	3.62	2.07

Notes: $n = 30$. Factors are ordered according to Friedman mean ranking (range 1–9), which is (slightly) different to the order of mean importance scores. Mean importance score (range 0–4).

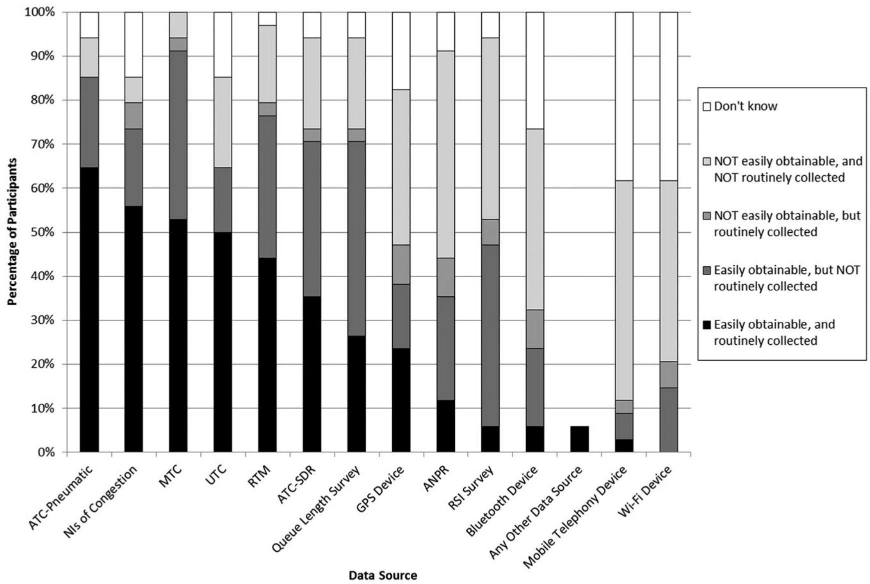

Figure 1. Participant perception of the availability of road traffic data sources.
Notes: $n = 34$. Two participants specified an 'Any Other Data Source', which were TRICS and UK road traffic collision data.

rankings are shown in Table 3, with a higher ranking (range 1–9) indicating a more important factor.

Participant perceptions of the availability of road traffic data sources are shown in Figure 1. Time periods when data were collected from these sources are shown in Figure 2, and are displayed in descending order of the percentage of participants selecting 'Planned for future collection' in response to a particular data source. LGAs' use of different RTM software applications is shown in Figure 3. LGAs' use of different EM software applications is shown in Figure 4. It should be noted that WebTAG is not a software application. Instead, it is the UK central government's Department for Transport (DfT) guidance on conducting transport studies, and includes methods for calculating road traffic emissions. This is also the case for the design manual for roads and bridges (DMRB), which is the DfT's guidance on the design, assessment and operation of trunk roads and motorways (although a software application based on the DMRB is available). Figure 5 shows participant responses when aggregated according to EM type.

For the two questions quantifying LGAs' willingness to commit resources to the emissions modelling process, the mean valuation of CO_2 emissions from responses to the first question was £11.51/tonne (Standard Deviation, SD £18.56) and from responses to the second question was £14.08/tonne (SD £27.50), with an overall mean valuation of £12.77/tonne (SD £23.35). For comparison, for 2015 the UK central government values CO_2 emissions from the untraded sector (i.e. emissions not included in the EU Emissions Trading System, which is the case for petrol and diesel used in road vehicles) at £62.78/tonne (SD £31.39), based on a valuation of £57.40/tonne (SD £28.70) in 2010£s corrected for inflation (DfT 2014). Therefore, LGAs' mean valuations determined here are less than a quarter of central government values but the standard deviations are of a similar order of

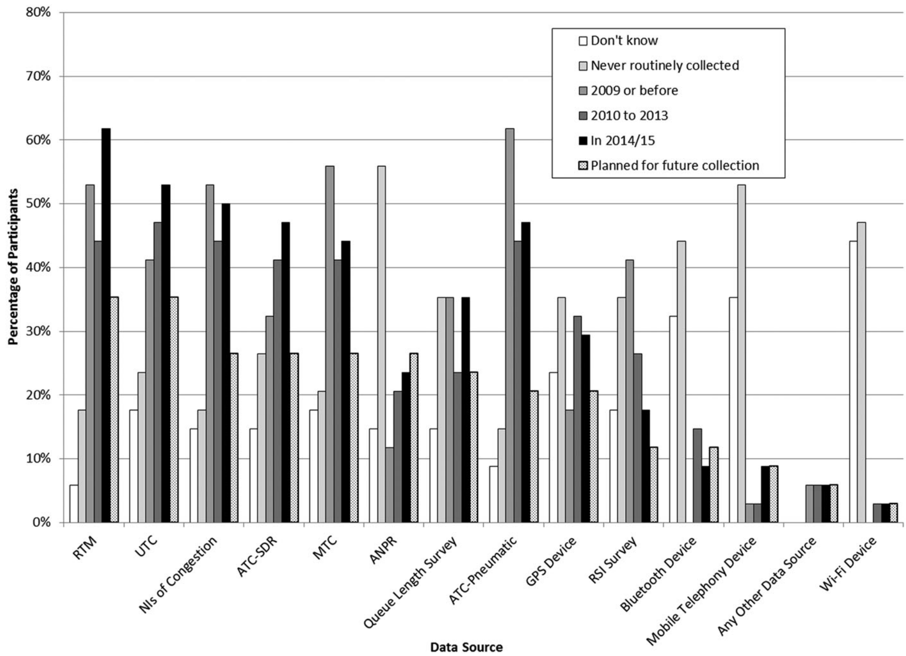

Figure 2. Time periods when data were (or are planned to be) collected by (or on behalf of) LGAs from road traffic data sources.

Notes: $n = 34$. Two participants specified an 'Any Other Data Source', which were TRICS and UK road traffic collision data.

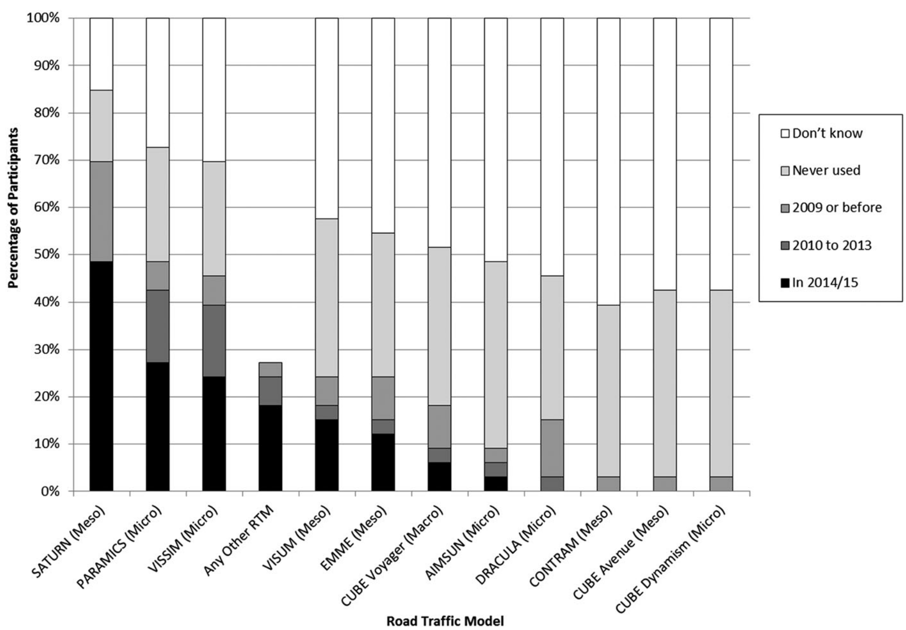

Figure 3. Time periods when RTM software applications were last used by (or on behalf of) LGAs.

Notes: $n = 33$. RTM types are Macro, Meso or Micro. Nine participants specified an 'Any Other RTM', which were ARCADY, DELTA, LINSIG, PICADY, QUADRO, TRANSYT and TRIPS.

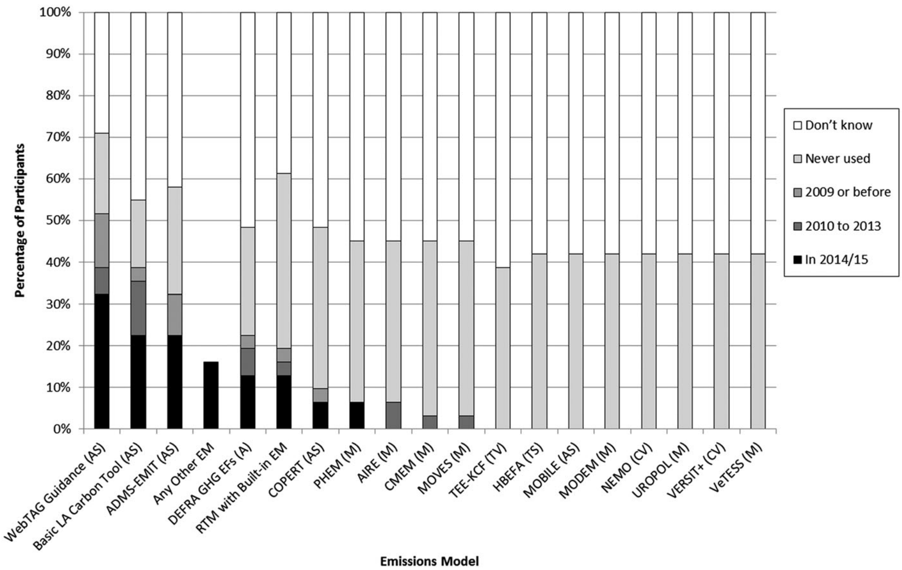

Figure 4. Time periods when EM software applications were last used by (or on behalf of) LGAs.

Notes: $n = 31$. EM types are Aggregate (A), Average Speed (AS), Traffic Situation (TS), Traffic Variable (TV), Cycle Variable (CV) and Modal (M). Six participants specified a 'RTM with Built-in EM', which were VISUM (AS), SATURN (TV), PARAMICS (M) and VISSIM (M). Note: Five participants specified an 'Any Other EM', which were DMRB guidance (AS), Greater Manchester EM (AS), TUBA (AS) and PITHEM (AS).

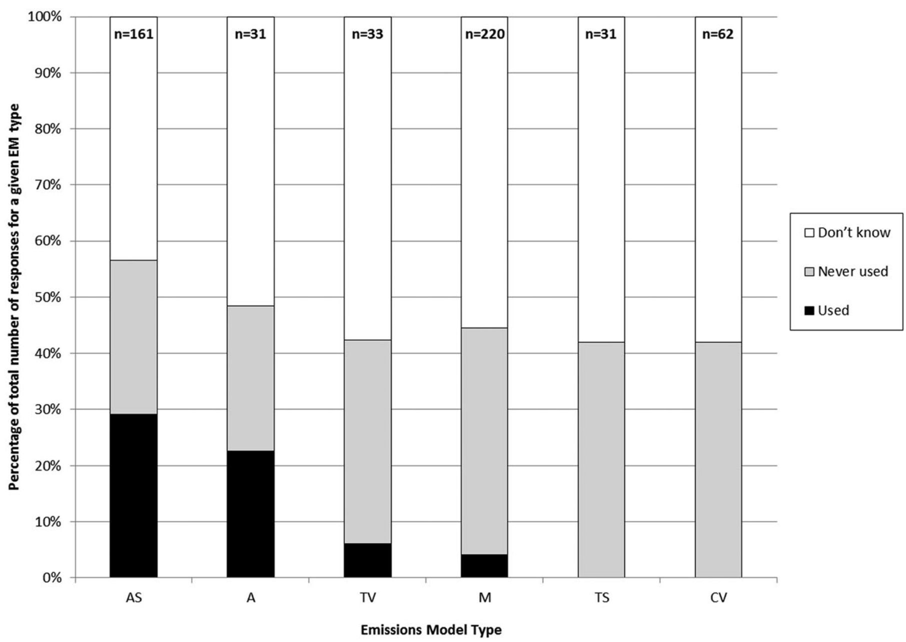

Figure 5. Types of EM software applications used by (or on behalf of) LGAs.

Notes: Some EM types appeared more frequently than others in the list of EM software applications presented to participants. Hence, number of responses (n) varies from type to type. EM types are Aggregate (A), Average Speed (AS), Traffic Situation (TS), Traffic Variable (TV), Cycle Variable (CV) and Modal (M).

magnitude. This indicates the limitations of this comparison in that it is not an ideal like-for-like comparison (i.e. the value of EM accuracy is not the same as the value of emissions). However, the comparison serves the purpose of providing a context against which a general sense can be gained of whether the LGA values are plausible, and the fact that they are less than central government values of actual emissions was consistent with expected results.

4. Discussion

An aim of the research was to investigate the emissions modelling process that is the best-fit for (ideally) all LGAs, rather than considering the situation where different EMs are developed to suit different LGAs characterised by urbanisation, population size, location, etc. Hence, in the analysis of survey results LGAs were not disaggregated according to these characteristics. Benefits of a single approach to CO_2 emissions modelling are that it allows comparability of results from transport intervention assessments across different LGAs, and that research and development can be focused on one particular methodology; although it is acknowledged that these benefits would have to be weighed against the benefits of using EMs tailored to specific circumstances. A potential procedure for establishing a consensus on LGA requirements would be a regular survey of LGAs across the globe; although it is acknowledged that the interval between such surveys is likely to be measured in decades due to the size of the undertaking, and that there are considerable difficulties (impossibilities?) inherent in securing such international agreements on mitigation of CO_2 emissions.

Generally, LGAs indicated concern for all the factors affecting allocation of resources to road traffic emissions modelling (mean importance scores all >2), highlighting an overall opinion that resource scarcity is an important issue. Whilst statistically significant differences only existed between factors at the extremes of the Friedman test mean rankings, inspection of Table 3 suggests that survey participants considered model reusability to be the most important factor, that is, a preference for EMs that have the flexibility to be used in assessment of future, as yet undetermined, interventions. From the LGA viewpoint, EMs tailored to the one-off assessment of a particular intervention are best avoided. Reusable EMs bring many additional benefits which may explain the importance attached to this factor, such as: staff familiarity; goodness of fit with existing skills; shorter timescales required to use familiar software applications; avoidance of regular staff retraining; reliability of operation; trust in validity of results; comparability of results across different intervention assessments and goodness of fit with road traffic data routinely collected.

Easily available input data also was considered an important factor, being ranked second by participants. Of all the road traffic data sources, the options that appear to be most convenient for LGAs are RTMs and UTC systems. This is for three reasons: (1) they are ranked highly by participants as easily obtainable and routinely collected; (2) they are ranked highest and second-highest, respectively, as planned for future collection which is an important indicator of the data LGAs expect to be available for future emissions modelling and (3) they are available on a link-by-link basis enabling emissions calculations for all (or mostly all) links in a network to be performed. Other data sources considered easily available by LGAs typically do not provide link-by-link data. For example, availability of traffic counts (manual or automatic), surveys and ANPR data are restricted to only a few locations (spatially and also sometimes temporally) within a network, and NIs of congestion are normally only available for certain key routes. Where sufficient penetration is achieved (i.e. number of vehicles from which data can be gathered compared to total number of vehicles), vehicle tracking data from GPS, Bluetooth, mobile telephony and Wi-Fi devices are available on a link-by-link basis. However, these technologies are not considered easily available by LGAs and have not been widely collected, indicating a lack of familiarity and experience in their use. By inspection of Figure 2 a general trend appears of a move away from manual, labour-intensive data collection towards automatic, less labour-intensive sources. Manual traffic counts (MTCs) and RSI surveys are both decreasing (although queue length surveys are fairly constant), whilst RTMs, UTC, automatic traffic count by speed detection radar (ATC-SDR) and ANPR are all increasing (although ATC-pneumatic are decreasing). Explanations for this trend could be the increasing pressure on LGA resource budgets and/or an expectation that the rise in telematics and 'big' data will satisfy LGA traffic data requirements, although the technologies underpinning telematics have low ranks as data planned for future collection.

Due to convenience, LGAs are likely to use RTMs and UTC systems as sources for EM input data. Data available from UTC systems are traffic variables, that is, describing traffic as an aggregate whole rather than describing individual vehicles. However, accuracy of the traffic data provided by ILDs is an issue, particularly for single-loop ILDs which are often installed in urban areas (Han et al. 2010). For example, where traffic average speed is a required EM input this is typically space-mean-speed,[12] whereas ILDs can only provide estimates of time-mean-speed (which in themselves may be of questionable accuracy). Nonetheless, results of the survey indicate use of this convenient data source (with its associated inherent inaccuracies) to provide EM inputs is a subject worthy of further research. Data output from RTMs depend on RTM type. The RTM most widely used by LGAs is SATURN, which is a meso-RTM that outputs traffic variables rather than individual vehicle driving patterns. PARAMICS and VISSIM are the second and third most used RTMs, respectively, and are both micro-RTMs that can output individual vehicle driving patterns. However, collecting and processing driving patterns for every vehicle in a network is a resource-intensive task. Additionally, micro-RTMs are typically calibrated and validated for aggregate traffic measures (e.g. traffic average speed, traffic flow and average delay) rather than for driving patterns of individual vehicles (Hirschmann et al. 2010; Song, Yu, and Zhang 2012; Toffolo et al. 2013; Song, Yu, and Xu 2013). Therefore, driving pattern outputs from micro-RTMs are rarely properly validated, and do not necessarily accurately represent the real-world (Song, Yu, and Zhang 2012; Song, Yu, and Xu 2013), whereas link-level traffic variable outputs are more likely to be accurate.

A preference for calculating emissions from traffic variables is demonstrated by the common use of Average Speed EMs by LGAs, with the three most used EMs all being of the Average Speed type. Most EMs are currently based on average speed (Boulter et al. 2012), and a suggested reason for this prevalence is that readily available data are often restricted to estimates of traffic average speed for each link (Smit, Poelman, and Schrijver 2008). However, average speed is not the only traffic variable readily available from sources such as RTMs and UTC systems, and inclusion of the explanatory power of other traffic variables may present an opportunity to improve the accuracy of emissions calculations. To take advantage of this opportunity, the feasibility of developing Traffic Situation EMs or Traffic Variable EMs (both currently not widely used by LGAs) for use by LGAs is worthy of further investigation. Cycle Variable EMs and Modal EMs are also both currently not widely used by LGAs. Likely reasons for this are that these types of EMs are resource-intensive to use, and that they require accurate driving patterns as inputs which cannot be obtained from the data sources regarded as easily available to LGAs, a situation unlikely to change in the near future based on LGA future data collection plans.

A surprising result was that no participant mentioned using the emissions factors toolkit (EFT) EM, which is an Average Speed EM developed by the UK central government's Department for Environment Food & Rural Affairs (DEFRA) specifically to assist LGAs in carrying out their statutory duty to assess local AQ. Given that approximately 60% of UK LGAs have designated areas where AQ objectives are not being met (2014a) and that road traffic emissions are the reason for such designations in 90% of cases (Bell et al. 2013), it seems likely the EFT will have been widely used. A possible reason for omission by participants is its specific design for AQ emissions (although it can also calculate CO_2 emissions), whereas the survey was focused on CO_2 emissions.

Comparison of results with central government CO_2 valuations indicates LGAs are willing to commit far fewer resources to the emissions modelling process than might be expected. The majority of LGAs appear to accept the accuracy provided by EMs currently used (mostly Average Speed EMs) and are reluctant to commit extra resources for increased accuracy, even if that increased accuracy indicates interventions are producing greater emissions reduction outcomes than originally calculated. This highlights that, in order to be tractable, any improvements to CO_2 EM accuracy must be at minimal additional cost to LGAs. Both questions produced similarly low mean valuations even though scenarios were worded in different ways.

An important issue with the survey results is the impossibility of being completely certain what was in participants' minds when answering, and hence uncertainty about whether responses are reflective of organisational-level attitudes or individual-level attitudes. As this article's title implies, it is organisation-level attitudes that are sought because LGAs engage in the emissions modelling process as a result of organisational decisions, rather than decisions made by a single individual employee. Particularly susceptible to this issue are the two questions designed to quantify LGAs' willingness to commit resources to emissions modelling. Rather than a simple statement of fact (as in most other questions, e.g. whether particular EMs have been used or not), these questions involved complex, hypothetical scenarios and subjective judgements, but are unlikely to have been discussed at organisational-level prior to response. Hence, comparison with organisational-level central government valuations of CO_2 should be treated with caution, although the tendency to under-valuation shown by participants was substantial.

British LGAs do not have a statutory obligation to reduce GHG emissions (DECC 2014b). Therefore, non-compliance with any GHG emissions reduction targets LGAs may set voluntarily incurs little penalty, and low CO_2 valuations perhaps should not come as a surprise. An interesting contrast is the situation for emissions of oxides of nitrogen (NO_x) (of which road traffic is a major source), where the UK is facing potential fines imposed by the European Commission for breach of nitrogen dioxide (NO_2) concentration limit values under the EU Air Quality Directive. This financial sanction has been estimated at up to £300 million (Kidney and Price 2012), and UK central government is threatening to pass on (full or partial) payment of any fines to LGAs in whose regions these exceedances are occurring[13] (DEFRA 2014b). In this situation, LGAs may be willing to commit extra resources to emissions modelling, if that modelling could contribute to a process that demonstrated they were no longer breaching NO_2 limits (a pollutant dispersion model and concentration monitoring would be required to complete this process) and fines be avoided. If the threat of financial penalties does lead to NO_2 emissions reductions, other pollutant emissions (including CO_2) may also be reduced because of potential co-benefits from integrated reduction strategies (DEFRA 2009; EEA 2009; King et al. 2010; Tiwary, Chatterton, and Namdeo 2013); although this is not always the case, and a reduction in emissions of one pollutant can sometimes cause increases in another. From a cost-benefit perspective, at a time of scarce resources, there is an increasing need for LGAs to include all possible emissions reduction benefits (i.e. for all pollutants, rather than just NO_2) if an argument for implementation of a proposed intervention is to be successful (Tiwary, Chatterton, and Namdeo 2013).

Results show that if a transport intervention has high significance to the local political agenda then this was regarded as an important factor in allocation of resources for emissions modelling (third highest factor in Table 3). This finding was reinforced by one participant's free-text supplementary response which stated that if a 'political decision has been made that a problem needs to be addressed, as a rule of thumb, we will do whatever it takes (within reason) to make this happen, such as, for example, spend more on a more accurate/detailed modelling package to make sure the case is made and investment is secured'. Threat of fines for breaching NO_2 limits has pushed this issue up the local political agenda, and it seems likely more resources will be available for any mitigation actions (including modelling the impact of transport interventions). For example, the DfT recently (November 2015) invited proposals to be submitted for novel solutions to the local transport and AQ problem, with grants available for successful submissions from a total fund of £250,000 (DfT 2015). In general, placing increasing responsibility on LGAs to be accountable for achieving their environmental targets should result in the impact of transport interventions on emissions (including CO_2) being increasingly pushed up the local political agenda. In turn, this should lead to an increasing willingness on the part of LGAs to commit more resources to the emissions modelling process.

5. Conclusions

A central message of the survey results is that scarcity of resources is an important issue for LGAs when conducting road traffic emissions modelling. Participants placed particular importance on EMs having the flexibility to be reusable for assessment of future transport interventions, and on a requirement for input data to be easily available. Of the road traffic data sources that can provide EM inputs, RTMs and UTC systems represent the most convenient options for LGAs for three reasons: (1) they are ranked highly as easily obtainable and routinely collected; (2) they are ranked highest and second-highest, respectively, as planned for future collection and (3) they can provide traffic variables on a link-by-link basis for all (or mostly all) links in a network. Micro-RTMs can additionally generate individual vehicle driving pattern outputs, but doubts exist concerning their accuracy and their collection and processing is resource-intensive.

Therefore, an EM based on traffic variable outputs from RTMs and UTC systems appears to be the most appropriate option for LGAs. An ability to use data from either source is important to overcome situations where UTC data are not available (i.e. links with no ILD installed or hypothetical scenarios). A trend was identified of a move away from road traffic data sources involving manual, labour-intensive data collection processes, and a move towards sources involving automatic, less labour-intensive collection processes. Explanations for this trend could be increasing pressure on LGA resource budgets, and/or an expectation that the rise in telematics and 'big' data will satisfy LGA traffic data requirements.

The large majority of LGA emissions modelling is currently achieved using Average Speed EMs, with more detailed EM types being used rarely (if at all). However, other traffic variables (in addition to traffic average speed) are easily available for incorporation and could offer opportunities to improve the accuracy of EMs for LGAs. This is an area for further investigation and development work. Any accuracy improvements must come at minimal cost to LGAs because they have indicated a reluctance to commit extra resources for improved accuracy. However, overcoming this barrier is likely to be possible where a transport intervention is of high significance to the local political agenda. In these circumstances, more resources are likely to be made available for the emissions modelling process.

Notes

1. In contrast to private roads, adopted roads (which constitute the vast majority of British roads) are those maintained at public expense.
2. Great Britain comprises England, Scotland and Wales.
3. In this article, LGA is used in preference to LHA because it is a more typical term used to describe local government institutions. However, where LGA is used, this implies a local authority with responsibility for non-SRN roads in their area of administration.
4. CO_2-equivalent: amount of CO_2 emitted that would cause the same time-integrated radiative forcing, over a given time horizon, as an emitted amount of another GHG.
5. Whilst Wales is not included in this quote, the comparison has merits because England and Scotland together comprise 184 out of the total for Britain of 206 LHAs.
6. The Local Government Association is the national organisation representing LGAs in England and Wales.
7. Produced by Mott MacDonald.
8. Simulation and Assignment of Traffic to Urban Road Networks – developed at the Institute for Transport Studies, University of Leeds and distributed by Atkins Limited.
9. A platoon-dispersion module simulates how a platoon of vehicles released by a green traffic signal disperses as the vehicles progress through the network.
10. Regional Associate, Highways and Transportation, Parsons Brinckerhoff.
11. Net revenue expenditure is gross expenditure less fees and charges for LGA services and specific grants, where specific grants are grants ring-fenced for dedicated purposes.
12. Space-mean-speed is calculated from the arithmetic mean of measured travel times over a measured distance of all vehicles during a given survey period. In contrast, time-mean-speed is the arithmetic mean of measured speeds (i.e. spot speeds) over a short measured distance of all vehicles during a given survey period.
13. At the time of paper revision (June 2016), the UK has just voted to leave the EU and the threat of this fine will recede, which could mean resources for emissions modelling may start to slip down in priority.

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Appendix. Glossary

A	Aggregate EM
ADMS	Atmospheric Dispersion Modelling System – produced by Cambridge Environmental Research Consultants
AIMSUN (RTM)	Advanced Interactive Microscopic Simulator for Urban and Non-Urban Networks – produced by Transport Simulation Systems
AIRE (EM)	Analysis of Instantaneous Road Emissions – produced by Transport for Scotland and SIAS
ANPR	Automatic Number Plate Recognition
AQ	Air quality
ARCADY (RTM)	Assessment of Roundabout Capacity and Delay – produced by TRL
ARTEMIS	Assessment and Reliability of Transport Emission Models and Inventory Systems – European Commission 5th Framework project
AS	Average Speed EM
ATC-Pneumatic	Automatic Traffic Count by pneumatic tube
ATC-SDR	Automatic Traffic Count by Speed Detection Radar
Basic LA Carbon Tool (EM)	Basic Local Authority Carbon Tool – produced by the DfT
CONTRAM (RTM)	Continuous Traffic Assignment Model – produced by Mott MacDonald and TRL, but no longer available to new users
COPERT (EM)	Computer Programme to calculate Emissions from Road Transport – coordinated by the European Environment Agency
CMEM (EM)	Comprehensive Modal Emissions Model – produced by the University of California's College of Engineering
CUBE Avenue (RTM)	Produced by Citilabs
CUBE Dynamism (RTM)	Produced by Citilabs
CUBE Voyager (RTM)	Produced by Citilabs
CV	Cycle Variable EM
DCLG	Department for Communities and Local Government
DECADE	European Commission 5th Framework project
DECC	Department of Energy & Climate Change
DEFRA	Department for Environment Food and Rural Affairs
DEFRA GHG EFs (EM)	Greenhouse Gas Conversion Factor Repository – produced by the DEFRA

DELTA	Land-use software application – produced by David Simmonds Consultancy
DfT	Department for Transport
DMRB	Design Manual for Roads and Bridges – DfT guidance on the design, assessment and operation of trunk roads and motorways, including methods for calculating road traffic emissions
DRACULA (RTM)	Dynamic Route Assignment Combining User Learning and Microsimulation – produced by the University of Leeds
DRIVE	Dedicated Road Infrastructure for Vehicle safety in Europe – European Commission 2nd Framework project
EFT (EM)	Emissions Factors Toolkit – produced by the DEFRA
EM	Emissions Model
EMIT (EM)	Emissions Inventory Toolkit – sub-model of ADMS
EMME (RTM)	Produced by INRO
EPA	USA Environmental Protection Agency
EU	European Union
GHG	Greenhouse Gas
HBEFA (EM)	Handbook of Emission Factors – coordinated by INFRAS
HGV	Heavy Goods Vehicle
ILD	Inductive Loop Detector
LGA	Local Government Authority
LGV	Light Goods Vehicle
LINSIG (RTM)	Signal-controlled intersections analysis software application – Produced by JCT Consultancy
M	Modal EM
MOBILE (EM)	Produced by the EPA
MODEM (EM)	Modelling of Emissions and Consumption in Urban Areas – produced during DRIVE
MOVES (EM)	Motor Vehicle Emission Simulator – produced by the EPA
MTC	Manual Traffic Count
NEMO (EM)	Network Emissions Model – produced during ARTEMIS
NI	National Indicator
PARAMICS (RTM)	Parallel Microscopic Simulation – produced by SIAS Limited
PHEM (EM)	Passenger car and Heavy duty Emission Model – coordinated by Technische Universität Graz
PICADY (RTM)	Priority Intersection Capacity and Delay (now called Junctions 8) – produced by TRL
PITHEM	Platform for Integrated Transport, Health and Environmental Modelling – produced by the University of Newcastle
QUADRO	Road works cost appraisal software application – produced by TRL
RSI	Roadside Interview
RTM	Road Traffic Model
RTMS	Remote Traffic Microwave Sensor – also known as SDR
SATURN (RTM)	Simulation and Assignment of Traffic to Urban Road Networks – developed by the University of Leeds and distributed by Atkins Limited
SD	Standard Deviation
SDR	Speed Detection Radar – also known as RTMS
TEE-KCF (EM)	Traffic Energy and Emissions-Kinematic Correction Factor
TRANSYT (RTM)	Traffic Network and Isolated Intersection Study Tool – produced by TRL
TRICS	UK database for trip generation analysis
TRIPS	Transport Improvement Planning System – produced by MVA Consultancy (now called Systra)
TRL	Transport Research Laboratory
TS	Traffic Situation EM
TUBA	Transport User Benefit Appraisal – software application for road and multi-modal scheme appraisal produced by the DfT and Atkins Limited
TV	Traffic Variable EM
UROPOL (EM)	Urban Road Pollution
UTC	Urban Traffic Control
VERSIT+ (EM)	Verkeers Situatie – produced by TNO
VeTESS (EM)	Vehicle Transient Emissions Simulation Software – produced during DECADE
VISSIM (RTM)	Produced by PTV
VISUM (RTM)	Produced by PTV
VKM	Vehicle-Kilometre
VKT	Vehicle-Kilometre Travelled
WebTAG	DfT guidance on conducting transport studies, including methods for calculating road traffic emissions

Local Government Authority Road Traffic Emissions Questionnaire

PARTICIPANT INFORMATION SHEET [Version 1.1, Feb 2015]

Study Title: Local Government Authority road traffic and emissions survey

Researcher: Mr Matt Grote **Research ethics committee number:** 13144

Please read this information carefully before deciding to take part in this research. If you are happy to participate you will be asked to tick a consent box at the end of this page.

What is the research about?
The University of Southampton is investigating the use by Local Government Authorities (LGAs) of data and computer models to estimate exhaust emissions from road traffic. Your views are an important part of this investigation, helping to make any present and future emissions calculation techniques more efficient, cost effective and environmentally beneficial. We need your help to make this investigation as meaningful as possible.

Why have I been chosen?
You have been chosen as a potential participant because of your expertise in how LGAs make decisions regarding the transport system for which they are responsible. Your contact details were provided to us by Oscar Research Ltd.

What will happen to me if I take part?
Your participation will involve answering an online survey questionnaire that should take around 20-30 minutes to complete. Whilst most questions are fairly straightforward to answer, there are a few that may require you to perform some simple calculations, and we are very appreciative of your efforts in answering these questions.

Are there any benefits in my taking part?
Your views will assist our efforts to provide LGAs with appropriate tools for calculating road traffic emissions. Ultimately, the survey results, and future work based on those results, will be more meaningful as a result of your contribution. As a thank you for taking part, you are welcome to receive a report summarising the results of the survey.

Are there any risks involved?
There are no risks involved.

Will my participation be confidential?

All data collected during this study will be confidential, and handled in compliance with the Data Protection Act and University policy. Data will be stored on a password protected computer, and will only be used for the purposes of this study. Only those involved with the study will be able to access information. Whilst complete anonymity cannot be promised, all files containing any personal information will be made anonymous to prevent identification of participants. Confidentiality will be maintained as the data will remain anonymous in any publication of results.

What happens if I change my mind?

You have the right to withdraw at any time without your legal rights being affected.

What happens if something goes wrong?

In the unlikely case of concern or complaint, please contact:

- Professor Neville Stanton (Chairman of the Faculty of Engineering and the Environment Ethics Committee)
- N.Stanton@soton.ac.uk
- 02380 599065

Where can I get more information?

If you have any questions or concerns regarding completion of the questionnaire, please contact:

- Mr Matt Grote
- mjg1g12@soton.ac.uk

Survey consent

Please read the following statements, and if you agree with the statements tick the box below.

- **I have read and understood the Participant Information Sheet [Version 1.1, Feb 2015] and have had the opportunity to ask questions about the study.**
- **I understand my participation is voluntary and I may withdraw at any time without my legal rights being affected.**
- **I have read and understood the section on "Will my participation be confidential?" and agree for my data to be used for the purpose of this study.**
- **I agree to take part in this research project.**

☐ Please tick (check) this box to indicate that you consent to taking part in this survey.

ROAD TRAFFIC DATA

Question 1

In your opinion are the following road traffic data considered easily obtainable by (or on behalf of) your organisation; and are (or were) they ever routinely collected by (or on behalf of) your organisation?

(For each item of data, select ONE button in the column that best reflects your opinion.)

Data source	Easily obtainable, and routinely collected	Easily obtainable, but NOT routinely collected	NOT easily obtainable, but routinely collected	NOT easily obtainable, and NOT routinely collected	Don't know
Automatic Number Plate Recognition	○	○	○	○	○
Automatic traffic count – Pneumatic tube	○	○	○	○	○
Automatic traffic count – Speed Detection Radar traffic classifier	○	○	○	○	○
Bluetooth device	○	○	○	○	○
GPS device	○	○	○	○	○
Manual traffic count	○	○	○	○	○
Mobile telephony device	○	○	○	○	○
National Indicators of road traffic congestion	○	○	○	○	○
Queue length survey	○	○	○	○	○
Roadside interview survey	○	○	○	○	○
Road traffic model outputs	○	○	○	○	○
Urban Traffic Control system	○	○	○	○	○
WiFi device	○	○	○	○	○
Other data source (please specify).............	○	○	○	○	○

Question 2

For the following road traffic data, indicate when they have been routinely collected by (or on behalf of) your organisation.

(For each item of data, place ticks in ALL columns that apply.)

Data source	Never routinely collected	Routinely collected				Don't know
		2009 or before	2010 to 2013	2014/15	Planned for future collection	
Automatic Number Plate Recognition	☐	☐	☐	☐	☐	☐
Automatic traffic count – Pneumatic tube	☐	☐	☐	☐	☐	☐
Automatic traffic count – Speed Detection Radar traffic classifier	☐	☐	☐	☐	☐	☐
Bluetooth device	☐	☐	☐	☐	☐	☐
GPS device	☐	☐	☐	☐	☐	☐
Manual traffic count	☐	☐	☐	☐	☐	☐
Mobile telephony device	☐	☐	☐	☐	☐	☐
National Indicators of road traffic congestion	☐	☐	☐	☐	☐	☐
Queue length survey	☐	☐	☐	☐	☐	☐
Roadside interview survey	☐	☐	☐	☐	☐	☐
Road traffic model outputs	☐	☐	☐	☐	☐	☐
Urban Traffic Control system	☐	☐	☐	☐	☐	☐
Wi-Fi device data	☐	☐	☐	☐	☐	☐
Other data source (please specify).....	☐	☐	☐	☐	☐	☐

ROAD TRAFFIC MODELS

In this section, road traffic models are defined as computer software packages that simulate the movement of traffic through a road network.

Question 3

To your knowledge, which (if any) of these road traffic modelling software packages have been used by (or on behalf of) your organisation?

(For each road traffic model, select ONE button in the column that best describes when the model was LAST used.)

Road traffic modelling software	Never Used	Used			Don't know
		2009 or before	2010 to 2013	2014/15	
AIMSUN (Advanced Interactive Microscopic Simulator for Urban and Non-Urban Networks)	○	○	○	○	○
CUBE Avenue	○	○	○	○	○
CUBE Dynamism	○	○	○	○	○
CUBE Voyager	○	○	○	○	○
CONTRAM (Continuous Traffic Assignment Model)	○	○	○	○	○
DRACULA (Dynamic Route Assignment Combining User Learning and micro-simulation)	○	○	○	○	○
EMME	○	○	○	○	○
PARAMICS (Parallel Microscopic Simulation)	○	○	○	○	○
SATURN (Simulation and Assignment of Traffic to Urban Road Networks).	○	○	○	○	○
VISSIM	○	○	○	○	○
VISUM	○	○	○	○	○
Other road traffic modelling software (please specify)................................	○	○	○	○	○

If your organisation has used any road traffic models, briefly explain the purpose(s):

ROAD TRAFFIC EMISSIONS MODELS

In this section, road traffic emissions models are defined as computer software packages that calculate the exhaust emissions resulting from the movement of vehicles through a road network.

Question 4

To your knowledge, which (if any) of these road traffic emissions modelling software packages have been used by (or on behalf of) your organisation?

(For each road traffic emissions model, select ONE button in the column that best describes when the model was LAST used.)

Road traffic emissions modelling software	Never Used	Used			Don't know
		2009 or before	2010 to 2013	2014/15	
ADMS 5 emissions sub-model EMIT (Emissions Inventory Toolkit)	○	○	○	○	○
AIRE (Analysis of Instantaneous Road Emissions)	○	○	○	○	○
CMEM (Comprehensive Modal Emissions Model)	○	○	○	○	○
COPERT (Computer Programme to calculate Emissions from Road Transport)	○	○	○	○	○
DEFRA greenhouse gas emission factors	○	○	○	○	○
DfT Basic Local Authority Carbon Tool	○	○	○	○	○
HBEFA (Handbook of Emission Factors)	○	○	○	○	○
MOBILE	○	○	○	○	○
MODEM (Modelling of Emissions and Consumption in Urban Areas)	○	○	○	○	○
MOVES (Motor Vehicle Emission Simulator)	○	○	○	○	○
NEMO (Network Emissions Model)	○	○	○	○	○
PHEM (Passenger car and Heavy-duty Emissions Model)	○	○	○	○	○
TEE-KCF (Traffic Energy and Emissions – Kinematic Correction Factor)	○	○	○	○	○
UROPOL (Urban Road Pollution)	○	○	○	○	○
VERSIT+	○	○	○	○	○

VeTESS (Vehicle Transient Emissions Simulation Software)	◯	◯	◯	◯	◯
WebTAG guidance on calculating fuel consumption/emissions (Units A1.3 & A3)	◯	◯	◯	◯	◯
Road traffic modelling software with built-in emissions calculator (please specify)………….	◯	◯	◯	◯	◯
Other road traffic emissions modelling software (please specify).....................	◯	◯	◯	◯	◯

If your organisation has used any road traffic emissions models, briefly explain the purpose(s):

RESOURCES CONSUMED BY MODELLING ACTIVITIES

Question 5

In your professional opinion, if you were considering undertaking a modelling project (either traffic or traffic emissions), indicate the extent to which you agree or disagree with the following statements.

(For each statement, select ONE button that best describes the extent of your agreement.)

Factor	Strongly disagree	Disagree	Neither agree nor disagree	Agree	Strongly agree
It is important that the modelling is inexpensive	◯	◯	◯	◯	◯
Completing the modelling quickly is not important	◯	◯	◯	◯	◯
Easily available model input data is an important factor	◯	◯	◯	◯	◯
It is important that the modelling does not require high manpower resources	◯	◯	◯	◯	◯
Avoiding the need to employ external consultants for their modelling expertise is not an important factor	◯	◯	◯	◯	◯
It is important that the modelling does not require high levels of staff training	◯	◯	◯	◯	◯
It is important that the model can be used on an ongoing basis to assess other transport interventions in the future	◯	◯	◯	◯	◯
The model being highly accurate is important, even if this means the model is more expensive	◯	◯	◯	◯	◯
The project being significant to the local political agenda is not an important factor	◯	◯	◯	◯	◯

COST AND ACCURACY OF EMISSIONS MODELS – Part 1

In this section you are asked to compare the cost and accuracy of using TWO different emissions models (EM1 and EM2) for the same task. **EM2 is both more expensive AND more accurate than EM1.**

SCENARIO: Transport interventions implemented in the past year have reduced CO_2-equivalent (CO_2e) emissions from traffic on the road network of an urban area (population *circa* 250,000) from 250,000 tonnes per year to 245,000 tonnes per year, at a cost of £300,000. Therefore, the true quantity of CO_2e saved is **5,000 tonnes** per year.

Initially you choose EM1 to assess the interventions, which costs £50,000 to use and predicts a saving of 4,000 tonnes per year (an under-prediction of the true saving). However, you also have the option of using EM2 instead, which costs more to use and gives more accurate predictions.

Question 6

If EM1 costs £50,000 and EM2 costs £60,000, moving from left to right, select the button that best indicates the point at which the improvement in accuracy offered by EM2 becomes large enough to justify the extra cost of using EM2.

EM1 predicted saving (tonnes)	EM1 4,000	EM1 4,000	EM1 4,000	EM1 4,000	EM1 4,000	EM1 4,000	EM1 4,000	EM1 4,000	EM1 4,000	EM1 4,000	Would not switch to EM2
EM2 predicted saving (tonnes)	EM2 4,100	EM2 4,200	EM2 4,300	EM2 4,400	EM2 4,500	EM2 4,600	EM2 4,700	EM2 4,800	EM2 4,900	EM2 5,000	
	○	○	○	○	○	○	○	○	○	○	○

If EM1 costs £50,000 and EM2 costs £70,000, moving from left to right, select the button that best indicates the point at which the improvement in accuracy offered by EM2 becomes large enough to justify the extra cost of using EM2.

EM1 predicted saving (tonnes)	EM1 4,000	EM1 4,000	EM1 4,000	EM1 4,000	EM1 4,000	EM1 4,000	EM1 4,000	EM1 4,000	EM1 4,000	EM1 4,000	Would not switch to EM2
EM2 predicted saving (tonnes)	EM2 4,100	EM2 4,200	EM2 4,300	EM2 4,400	EM2 4,500	EM2 4,600	EM2 4,700	EM2 4,800	EM2 4,900	EM2 5,000	
	○	○	○	○	○	○	○	○	○	○	○

If EM1 costs £50,000 and EM2 costs £80,000, moving from left to right, select the button that best indicates the point at which the improvement in accuracy offered by EM2 becomes large enough to justify the extra cost of using EM2.

EM1 predicted saving (tonnes)	EM1 4,000	EM1 4,000	EM1 4,000	EM1 4,000	EM1 4,000	EM1 4,000	EM1 4,000	EM1 4,000	EM1 4,000	EM1 4,000	Would not switch to EM2
EM2 predicted saving (tonnes)	EM2 4,100	EM2 4,200	EM2 4,300	EM2 4,400	EM2 4,500	EM2 4,600	EM2 4,700	EM2 4,800	EM2 4,900	EM2 5,000	
	○	○	○	○	○	○	○	○	○	○	○

If EM1 costs £50,000 and EM2 costs <u>£90,000</u>, moving from left to right, select the button that best indicates the point at which the improvement in accuracy offered by EM2 becomes large enough to justify the extra cost of using EM2.

EM1 predicted saving (tonnes)	EM1 4,000	EM1 4,000	EM1 4,000	EM1 4,000	EM1 4,000	EM1 4,000	EM1 4,000	EM1 4,000	EM1 4,000	EM1 4,000	Would not switch to EM2
EM2 predicted saving (tonnes)	EM2 4,100	EM2 4,200	EM2 4,300	EM2 4,400	EM2 4,500	EM2 4,600	EM2 4,700	EM2 4,800	EM2 4,900	EM2 5,000	
	○	○	○	○	○	○	○	○	○	○	○

If EM1 costs £50,000 and EM2 costs <u>£100,000</u>, moving from left to right, select the button that best indicates the point at which the improvement in accuracy offered by EM2 becomes large enough to justify the extra cost of using EM2.

EM1 predicted saving (tonnes)	EM1 4,000	EM1 4,000	EM1 4,000	EM1 4,000	EM1 4,000	EM1 4,000	EM1 4,000	EM1 4,000	EM1 4,000	EM1 4,000	Would not switch to EM2
EM2 predicted saving (tonnes)	EM2 4,100	EM2 4,200	EM2 4,300	EM2 4,400	EM2 4,500	EM2 4,600	EM2 4,700	EM2 4,800	EM2 4,900	EM2 5,000	
	○	○	○	○	○	○	○	○	○	○	○

COST AND ACCURACY OF EMISSIONS MODELS – Part 2

In this section (as in the previous section) you are asked to compare the cost and accuracy of using TWO different emissions models (EM1 and EM2) for the same task. Again **EM2 is both more expensive AND more accurate than EM1.**

SCENARIO: A proposed transport intervention will reduce CO_2e emissions from traffic on the road network of an urban area (population *circa* 250,000) from 250,000 tonnes per year to 249,000 tonnes per year, at a cost of £60,000. Therefore, the true quantity of CO_2e saved will be **1,000 tonnes** per year.

However, EM1 predicts **NO** reduction in emissions (an under-prediction of the true saving) and so the decision is made **NOT** to implement the proposed intervention. Conversely, EM2 (which is more accurate) does predict a reduction in emissions.

Question 7

If EM1 costs £50,000 and EM2 costs £60,000, moving from left to right, select the button that best indicates the point at which the emissions saving predicted by EM2 becomes large enough to justify using EM2, leading to the decision being REVERSED and the proposed intervention being implemented.

EM1 predicted saving (tonnes)	EM1 0	EM1 0	EM1 0	EM1 0	EM1 0	EM1 0	EM1 0	EM1 0	EM1 0	EM1 0	Would not reverse decision
EM2 predicted saving (tonnes)	EM2 100	EM2 200	EM2 300	EM2 400	EM2 500	EM2 600	EM2 700	EM2 800	EM2 900	EM2 1,000	
	○	○	○	○	○	○	○	○	○	○	○

If EM1 costs £50,000 and EM2 costs £70,000, moving from left to right, select the button that best indicates the point at which the emissions saving predicted by EM2 becomes large enough to justify using EM2, leading to the decision being REVERSED and the proposed intervention being implemented.

EM1 predicted saving (tonnes)	EM1 0	EM1 0	EM1 0	EM1 0	EM1 0	EM1 0	EM1 0	EM1 0	EM1 0	EM1 0	Would not reverse decision
EM2 predicted saving (tonnes)	EM2 100	EM2 200	EM2 300	EM2 400	EM2 500	EM2 600	EM2 700	EM2 800	EM2 900	EM2 1,000	
	○	○	○	○	○	○	○	○	○	○	○

If EM1 costs £50,000 and EM2 costs <u>£80,000</u>, moving from left to right, select the button that best indicates the point at which the emissions saving predicted by EM2 becomes large enough to justify using EM2, leading to the decision being REVERSED and the proposed intervention being implemented.

EM1 predicted saving (tonnes)	EM1 0	EM1 0	EM1 0	EM1 0	EM1 0	EM1 0	EM1 0	EM1 0	EM1 0	EM1 0	Would not reverse decision
EM2 predicted saving (tonnes)	EM2 100	EM2 200	EM2 300	EM2 400	EM2 500	EM2 600	EM2 700	EM2 800	EM2 900	EM2 1,000	
	◯	◯	◯	◯	◯	◯	◯	◯	◯	◯	◯

If EM1 costs £50,000 and EM2 costs <u>£90,000</u>, moving from left to right, select the button that best indicates the point at which the emissions saving predicted by EM2 becomes large enough to justify using EM2, leading to the decision being REVERSED and the proposed intervention being implemented.

EM1 predicted saving (tonnes)	EM1 0	EM1 0	EM1 0	EM1 0	EM1 0	EM1 0	EM1 0	EM1 0	EM1 0	EM1 0	Would not reverse decision
EM2 predicted saving (tonnes)	EM2 100	EM2 200	EM2 300	EM2 400	EM2 500	EM2 600	EM2 700	EM2 800	EM2 900	EM2 1,000	
	◯	◯	◯	◯	◯	◯	◯	◯	◯	◯	◯

If EM1 costs £50,000 and EM2 costs <u>£100,000</u>, moving from left to right, select the button that best indicates the point at which the emissions saving predicted by EM2 becomes large enough to justify using EM2, leading to the decision being REVERSED and the proposed intervention being implemented.

EM1 predicted saving (tonnes)	EM1 0	EM1 0	EM1 0	EM1 0	EM1 0	EM1 0	EM1 0	EM1 0	EM1 0	EM1 0	Would not reverse decision
EM2 predicted saving (tonnes)	EM2 100	EM2 200	EM2 300	EM2 400	EM2 500	EM2 600	EM2 700	EM2 800	EM2 900	EM2 1,000	
	◯	◯	◯	◯	◯	◯	◯	◯	◯	◯	◯

YOUR DETAILS

Question 8
Please enter the name of the Local Government Authority for which you work.

Question 9
If you would like a summary report of the survey results, please provide an email address for us to send it to you.

Thank you very much for your time in completing this survey. Your views are greatly appreciated.

A PRACTICAL METHOD FOR PREDICTING ROAD TRAFFIC CARBON DIOXIDE EMISSIONS

Matt Grote, Corresponding Author
University of Southampton
Highfield Campus, Southampton, SO17 1BJ, United Kingdom
Tel: +44-23-8059-8755; Fax: +44-23-8066-7519; Email: mjg1g12@soton.ac.uk

Ian Williams
University of Southampton
Highfield Campus, Southampton, SO17 1BJ, United Kingdom
Tel: +44-23-8059-8755; Fax: +44-23-8066-7519; Email: I.D.Williams@soton.ac.uk

John Preston
University of Southampton
Boldrewood Campus, Southampton, S016 7QF, United Kingdom
Tel: +44-23-8059-4660; Fax: +44-23-8059-3152; Email: j.m.preston@soton.ac.uk

Simon Kemp
University of Southampton
Highfield Campus, Southampton, SO17 1BJ, United Kingdom
Tel: +44-23-8059-5868; Fax: +44-23-8066-7519; Email: S.Kemp@soton.ac.uk

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ABSTRACT

Responsibility for roads outside a country's strategic road network typically lies with Local Government Authorities (LGAs). LGAs have a key role therefore in facilitating the reduction of emissions from road traffic, and must engage in emissions modelling to assess the impact(s) of transport interventions. Previous research has identified a requirement for road traffic Emissions Models (EMs) that strike a balance between capturing the impact on emissions of vehicle dynamics (e.g. due to congestion), whilst remaining practical to use.

This study developed such an EM through investigating the prediction of network-level carbon dioxide (CO_2) emissions based on readily available data generated by Inductive Loop Detectors (ILDs) installed as part of Urban Traffic Control (UTC) systems. Using Southampton, UK as a testbed, 514 Global Positioning System (GPS) driving patterns (1Hz speed-time profiles) were collected from 49 drivers of different vehicle types and used as inputs to an instantaneous EM to calculate accurate vehicle emissions (assumed to represent 'real-world' emissions). In parallel, concurrent data were collected from ILDs crossed by vehicles during their journeys. Statistical analysis was used to examine relationships between traffic variables derived from the ILD data (predictor variables) and accurate emissions (outcome variable). Results showed that ILD data (when used in conjunction with categorization of vehicle types) can form the basis for a practical road traffic CO_2 EM that outperforms the next-best alternative EM available to LGAs, with mean predictions found to be 2% greater than observed values.

Keywords: Road, Traffic, Carbon dioxide, Emissions, Model, ILD

INTRODUCTION

The world's population is increasingly urbanized *(1)*. One impact of these shifting demographics is greater congestion on urban road networks, resulting in larger volumes of tailpipe emissions from road traffic. Typically, Local Government Authorities (LGAs) administer roads outside a country's strategic road network, and are therefore responsible for facilitating the reduction of emissions from traffic in urban areas. To discharge this responsibility properly, LGAs must quantify the emissions impact(s) of any changes to the transport system. At the network-level, measurement of real-world emissions is impractical *(2, 3)*, which means LGAs must engage in emissions modelling. However, LGAs' resources are scarce *(4)*.

Emissions Models (EMs) used by LGAs must strike a balance between being so simple that they fail to capture the extent of a transport intervention's impact, and being so complex that the resources required to use the model are prohibitive *(5)*. In general, more complex models are more accurate representations of the real-world than less complex models *(6)*. However, more complex models require more detailed input data *(3)*, which are more susceptible to errors. Optimum model complexity occurs at the point beyond which the decreasing accuracy of input data begins to offset any accuracy gains through increasing model complexity *(7, 3, 8)*.

EMs range in complexity, and are briefly detailed here in accordance with the classification framework published in *(3, 5)*. Aggregate EMs are the simplest, and typically use a fixed Emission Factor (EF, e.g. gCO_2/km) for each vehicle category travelling on a particular road type (e.g. urban, rural or motorway). Average Speed EMs calculate vehicle category-specific EFs as a function of traffic average speed. Traffic Situation EMs correlate vehicle category-specific EFs with a range of defined traffic situations (characterized by road type and a qualitative description of traffic conditions). Traffic Variable EMs calculate vehicle category-specific EFs as a function of variables that describe the traffic as a whole (e.g. traffic average speed, traffic density). Cycle Variable EMs calculate EFs for individual vehicles based on variables derived from driving patterns (fine-grained time series of speed points) (e.g. number of stops per km, maximum acceleration). Modal EMs calculate EFs for individual vehicles based on vehicle/engine operating modes, with the latest generation performing at temporal resolutions of 1Hz (typically termed Instantaneous EMs, IEMs).

Aggregate, Average Speed, Traffic Situation and Traffic Variable EMs all require inputs that can be broadly described as traffic variables; whereas both Cycle Variable and Modal EMs require an individual vehicle's driving pattern as input. Traffic variables are typically readily available from sources such as Urban Traffic Control (UTC) systems, Road Traffic Model (RTM) outputs, traffic counts, or vehicle telematics data available from Intelligent Transport Systems (ITS) *(5)*. UTC systems are particularly appealing because their operation is based on vehicle detection by Inductive Loop Detectors (ILDs) buried under the road surface at strategic network points, and these ILD data can be considered 'free' by-products of the traffic control system *(9, 10)*. In contrast, whether using in-vehicle Global Positioning Satellite (GPS) devices or through RTM outputs, driving patterns for each vehicle in a network are difficult to collect *(5)*. Unlike traffic variables, they lack availability because they are seldom used in traffic engineering to describe network performance *(11)*. Additionally, driving patterns generated by RTMs have been found to be of questionable accuracy *(12, 13)*.

Given that traffic variables are the data most readily available, the best options for LGAs are likely to be EMs that accept these data as inputs (i.e. Aggregate, Average Speed, Traffic Situation or Traffic Variable). Use of Average Speed EMs is already widespread, which has been attributed to the easy availability of traffic average speed data *(14)*. However, it is well known that Average Speed EMs (and Aggregate EMs) do not account well for the influence on emissions of congestion *(8, 15, 16)*, which increases emissions through increased vehicle stop-start events *(17-19)*.

Key findings of this review are twofold: (1) Traffic Variable EMs were identified as potentially offering improved ability to capture congestion influence compared to the widely used alternative of Average Speed EMs, through including other traffic variables (in addition to traffic average speed) as quantifiable measures of congestion, with little associated increase in complexity; and (2) ILDs were identified as a readily available source of traffic variables, where collection does not entail additional expenditure of LGAs' resources. These two findings form the basis of this study. The approach taken was to investigate the prediction of network-level CO_2 emissions based on traffic variables derived from ILD data, with the methods employed described in the next section. The new EM developed during this investigation, termed the Practical EM for Local Authorities (PEMLA), is presented and discussed in subsequent sections.

METHOD

Vehicle Categories

EMs in Europe typically have highly disaggregated vehicle categories (e.g. the UK National Atmospheric Emissions Inventory (NAEI) distinguishes 231 vehicle categories). For practicality, a reduced number of vehicle categories was sought. This was achieved by analyzing the contribution to a composite traffic EF (EF_T, gCO_2/km) made by each of the NAEI categories at various traffic average speeds. The analysis was conducted using the Transport Research Laboratory (TRL) Average Speed EM (UK's officially recommended EM *(20)*), with average speed emission functions for each vehicle category weighted by a category's fraction of total national vehicle-kilometers (VKMs) in urban areas according to the NAEI national fleet model (hereafter TRL/NAEI EM). The target number of vehicle categories was closer to that found in EMs such as Motor Vehicle Emission Simulator (MOVES) EM produced by the USA's Environmental Protection Agency, which combines 13 vehicle types with 2 fuel types (if alternatives to conventional diesel or gasoline are ignored) *(21)*. NAEI categories were aggregated into PEMLA categories whilst ensuring that no PEMLA category contributed more than 10% to the EF_T at any speed, which resulted in 24 vehicle categories (Table 1).

TABLE 1 PEMLA Vehicle Categories and Closest Corresponding AIRE Vehicle Categories

PEMLA Vehicle Cat.	NAEI Vehicle Cat. Within the PEMLA Vehicle Cat. Making Greatest Contribution[a] to EF_T[b]	Closest Corresponding AIRE[c] Cat. (x SAF[d] where applicable)
Cat. 01: Car, Gasoline, <1400cc[e], Pre-Euro[f] 5	Car, Gasoline, <1400cc, Euro 4	Car, Gasoline, <1400cc, Euro 4
Cat. 02: Car, Gasoline, <1400cc, Euro 5	Car, Gasoline, <1400cc, Euro 5	(Car, Gasoline, <1400cc, Euro 4) x Euro 5 SAF
Cat. 03: Car, Gasoline, <1400cc, Euro 6	Car, Gasoline, <1400cc, Euro 6	(Car, Gasoline, <1400cc, Euro 4) x Euro 6 SAF
Cat. 04: Car, Gasoline, 1400-2000cc, Pre-Euro 5	Car, Gasoline, 1400-2000cc, Euro 4	Car, Gasoline, 1400-2000cc, Euro 4
Cat. 05: Car, Gasoline, 1400-2000cc, Euro 5	Car, Gasoline, 1400-2000cc, Euro 5	(Car, Gasoline, 1400-2000cc, Euro 4) x Euro 5 SAF
Cat. 06: Car, Gasoline, 1400-2000cc, Euro 6	Car, Gasoline, 1400-2000cc, Euro 6	(Car, Gasoline, 1400-2000cc, Euro 4) x Euro 6 SAF
Cat. 07: Car, Gasoline, >2000cc, Pre-Euro 5	Car, Gasoline, >2000cc, Euro 4	Car, Gasoline, >2000cc, Euro 4
Cat. 08: Car, Gasoline, >2000cc, Euro 5	Car, Gasoline, >2000cc, Euro 5	(Car, Gasoline, >2000cc, Euro 4) x Euro 5 SAF

Cat. 09: Car, Gasoline, >2000cc, Euro 6	Car, Gasoline, >2000cc, Euro 6	(Car, Gasoline, >2000cc, Euro 4) x Euro 6 SAF
Cat. 10: Car, Diesel, <2000cc, Pre-Euro 5	Car, Diesel, 1400-2000cc, Euro 4	Car, Diesel, 1400-2000cc, Euro 4
Cat. 11: Car, Diesel, <2000cc, Euro 5	Car, Diesel, 1400-2000cc, Euro 5	(Car, Diesel, 1400-2000cc, Euro 4) x Euro 5 SAF
Cat. 12: Car, Diesel, <2000cc, Euro 6	Car, Diesel, 1400-2000cc, Euro 6	(Car, Diesel, 1400-2000cc, Euro 4) x Euro 6 SAF
Cat. 13: Car, Diesel, >2000cc, Pre-Euro 5	Car, Diesel, >2000cc, Euro 4	Car, Diesel, >2000cc, Euro 4
Cat. 14: Car, Diesel, >2000cc, Euro 5	Car, Diesel, >2000cc, Euro 5	(Car, Diesel, >2000cc, Euro 4) x Euro 5 SAF
Cat. 15: Car, Diesel, >2000cc, Euro 6	Car, Diesel, >2000cc, Euro 6	(Car, Diesel, >2000cc, Euro 4) x Euro 6 SAF
Cat. 16: LGV[g], Gasoline, All	LGV, Gasoline, All Weights, Euro 4	LGV, Gasoline, All Weights, Euro 4
Cat. 17: LGV, Diesel, All Weights, Pre-Euro 5	LGV, Diesel, All Weights, Euro 4	LGV, Diesel, All Weights, Euro 4
Cat. 18: LGV, Diesel, All Weights, Euro 5	LGV, Diesel, All Weights, Euro 5	(LGV, Diesel, All Weights, Euro 4) x Euro 5 SAF
Cat. 19: LGV, Diesel, All Weights, Euro 6	LGV, Diesel, All Weights, Euro 6	(LGV, Diesel, All Weights, Euro 4) x Euro 6 SAF
Cat. 20: HGV[h], Rigid[i], All	HGV, Rigid, 28-32t, Euro VI	(HGV, Rigid, 28-32t, Euro V) x Euro VI SAF
Cat. 21: HGV, Artic[j], All	HGV, Artic, 40-50t, Euro VI	(HGV, Artic, 40-50t, Euro V) x Euro VI SAF
Cat. 22: Bus, All	Bus, Standard, 15-18t, Euro V	Bus, Single Deck, Euro V
Cat. 23: Coach, All	Coach, Euro V	Coach, Euro V
Cat. 24: Two-Wheel, All	na	na

na = not applicable.
[a] Determination of the NAEI category within a PEMLA category that makes the greatest contribution to EF_T was performed at 45 km/h because this is approximately the average speed for vehicles on major roads in urban areas in England *(22)*.
[b] EF_T is a composite EF for the traffic (gCO_2/VKM_T), where VKM_T is vehicle-kilometre for the traffic.
[c] AIRE is Analysis of Instantaneous Road Emissions, an IEM produced by SIAS Limited and Transport for Scotland.
[d] SAF is Speed-specific Adjustment Factor.
[e] cc is engine capacity in cubic centimetres.
[f] Euro shows compliance with relevant European Emission Standards: Arabic numerals for Light Duty Vehicles (LDVs); and roman numerals for Heavy Duty Vehicles (HDVs).
[g,h] LGV is Light Goods Vehicle (in general < 3.5 tonnes gross vehicle mass); HGV is Heavy Goods Vehicle.
[i,j] Rigid is a rigid HGV; Artic is an articulated HGV.

Accurate Emissions Calculation

Southampton was used as the testbed. The unit of observation was termed a trip segment, and was defined as any segment of the GPS trace collected from a test vehicle's trip that runs continuously between two intersections along at least two links and crosses at least one operational ILD. Minimum segment length of two links was stipulated to ensure the effect of intersections was captured. An alternative trip segment definition based on a time interval rather than a minimum number of links (i.e. time rather than distance snippets) was rejected because trip traces were examined on a background map display which meant distance snippet extraction was more practical for ensuring an intersection and an operational ILD were crossed.

Drivers (Table 2) were recruited from contacts at institutions across Southampton. GPS devices were hand-held loggers that have been used successfully for recording travel data in previous studies, e.g. in *(23, 24)*. Trip traces were visually inspected for erroneous waypoints (i.e. misaligned with the road on the background map), which were avoided during trip segment extraction. Map-matching of GPS trip traces (i.e. software that relocates recorded waypoints so that vehicle routings follow the known positions of roads) was rejected because vehicle speed was the variable of interest, meaning the positional accuracy of waypoints was less important.

For trip segment collection, vehicles were aggregated into four categories: Bus; HDV (except Bus); LDV; and Two-Wheel (Table 2). Each trip segment produced a driving pattern that constituted vehicle speed and acceleration at 1Hz. These driving patterns (except Two-Wheel) were used as inputs to an IEM to calculate an accurate EF (gCO_2/VKM) for each trip segment in each of the 24 PEMLA vehicle categories, with HDV and LDV driving patterns being reused as IEM inputs for all relevant PEMLA categories (i.e. HDV for Categories 20-21 & 23; and LDV for Categories 01-19). The IEM was Analysis of Instantaneous Road Emissions (AIRE), which estimates emissions using look-up tables derived from Passenger car and Heavy duty EM (PHEM, an IEM based on engine speed and power). In the absence of a practical method to collect real-world emissions measurements (i.e. impractical to fit Portable Emissions Measurement Systems (PEMS) to vehicles in all categories), the assumption was made that AIRE outputs represented 'real-world' EFs, which was justified because AIRE has been independently validated by TRL *(25)*.

TABLE 2 Summary of the Characteristics of GPS Trip Segment Driving Patterns

Characteristic		**Bus**	**HDV (except Bus)**	**LDV**	**Two-Wheel**
Number of trip segments collected		153	113	137	111
Driving pattern IDs assigned to trip segments[a]		BDP001 to BDP165	HDP001 to HDP115	LDP001 to LDP156	TDP001 to TDP120
Dates between which trip segments were collected		03-Jul-15 to 09-Feb-16	19-Oct-15 to 20-Jan-16	17-Sep-15 to 14-Dec-15	14-Oct-15 to 07-Dec-15
Percent of trip segments occurring in the peak period[b]		51%	43%	39%	93%
Number of different drivers[c]		30	6	11	2
Average trip segment length (km)	Mean	0.725	1.480	1.350	0.925
	Median	0.602	1.214	1.012	0.865
Average trip segment duration (s)	Mean	183	211	189	129
	Median	164	191	157	123

[a] Occasionally, trip segments initially extracted from a GPS trip trace turned-out to be unusable (e.g. no ILD data available), and were discarded. Therefore, driving pattern IDs were not always consecutively numbered.
[b] Trip segments in peak periods were defined as any occurring between the hours of 07:00-10:00 or 16:00-19:00 on Monday to Friday.
[c] The number of different drivers for Bus assumes there was a different driver each time a change of bus was made, which may not always have been the case. Therefore, this characteristic is likely to be an over-estimation.

A vehicle category must be specified to run AIRE. However, AIRE vehicle categories did not correspond to PEMLA vehicle categories. Instead, AIRE categories corresponded more closely to TRL/NAEI EM categories. Analysis was therefore conducted to determine the

TRL/NAEI EM category within (the more aggregate) PEMLA category that made the greatest contribution to EF_T. The resulting TRL/NAEI EM category was then matched to the closest corresponding AIRE category (Table 1). AIRE only includes vehicle categories compliant with Euro Standards up to Euro 4 for LDVs and Euro V for HDVs. Therefore, for PEMLA categories represented by Euro 5/6 or Euro VI vehicles, a Speed-specific Adjustment Factor (SAF) was calculated for each trip segment as the ratio between emissions from a vehicle of the relevant newer Euro Standard and emissions from a vehicle of Euro 4/Euro V Standard using the TRL/NAEI EM, with vehicle average speed (as calculated from its GPS driving pattern) as input.

An assumption of zero road gradient was used as an AIRE input. This study is concerned with estimation of emissions at network-level (or substantially large parts of a network). Therefore, the validity of this assumption is strengthened because random errors introduced by not fully accounting for vehicle-specific values should (largely) average-out *(14)*.

AIRE does not include Two-Wheel vehicle categories. The alternative method used to estimate accurate EFs for this category was to use an Average Speed EM (TRL/NAEI EM), with vehicle average speeds (as calculated from GPS driving patterns) as inputs. Whilst not as accurate as using an IEM, this method has been found to be more accurate than using traffic average speed as input because it captures the deviation of vehicle average speeds from the average for the traffic *(14)*.

Traffic Variable Calculation

Southampton's UTC system is the Split, Cycle and Offset Optimization Technique (SCOOT) system, which operates in over 250 urban areas worldwide *(26)*. ILD data were provided by the U07 message, developed at the University of Southampton but available in any SCOOT system. This message returns values from each ILD for: estimated traffic average speed (kilometers per hour, km/h) over a 5 minute interval based on a relationship derived between Average Loop Occupancy Time Per Vehicle (ALOTPV) and vehicle speed; and traffic flow based on vehicle count in a 5 minute interval. Fuller explanations of the contents of the U07 message are available in *(27, 28)*.

Traffic variables for investigation as predictor variables were selected based on several criteria: successful use for predicting emissions in previous research; familiarity to LGAs (i.e. widely used in traffic engineering); easily available for routine collection; and ability to act as congestion indicators. Five variables were selected: (1) traffic average speed (km/h), extracted from the U07 message; (2) traffic density (vehicles/km), calculated by dividing U07 traffic flow (multiplied by 12 to convert to vehicles/h) by U07 traffic average speed (km/h); (3) traffic average delay rate (seconds/vehicle.km), calculated as the difference between travel time at free-flow speed (assumed to be link speed limit) and travel time at U07 traffic average speed (seconds), divided by distance travelled (km); (4) access density (intersections/km), which is not strictly a traffic variable but is easily measured and, once measured, subject to little variation over time; and (5) the square of traffic average speed.

Statistical analysis used to investigate relationships between traffic variables (predictor variables) and accurate EFs (outcome variable) required a single value for each traffic variable to be associated with each trip segment. An averaging process for the data from all the ILDs a vehicle crossed during a trip segment was therefore used, which involved traffic variable values being sampled at 1 minute intervals, followed by calculation of the arithmetic mean of the sampled values. A sampled value was from the link on which the vehicle was located at sample time, and was the value from the ILD situated on that link for the minute preceding sample time. Due to the mismatch between U07 (5 minutes) and sampling (1 minute) intervals, when a vehicle remained on the same link with the same ILD at successive sample times within the same U07 interval, the same values in the U07 message were sampled multiple times. The sampling interval could have been increased to 5 minutes to match the U07 interval, but this was too coarse to capture a vehicle's spatial position because, within a given U07 interval, a vehicle could well have travelled to another link with a different ILD.

ILD data can be susceptible to inaccuracies. For example, in congested conditions ILDs can suffer from nose-to-tail masking, where two (or more) slow moving, closely spaced vehicles may be registered as a single vehicle *(29)*. Other factors that affect ILD accuracy include vehicle chassis height, vehicle metallic content, and ILD responsiveness *(28-30)*. Additionally, ILDs can be either single-loop or double-loop installations, with single-loop being the most common *(27, 31, 32)* and the configuration installed in Southampton. Unlike double-loop ILDs, single-loop ILDs cannot calculate a true measure of vehicle speed (i.e. based on time taken to travel a known distance); instead, they can only provide estimates of vehicle speed based on loop occupancy periods. That said, it is these ILD data to which LGAs have ready access, and the ability of these data (with their inherent inaccuracies) to predict network-level CO_2 emissions is therefore worthy of investigation.

ILD data collection relied on the assumption that Southampton's UTC system layout was typical and embodied the usual range of ILD positions, in particular their positions relative to nearby intersections and traffic signals that will affect vehicle dynamics when crossing detectors. This assumption was supported by PEMLA's design for predicting network-level emissions, meaning any ILD-specific position variations should (largely) average-out.

Statistical Analysis

An appropriate method for exploring relationships between predictor and outcome variables is Multiple Linear Regression (MLR) *(33)*, with all analyses performed using IBM SPSS 22 software. Complex data relationships can go undetected when analysis is performed using conventional statistical methods such as MLR. Therefore, the advanced method of neural network analysis was performed as well *(34)*. The Multilayer Perceptron (MLP) is the most commonly used type of feed-forward neural network in the atmospheric sciences, and can represent relationships between predictor and outcome variables that are unconstrained by assumptions such as those underpinning MLR analysis *(35, 36)*.

However, MLR analysis results are easier to interpret and utilise than those of MLP analysis *(37)*. Hence, the purpose of MLP analysis in this study was to act as a standard against which MLR analysis could be judged. MLP analysis was conducted in parallel to MLR analysis, using the default settings in SPSS which were deemed to not need fine-tuning for the MLP to function as a comparative indicator. To allow comparison with MLR analysis, a R^2 value for MLP analysis was derived through a bivariate linear correlation of MLP predicted outcome values and observed outcome values, and then squaring of the resulting Pearson linear correlation coefficient (r). This provided an indication of the likely maximum R^2 value for the relationship between predictor and outcome variables when freed from any constraints imposed by MLR analysis.

Statistical analysis of the collected data was conducted in two phases: an exploratory, preliminary phase; and a principal phase in which six versions of PEMLA were developed before a final version was selected as offering the greatest potential for LGA use. A full description of this analysis is available in *(38)*. However, for brevity, this paper is limited to describing the final PEMLA version.

All 24 vehicle categories were analyzed together, with vehicle category included as a predictor variable alongside the five originals. Additionally, the curve estimation function in

SPSS was used to explore whether any correlations other than linear were present between predictor and outcome variables. The only alternative non-linear correlation that showed a statistically significant R^2 improvement consistently across the large majority of vehicle categories was the cubic form of access density. Therefore, the square and cube of access density were added to the five original traffic variables.

Interaction Variables (IVs) were created that encoded the interaction between vehicle category and the seven traffic variables. For each vehicle category, seven IVs were created, one for each traffic variable. For the seven IVs associated with a given vehicle category, for cases of vehicles from that category the value of each of the IVs corresponded to the value of each of the traffic variables; and for cases of vehicles from other categories the value of each of the IVs was zero. For example, the IV encoding Category 01 and traffic average speed (IV-Cat 01 & TraffAvSpd) took the value of traffic average speed for all cases involving Category 01 vehicles, but was zero for cases involving vehicles from any other categories.

Also included as predictor variables were road type and time of day, which were encoded using Dummy Variables (DVs). For road type (DV-Road Type by Speed Limit), 0 indicated 30 miles per hour (mph) limit and 1 indicated 40 mph limit. For time of day (DV-Time Period), 0 indicated off-peak period and 1 indicated peak period. MLR analysis was conducted by three blockwise entries of predictor variables: forced entry of all IVs in the first block; forced entry of the road type DV in the second; and forced entry of the time of day DV in the third.

Validation

Three methods were used to validate PEMLA. The first method involved splitting trip segment samples into those used for PEMLA calibration, and those reserved for validation based on the assumption that observed values for the outcome variable (EF from AIRE) were 'real-world' EFs (justified because AIRE has been independently validated by TRL). Trip segment samples were limited in number, meaning both calibration and validation were competing for a limited number of samples, with both processes benefiting from the largest sample size possible. A solution to this was cross-validation (CV), where validity is assessed over multiple, different splits of the samples, with Leave-One-Out (LOO) validation being the most classical, exhaustive data-splitting CV procedure *(39)*. In LOOCV each case is left out of the calibration process in turn, a new model without that particular case is then calibrated and used to predict an EF for the excluded case which can be compared to the 'real-world' EF as validation. The differences between predicted and 'real-world' EFs for all cases as they are excluded in turn is used to assess the validity of the overall model calibrated including all cases. For each case, an Accuracy Factor (AF) and an Absolute Percentage Error (APE) were calculated using (1) and (2).

$$\text{AF} = \frac{\text{Predicted EF when case excluded from PEMLA calibration}}{\text{EF from AIRE}} \quad (1)$$

$$\text{APE} = \frac{|\text{Predicted EF when case excluded from PEMLA calibration} - \text{EF from AIRE}|}{\text{EF from AIRE}} \text{ x } 100\% \quad (2)$$

The second method was by comparison to the TRL/NAEI EM, i.e. TRL/NAEI EM EFs were assumed to represent 'real-world' EFs. This was justified because GPS vehicle average speeds (as opposed to ILD traffic average speeds) were used as inputs, which (as suggested in *(14)*) is the most accurate method for applying an Average Speed EM. However, it is acknowledged that, similar to the LOOCV method, validation by comparison of PEMLA to predictions from another EM is not true validation (i.e. it is not comparison with independent real-world emissions measurements). That said, positive results when compared to well-established EMs gives confidence in PEMLA. For each case, an AF and an APE were calculated using (3) and (4).

$$\text{AF} = \frac{\text{Predicted EF}}{\text{EF from TRL/NAEI (veh. av. spd.)}} \quad (3)$$

$$\text{APE} = \frac{|\,\text{Predicted EF} - \text{EF from TRL/NAEI (veh. av. spd.)}|}{\text{EF from TRL/NAEI (veh. av. spd.)}} \times 100\% \quad (4)$$

The third method was by comparison to EFs calculated from PEMS data. Fifty three trip segments in the Bus category (Category 22) were collected from a bus being operated with PEMS on-board. Hence, these cases have EFs calculated from the PEMS data. Comparison of PEMLA predictions to PEMS EFs constituted true validation, but was only partial validation because PEMS data were only available for 53 cases within one vehicle category. For each case, an AF and an APE were calculated using (5) and (6).

$$\text{AF} = \frac{\text{Predicted EF}}{\text{EF from PEMS}} \quad (5)$$

$$\text{APE} = \frac{|\,\text{Predicted EF} - \text{EF from PEMS}|}{\text{EF from PEMS}} \times 100\% \quad (6)$$

Predictive Accuracy Comparison

The predictive accuracy of PEMLA was assessed in comparison to the predictive accuracy of TRL/NAEI EM, which is the next-best alternative EM available to UK LGAs. For this comparison, EFs from AIRE were assumed to be 'real-world' EFs. For each case, an AF and an APE were calculated using (7) and (8). For the TRL/NAEI EM predictions, ILD traffic average speeds (as opposed to GPS vehicle average speeds) were used as inputs for two reasons: (1) these are the data readily available to LGAs; and (2) to ensure a like-for-like comparison because ILD data (plus access density) were used as PEMLA inputs.

$$\text{AF} = \frac{\text{Predicted EF}}{\text{EF from AIRE}} \quad (7)$$

(8)

$$APE = \frac{|\text{Predicted EF} - \text{EF from AIRE}|}{\text{EF from AIRE}} \text{ x } 100\%$$

RESULTS

Collinear predictor variables were removed to satisfy the MLR assumption of no multi-collinearity (those with smallest t-statistic removed). Also removed were any predictor variables having non-significant t-statistics (i.e. not making a statistically significant contribution to the model). Results are shown in Table 3. Full details of diagnostic testing to examine compliance with MLR assumptions are available in *(38)*. The MLR assumption of homoscedasticity (tested with Breusch-Pagan and Koenker tests) was violated, but this was overcome using a heteroscedastic-consistent standard error estimator in the MLR analysis *(40)*. Additionally, a log transformation of the outcome variable prior to MLR analysis was used to improve compliance with the assumption of normally distributed residuals. Hence, the final form of PEMLA is given by (9). Results from PEMLA validation by the three different methods are shown in Table 4. Results of the comparison of the predictive accuracy of PEMLA with that of the TRL/NAEI Average Speed EM are also shown in Table 4.

(9)

$$\text{Predicted EF} = e^{f\,(\text{predictor variables})}$$

TABLE 3 Statistics from the MLR Analysis to Calibrate PEMLA

Predictor Variable	Model Coeff.	Std. Error of Model Coeff.	Standardised Model Coeff. β[a]	t-Statistic
(Constant)	5.9485	0.0152	na	392.54*
IV[b] - Cat01[c] & TraffAvSpd[d]	-0.0183	0.0009	-0.13	-20.14*
IV - Cat01 & TraffAvDlyRt[e]	-0.0016	0.0002	-0.05	-8.09*
IV - Cat02 & TraffAvSpd	-0.0212	0.0010	-0.15	-21.73*
IV - Cat02 & TraffAvDlyRt	-0.0019	0.0002	-0.05	-8.47*
IV - Cat03 & TraffAvSpd	-0.0239	0.0010	-0.17	-22.88*
IV - Cat03 & TraffAvDlyRt	-0.0021	0.0002	-0.06	-8.69*
IV - Cat04 & TraffAvSpd	-0.0140	0.0009	-0.10	-15.55*
IV - Cat04 & TraffAvDlyRt	-0.0011	0.0002	-0.03	-5.56*
IV - Cat05 & TraffAvSpd	-0.0170	0.0010	-0.12	-17.46*
IV - Cat05 & TraffAvDlyRt	-0.0013	0.0002	-0.04	-6.26*
IV - Cat06 & TraffAvSpd	-0.0197	0.0010	-0.14	-18.84*
IV - Cat06 & TraffAvDlyRt	-0.0016	0.0002	-0.05	-6.70*
IV - Cat07 & TraffAvSpd	-0.0057	0.0009	-0.04	-6.38*
IV - Cat07 & AccDensCubd[f]	$4\text{x}10^{-5}$	0.0000	0.02	2.60*
IV - Cat08 & TraffAvSpd	-0.0095	0.0010	-0.07	-9.78*
IV - Cat08 & AccDensCubd	$4\text{x}10^{-5}$	0.0000	0.02	2.31*
IV - Cat09 & TraffAvSpd	-0.0114	0.0011	-0.08	-10.66*
IV - Cat09 & TraffAvDlyRt	-0.0007	0.0002	-0.02	-2.70*
IV - Cat09 & AccDensCubd	$5\text{x}10^{-5}$	0.0000	0.02	2.77*
IV - Cat10 & TraffAvSpd	-0.0210	0.0010	-0.15	-21.90*

IV - Cat10 & TraffAvDlyRt	-0.0019	0.0002	-0.05	-8.93*
IV - Cat11 & TraffAvSpd	-0.0240	0.0010	-0.17	-23.34*
IV - Cat11 & TraffAvDlyRt	-0.0022	0.0002	-0.06	-9.20*
IV - Cat12 & TraffAvSpd	-0.0269	0.0011	-0.19	-24.36*
IV - Cat12 & TraffAvDlyRt	-0.0025	0.0003	-0.07	-9.35*
IV - Cat13 & TraffAvSpd	-0.0107	0.0009	-0.07	-11.87*
IV - Cat13 & TraffAvDlyRt	-0.0007	0.0002	-0.02	-3.73*
IV - Cat14 & TraffAvSpd	-0.0137	0.0010	-0.09	-14.35*
IV - Cat14 & TraffAvDlyRt	-0.0010	0.0002	-0.03	-4.85*
IV - Cat15 & TraffAvSpd	-0.0166	0.0010	-0.11	-16.33*
IV - Cat15 & TraffAvDlyRt	-0.0013	0.0002	-0.04	-5.67*
IV - Cat17 & TraffAvSpd	-0.0096	0.0008	-0.07	-12.19*
IV - Cat17 & TraffAvDlyRt	-0.0007	0.0001	-0.02	-4.91*
IV - Cat18 & TraffAvSpd	-0.0103	0.0008	-0.07	-12.77*
IV - Cat18 & TraffAvDlyRt	-0.0008	0.0002	-0.02	-5.13*
IV - Cat19 & TraffAvSpd	-0.0108	0.0008	-0.08	-13.24*
IV - Cat19 & TraffAvDlyRt	-0.0008	0.0002	-0.02	-5.30*
IV - Cat20[g] & TraffAvSpd	0.0374	0.0019	0.25	19.67*
IV - Cat20 & TraffAvDlyRt	0.0036	0.0006	0.09	5.82*
IV - Cat21 & TraffAvSpd	0.0405	0.0020	0.27	20.09*
IV - Cat21 & TraffAvDlyRt	0.0039	0.0007	0.10	5.92*
IV - Cat22[h] & TraffAvSpd	0.0439	0.0019	0.26	23.13*
IV - Cat22 & TraffAvDlyRt	0.0028	0.0003	0.15	8.51*
IV - Cat22 & AccDensCubd	0.0001	0.0000	0.04	5.15*
IV - Cat23 & TraffAvSpd	0.0410	0.0020	0.27	20.12*
IV - Cat23 & TraffAvDlyRt	0.0040	0.0006	0.10	6.25*
IV - Cat24[i] & TraffAvSpd	-0.0376	0.0009	-0.21	-40.90*
IV - Cat24 & TraffAvDlyRt	-0.0017	0.0002	-0.08	-7.60*
IV - Cat24 & AccDensCubd	-0.0003	0.0001	-0.04	-5.78*
DV[j] - Road Type by Speed Limit (1=40, 0=30)	-0.1292	0.0082	-0.08	-15.68*
DV - Time Period (1=Peak Period, 0=Off-Peak Period)	0.0730	0.0077	0.05	9.47*

Outcome variable is the natural log of EF from AIRE (gCO_2/VKM).
n = 3205.
Adj. R^2 = .93.
For comparison, equivalent MLP neural network analysis resulted in R^2 = .93.
* indicates t-statistic is significant at 0.05 level.
na = not applicable.
[a] Standardized version of the model coefficient, which represents the number of standard deviations (SDs) the outcome variable will change as a result of one SD change in the associated predictor variable and provides an indication of the relative importance of predictor variables.
[b] IV is Interaction Variable encoding the effect of vehicle category and the relevant traffic variable.
[c] Categories 01 to 19 are LDVs.
[d] TraffAvSpd is traffic average speed.
[e] TraffAvDlyRt is traffic average delay rate.
[f] AccDensCubd is access density cubed.
[g] Categories 20, 21 and 23 are HDVs (except Buses).
[h] Category 22 is Buses.
[i] Category 24 is Two-Wheel vehicles
[j] DV is Dummy Variable.

TABLE 4 Mean Accuracy Factors and Mean Absolute Percentage Errors from Validation and Predictive Accuracy Comparison of PEMLA

Process		n	MAF[a] (SD[b])	MAPE[c] (SD)
Validation Method	LOOCV[d]	3205	1.02 (0.22)	16% (15%)
	TRL/NAEI EM (GPS vehicle average speed)	3205	1.21 (0.26)	26% (21%)
	PEMS[e]	53	2.21 (0.72)	121% (72%)
Predictive Accuracy Comparison	PEMLA	3205	1.02 (0.21)	16% (14%)
	TRL/NAEI EM (ILD traffic average speed)	3204[f]	0.88 (0.24)	22% (16%)

[a] MAF is Mean Accuracy Factor.
[b] SD is standard deviation.
[c] MAPE is Mean Absolute Percentage Error.
[d] LOOCV is Leave-One-Out Cross Validation.
[e] PEMS is Portable Emissions Measurement System.
[f] n = 3204 for the TRL/NAEI EM prediction accuracy because for one case the ILD Traffic Average Speed was below the minimum speed for use of the TRL/NAEI emission function (for BDP159P Traffic Average Speed = 4km/h, whereas minimum speed for emission function = 6km/h).

DISCUSSION OF RESULTS

Table 3 shows the Time Period DV coefficient is positive, predicting an increase in emissions during peak periods, which was expected because increased congestion associated with peak periods increases stop-start events for vehicles and therefore increases emissions. The Road Type DV coefficient is negative, predicting a decrease in emissions on roads with a 40mph speed limit. In UK urban areas, 40mph limits tend to apply to arterial roads, whereas 30mph limits tend to apply to collector and local roads. Arterial roads tend to have greater segregation from potential hazards, i.e. pedestrians, other road users, access to residential and retail premises, and priority for green traffic signals. This segregation is designed to give smoother traffic flow, and therefore decreases emissions.

Some IV predictor variable coefficients in Table 3 have (superficially) unexpected signs. Coefficients associated with traffic average speed IVs were expected to be negative because higher traffic average speed is indicative of lower congestion, and because, over the range of measured speeds (traffic average speeds 4-41 km/h and vehicle average speeds 5-57 km/h), higher speeds tend towards optimum vehicle fuel efficiency *(8)*. However, for HDV categories (Categories 20-23), these coefficients were positive. Similarly, coefficients associated with traffic average delay rate IVs were expected to be positive because higher traffic average delay rate is indicative of higher congestion. However, for LDV and Two-Wheel categories (Categories 01-19 and 24), these coefficients were negative. Coefficients associated with access density cubed IVs were expected to be positive because higher access density is likely to lead to higher congestion due to the increased interaction of vehicles at intersections. However, for the Two-Wheel category (Category 24), this coefficient was negative.

The reason for the unexpected signs was because the predictor variables were IVs and represented the effect on emissions of the interaction between vehicle category and the traffic variables, rather than the effect of the traffic variables alone. The effect of vehicle category outweighed the effect of the traffic variables, and when in combination it was vehicle category that dominated and determined the sign of the coefficient. In relation to the EF represented by the constant in PEMLA ($e^{5.9485}$=383gCO_2/VKM), the effect of LDV and Two-Wheel vehicle categories was always downwards (i.e. all IV predictor variables had a negative coefficient regardless of the associated traffic variable; although there were three exceptions to this, which are discussed in the next paragraph), and the effect of HDV vehicle categories was always upwards (i.e. all IV predictor variables had a positive coefficient regardless of the associated traffic variable).

The three exceptions were: IV-Cat07 & AccDensCubd; IV-Cat08 & AccDensCubd; and IV-Cat09 & AccDensCubd. These IV predictor variables all had positive coefficients despite being LDV vehicle categories. A potential reason for this was that EFs for these vehicle categories (i.e. categories 07, 08 and 09) were typically close to the EF that corresponds to the constant in PEMLA (383 gCO_2/VKM). Therefore, in relation to the constant, the effect of vehicle category was less dominant, which allowed the effect of the traffic variable to manifest.

Validation by LOOCV produced good agreement (MAF=1.02 and MAPE=16%). For reference, in their meta-analysis of road traffic EM validation, Smit *et al. (3)* found that mean prediction errors for CO_2 were generally within a factor of 1.3 of observed values. Validation by comparison to TRL/NAEI EM (using GPS vehicle average speeds as inputs) produced reasonable agreement (MAF=1.21 and MAPE=26%). This MAF indicates that, on average, PEMLA predicts higher EFs than the TRL/NAEI EM. This was expected because, even though GPS vehicle average speeds were used as inputs (which are more accurate than using traffic average speeds *(14)*), this still falls short of fully accounting for increased emissions resulting from the influence of congestion on driving pattern dynamics, which is not well accounted for in Average Speed EMs. In contrast, PEMLA was purposefully designed to better account for this influence.

PEMLA performed poorly in partial validation against PEMS EFs (MAF=2.21 and MAPE=121%). Three potential reasons for this are: (1) the sample size for PEMS validation is small (53 cases compared to 3205 cases for the other validation methods), and drawn from only one vehicle category (Bus, All); (2) comparison of 'real-world' EFs used to calibrate PEMLA (i.e. EFs from AIRE) with PEMS EFs demonstrated a similar over-estimation by a factor of approximately two (MAF=2.08 and MAPE=108%); and (3) the PEMLA 'Bus, All' category is for an "average" bus, i.e. the category describes a fleet-average for buses of all masses and all Euro Standards, whereas PEMS data were collected from a single bus at the light-weight end of the scale (revenue weight 13,139 kgs) and compliant with a modern Euro Standard (Euro V).

Comparing predictive accuracy with the next-best alternative EM (TRL/NAEI EM), when using the same source for inputs (ILD data) PEMLA has a MAF that outperforms TRL/NAEI EM. MAF values in Table 4 suggest that on average (i.e. when applied to a whole network or substantially large parts of a network) PEMLA over-estimates emissions by 2% (MAF=1.02), whereas TRL/NAEI EM under-estimates by 12% (MAF=0.88). On a case-by-case basis, MAPE values in Table 4 suggest that on average PEMLA will be in error by 16% and TRL/NAEI EM by 22%.

The main issue affecting PEMLA's development was the use of AIRE EFs as proxies for real-world EFs, which was the only practical method available to estimate 'real-world' emissions for calibration, validation (LOOCV) and accuracy comparison of all PEMLA vehicle categories. However, in reason (2) suggested for PEMLA's poor performance during PEMS partial validation it was found that AIRE over-estimated bus EFs by a factor of approximately two when compared to actual real-world PEMS EFs. This discrepancy between AIRE and PEMS EFs was a cause for concern. AIRE, PEMLA and TRL/NAEI EM EFs were broadly in agreement during validation and accuracy comparison, and it was PEMS EFs that were substantially different. This may indicate a problem with the PEMS data; although it should be noted that similarities in EM predictions can be indicative of the considerable amount of data shared between the calibrations of different EMs, rather than indicative of the accuracy of EM predictions. Conversely, the PEMS equipment was serviced by the manufacturer prior to installation, and performed self-calibration tests (using a reference gas) both before and after each measurement period. Additionally, the installation was validated by comparison of fuel flow (g/s) outputs from PEMS with those from the engine control unit. There was therefore no obvious reason to suspect erroneous PEMS data. The discrepancy between EFs from AIRE, PEMLA and TRL/NAEI EM and EFs from PEMS needs further investigation to seek a satisfactory explanation.

PEMLA's validity is limited to urban roads with 30 or 40 mph speed limits because these were the road types from which trip segments were collected. The large majority of roads in UK urban areas are of these types, but extension to include urban roads with other speed limits would make PEMLA more comprehensive.

Due to Southampton-specific development, transferability of PEMLA requires validation before it can be confidently applied in other UK urban areas. This would also test the robustness of the assumption that Southampton's UTC system layout was typical and embodied the usual range of ILD positions relative to intersections. For urban areas outside the UK, it is likely PEMLA would need to be re-calibrated. The reason for this relates to inter-country differences in factors such as network characteristics, traffic management strategies, vehicle categorizations and fleet compositions *(5)*. A further consideration is that ILDs may be superseded by other methods of traffic detection (e.g. magnetometers or radar detectors). However, any detection systems that can provide data similar to those obtained from ILDs (i.e. average speed and count of vehicles passing detector locations) would be likely to provide the required PEMLA inputs.

CONCLUSIONS

This research has shown it is possible to develop an EM for use by LGAs which is designed to predict network-level road traffic CO_2 emissions based on readily available traffic variables. These traffic variables (except access density) are calculated from ILD data that are a by-product of UTC systems. The PEMLA out-performed the next best alternative (TRL/NAEI EM) in accuracy comparisons and is better able to capture the influence of congestion on emissions, without being so complex that it is beyond LGAs' limited resources.

Further development work is required to extend the road types covered by PEMLA, and to investigate transferability to other urban areas both within and without the UK. It would also be useful to investigate the transferability of the PEMLA methodology to prediction of other pollutant emissions. A time when the majority of the global road vehicle fleet is alternatively fueled (e.g. electric, natural gas, hydrogen) still appears to be some years (decades?) away. In the meantime modelling emissions from conventionally fueled vehicles remains a necessity, and PEMLA is an option to fulfill this requirement.

ACKNOWLEDGEMENT

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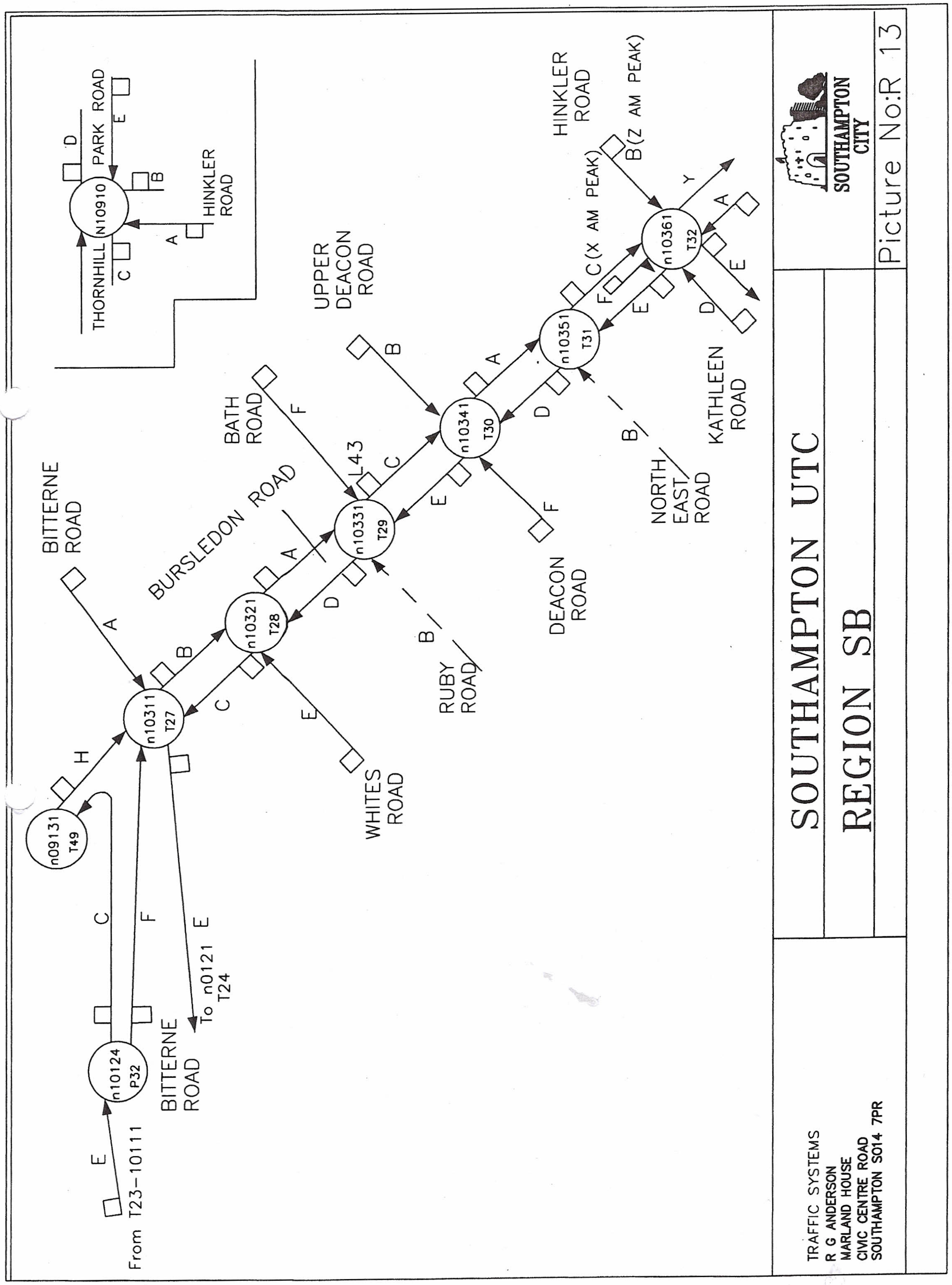
Appendix E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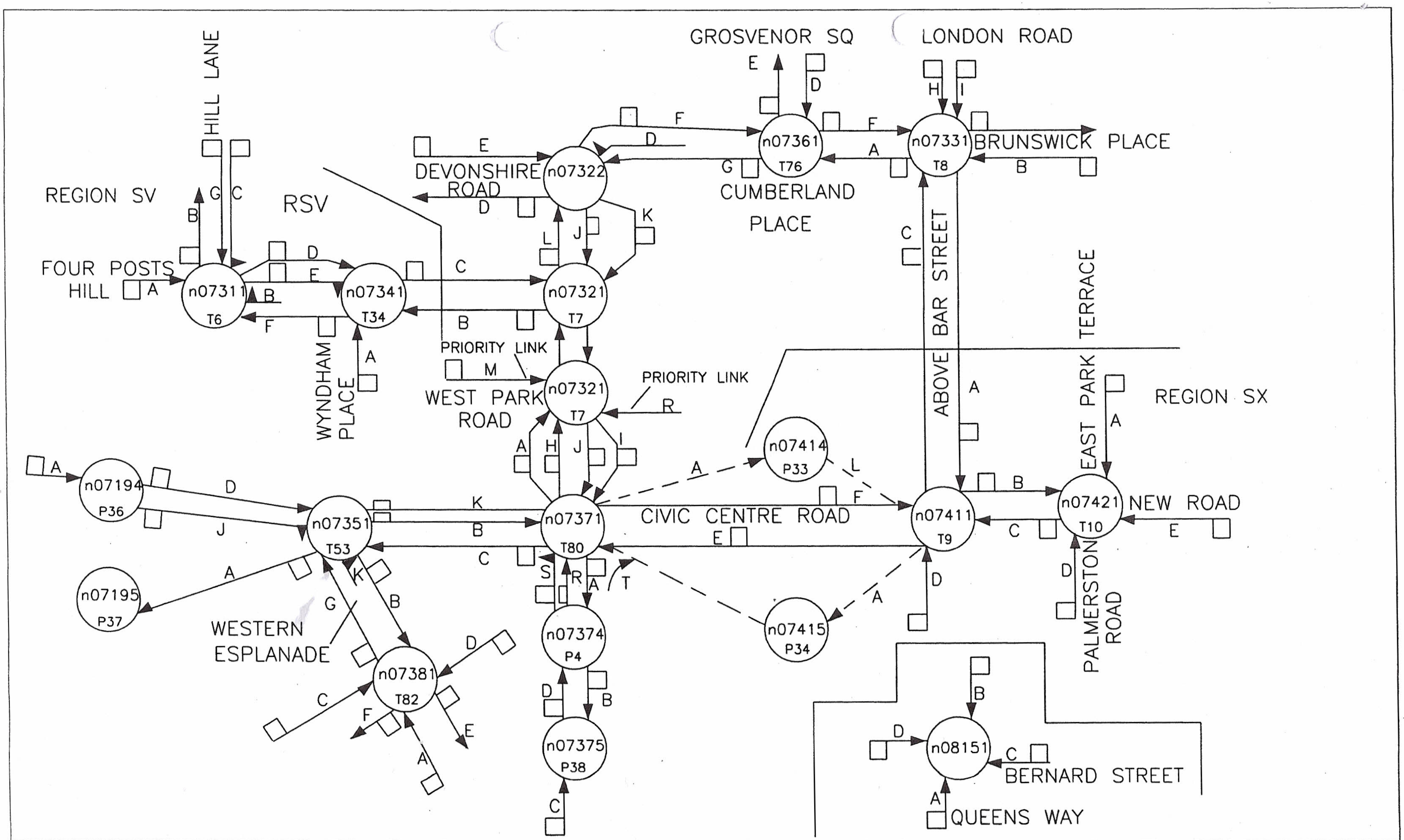

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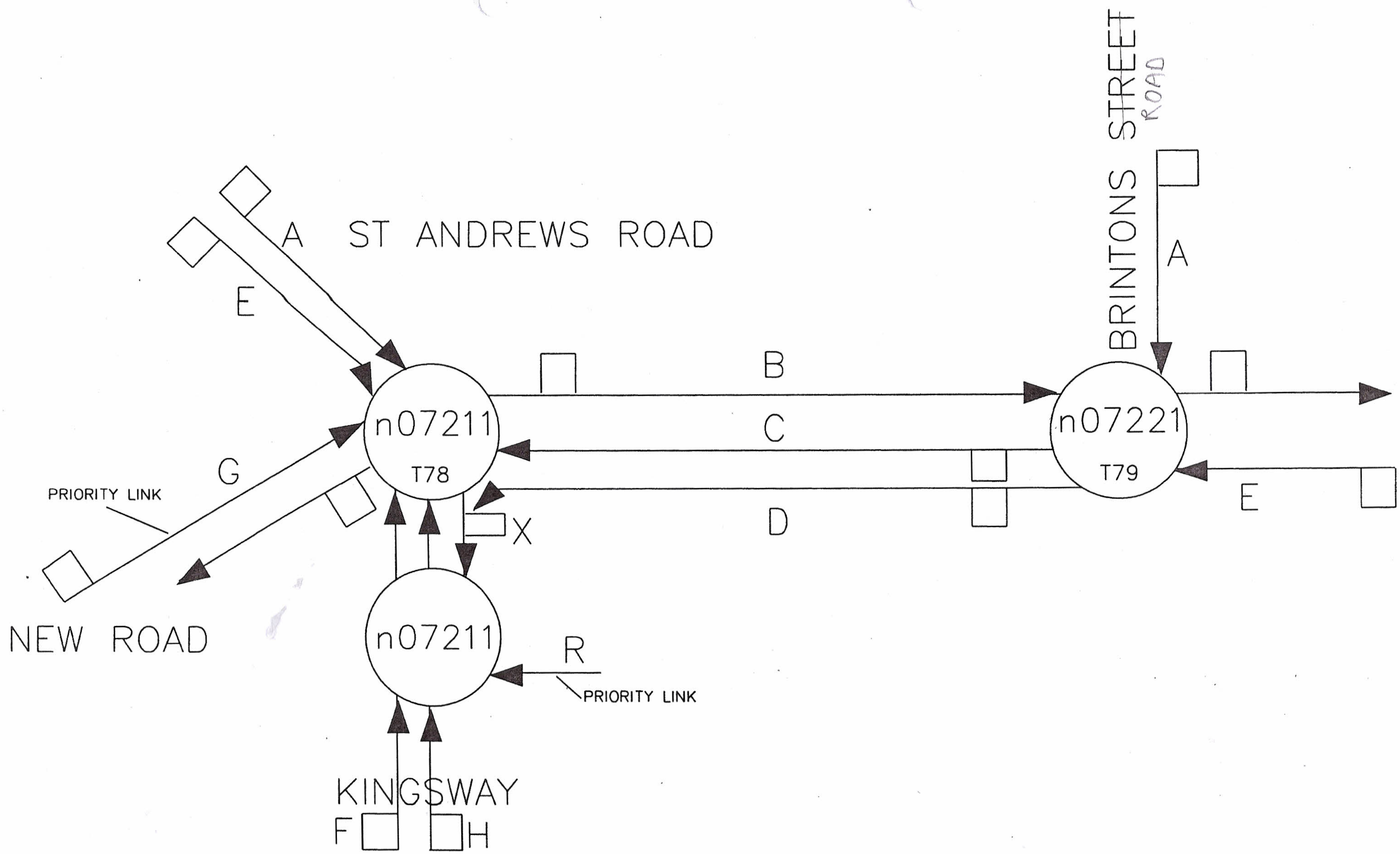

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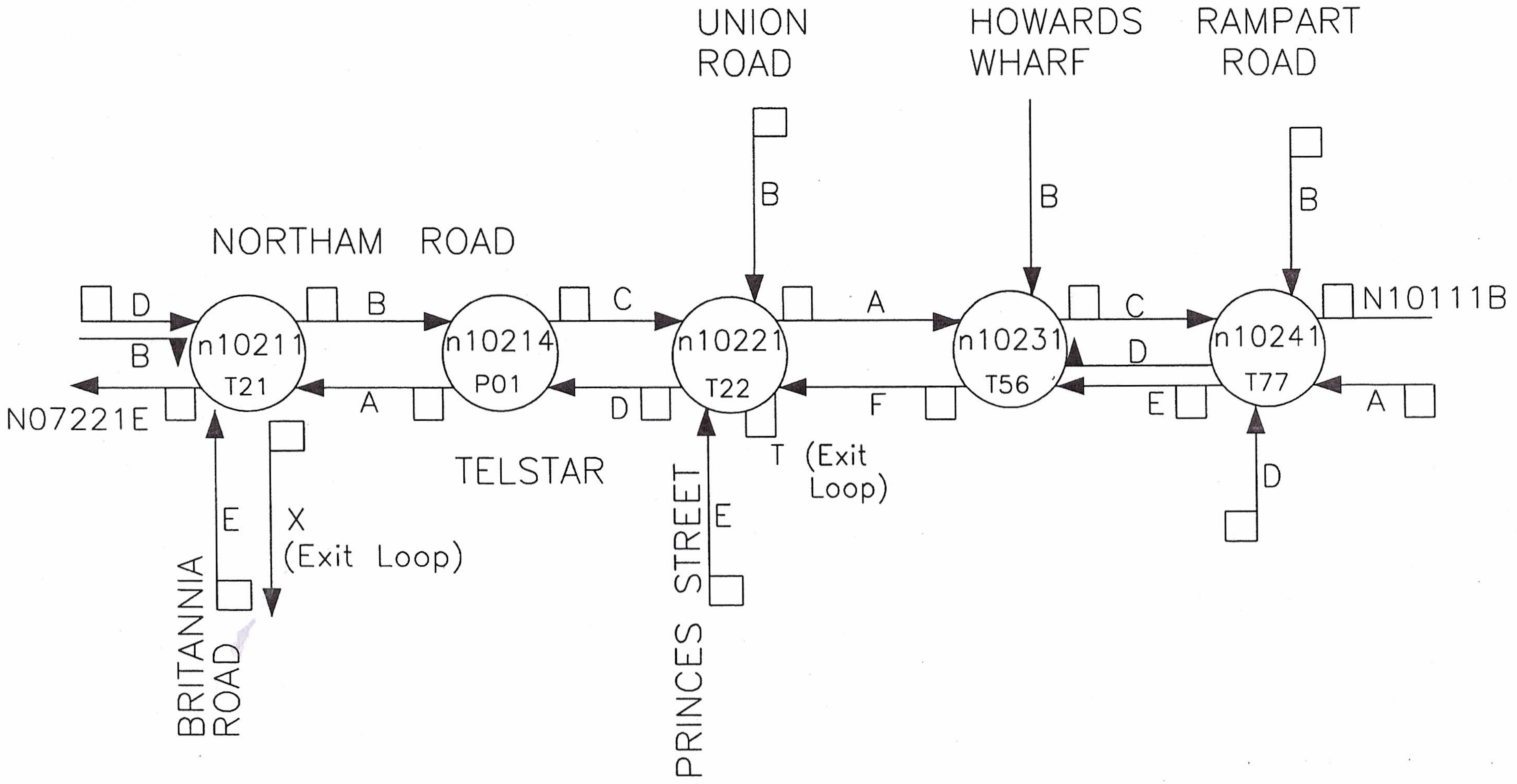

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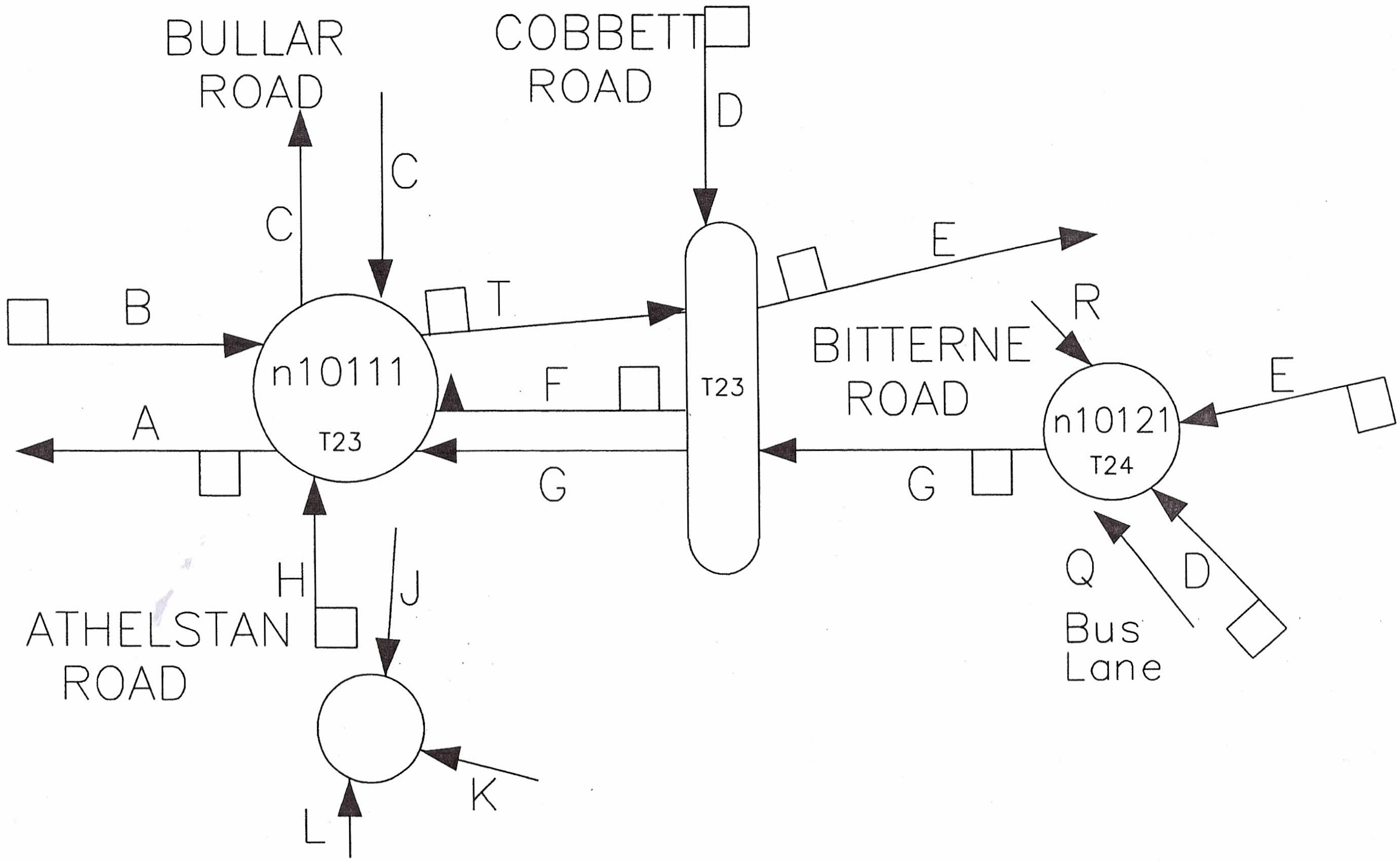

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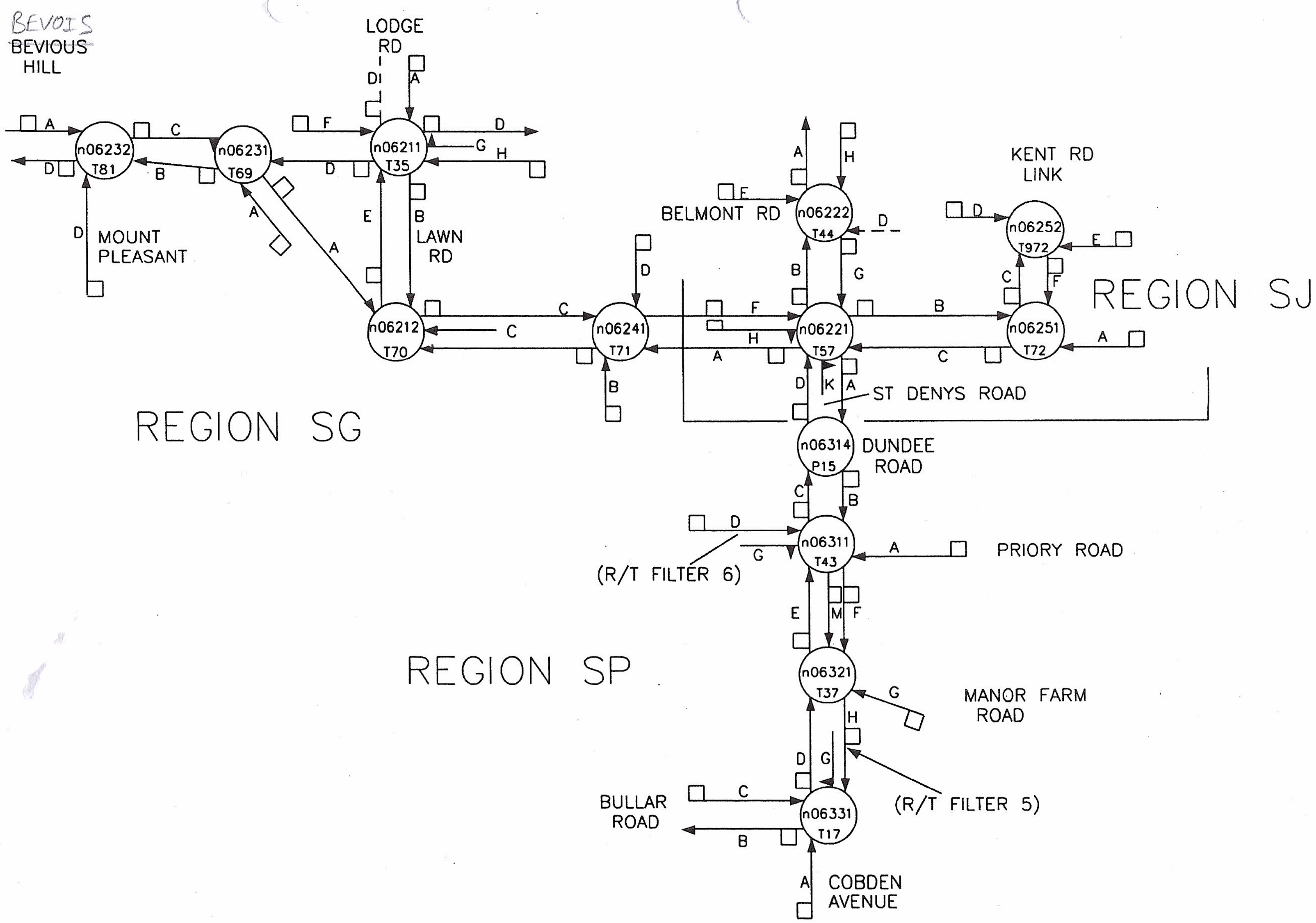

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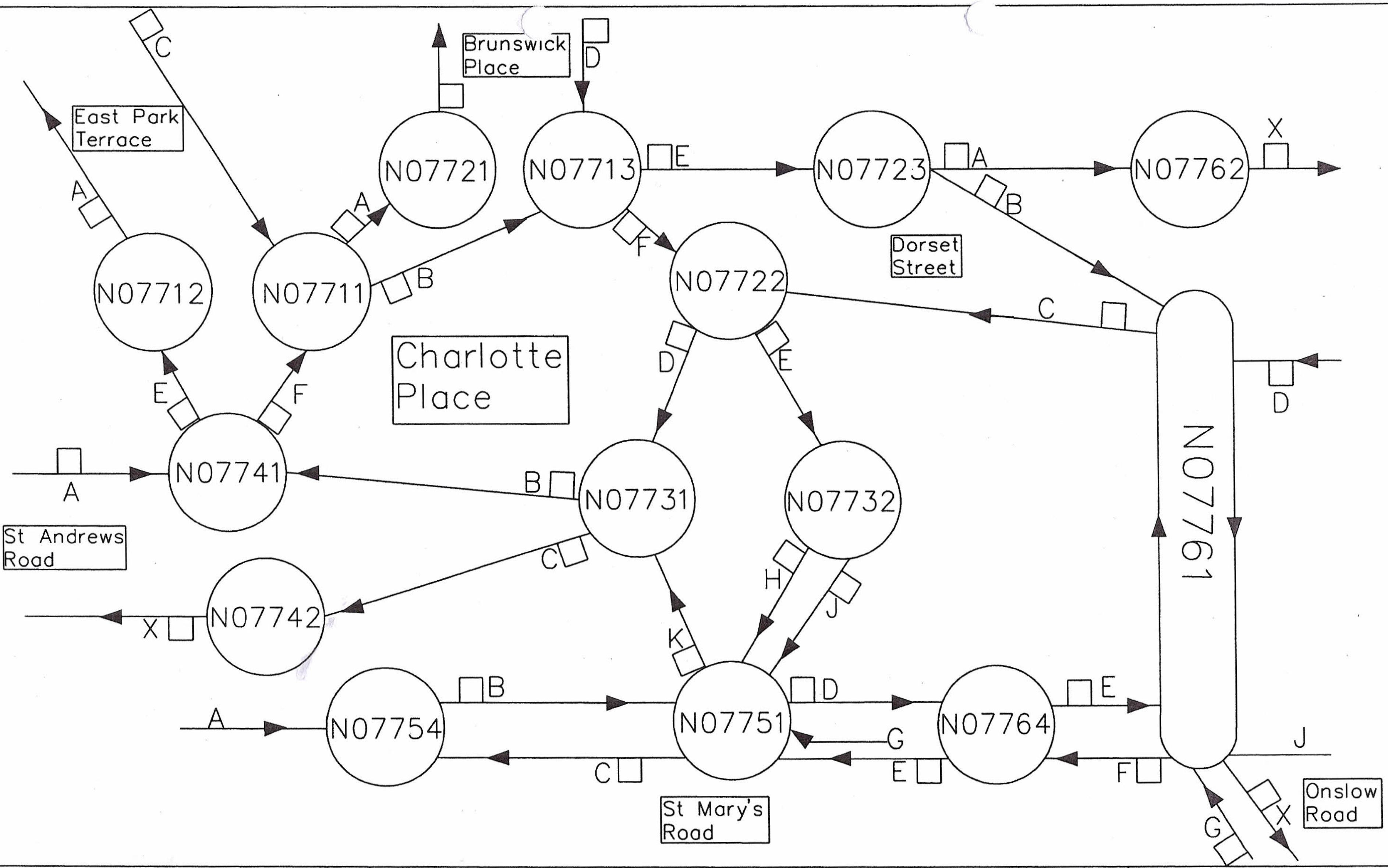

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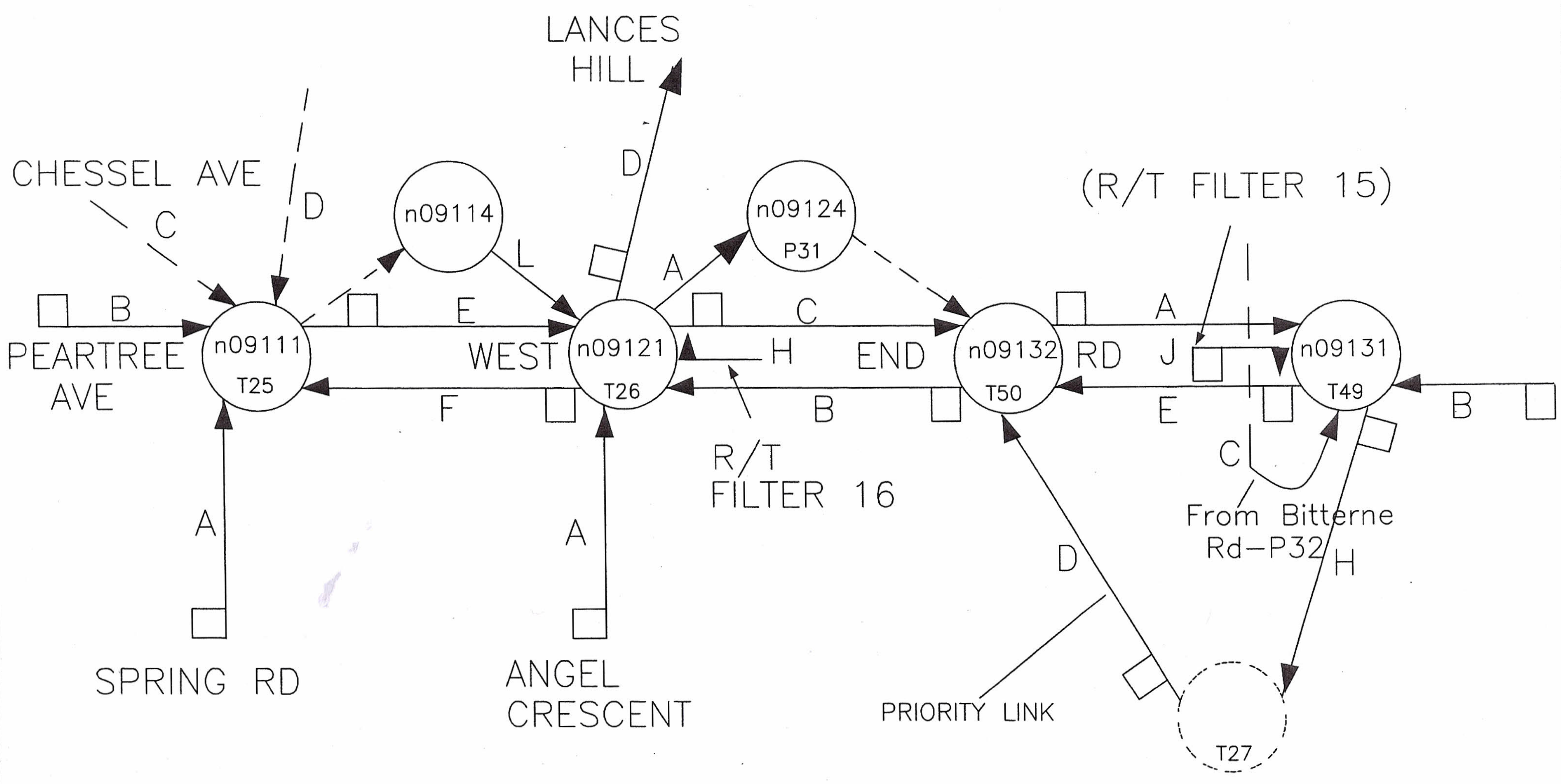

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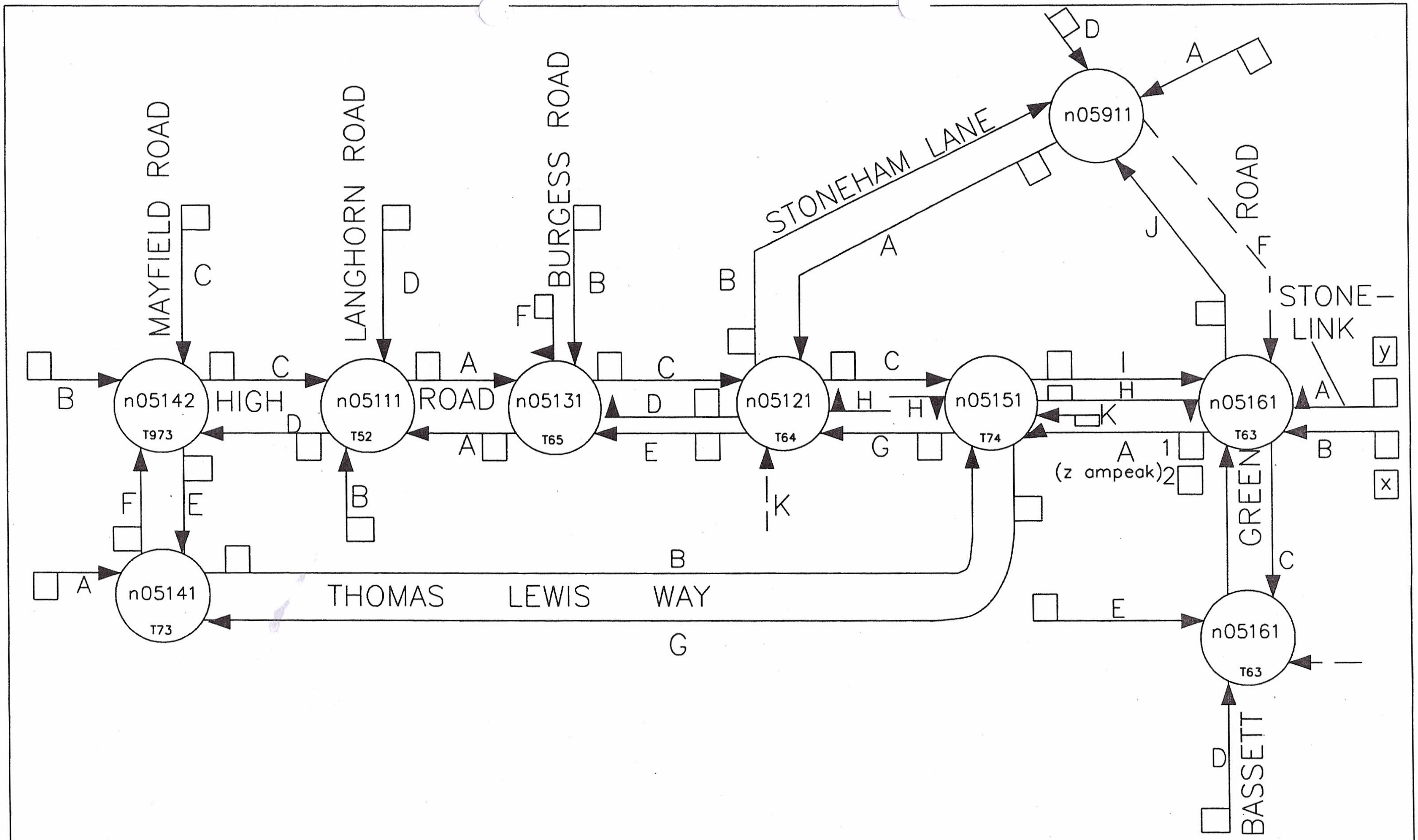

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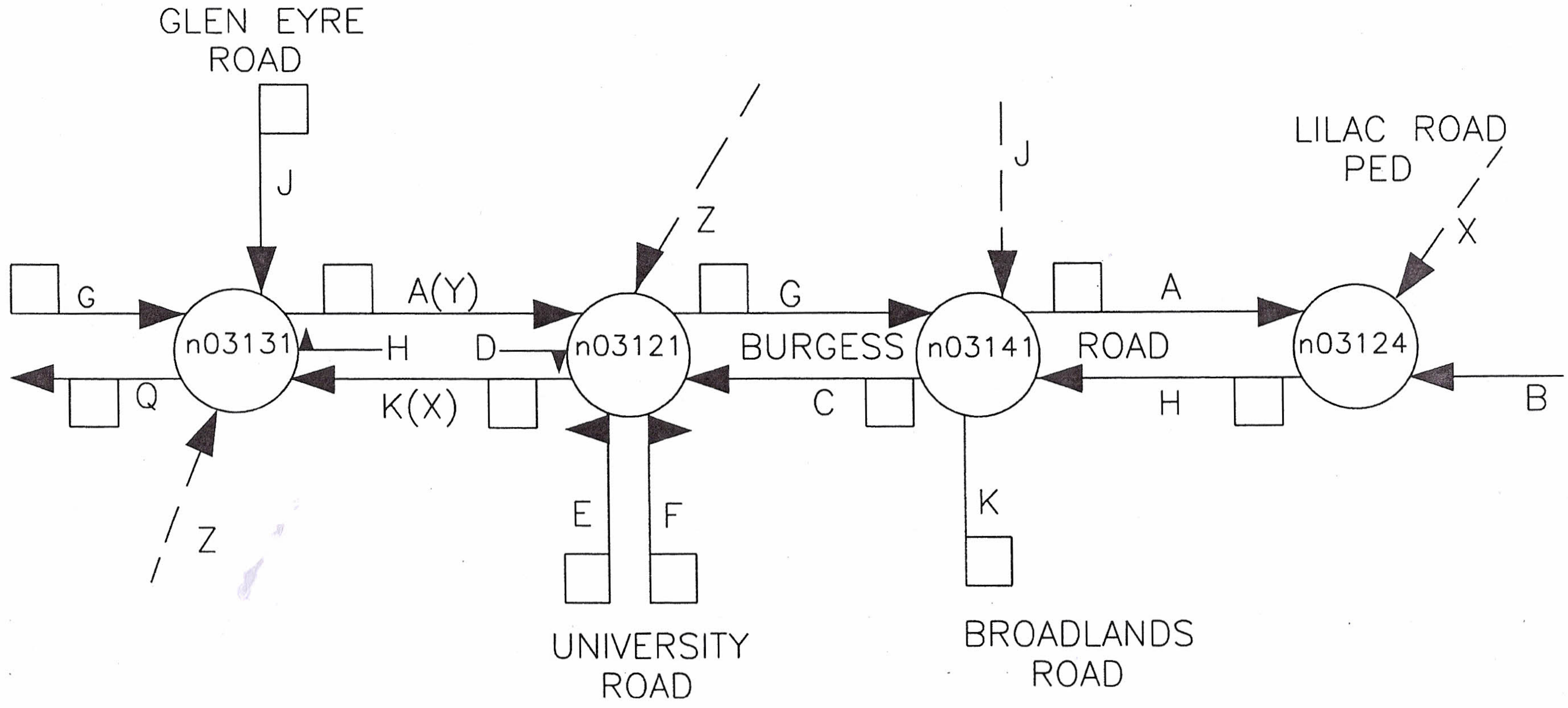

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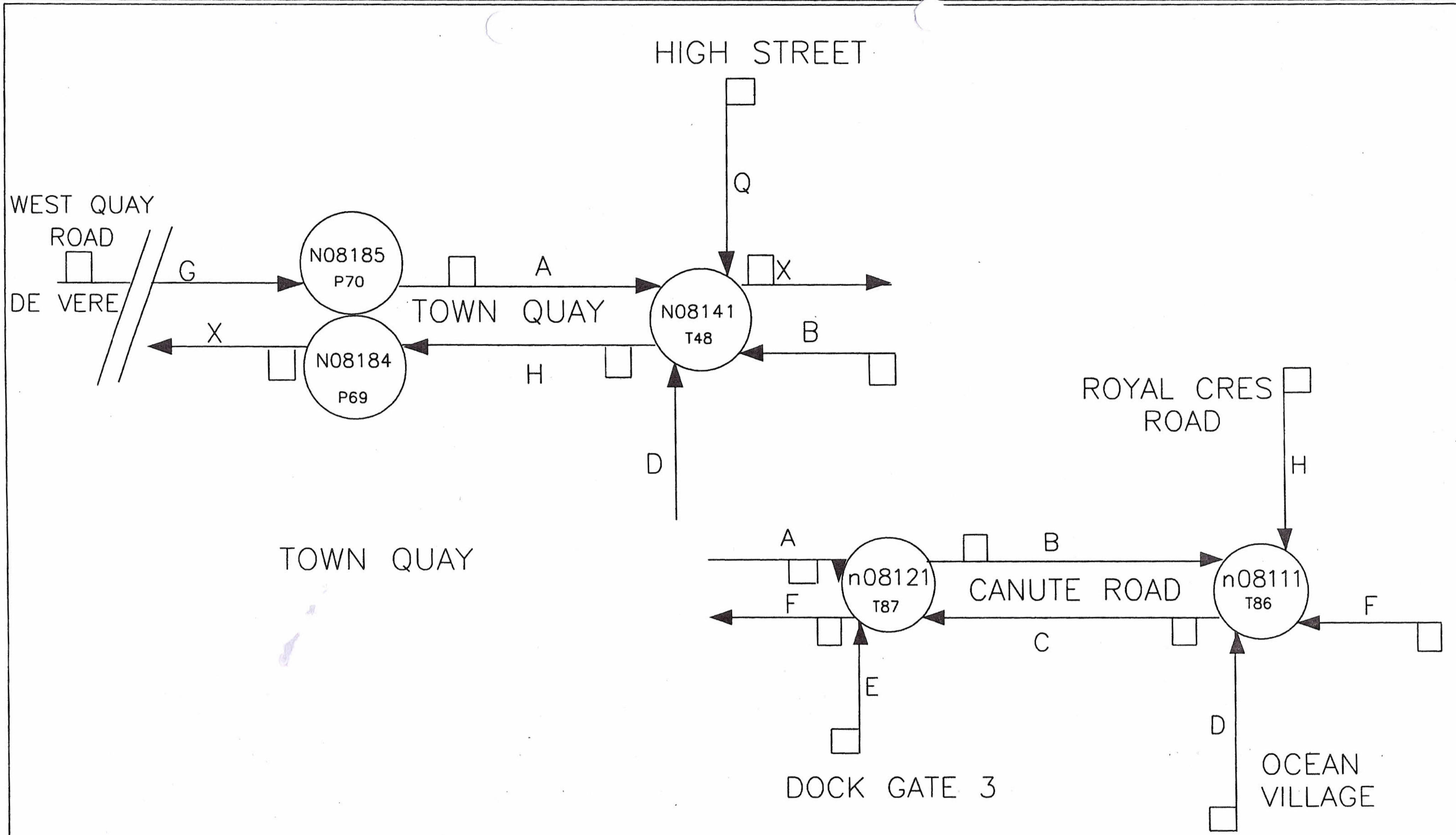

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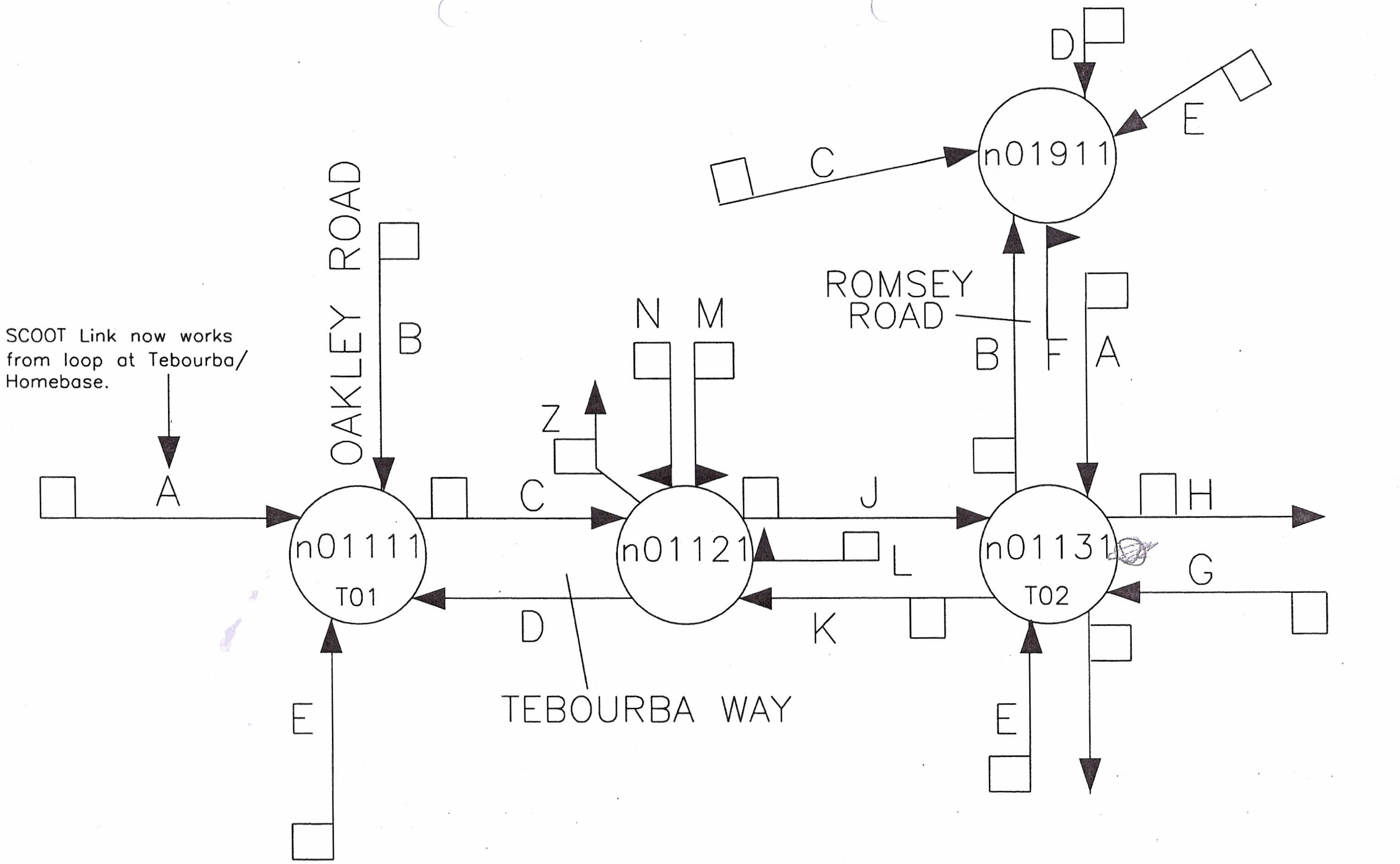

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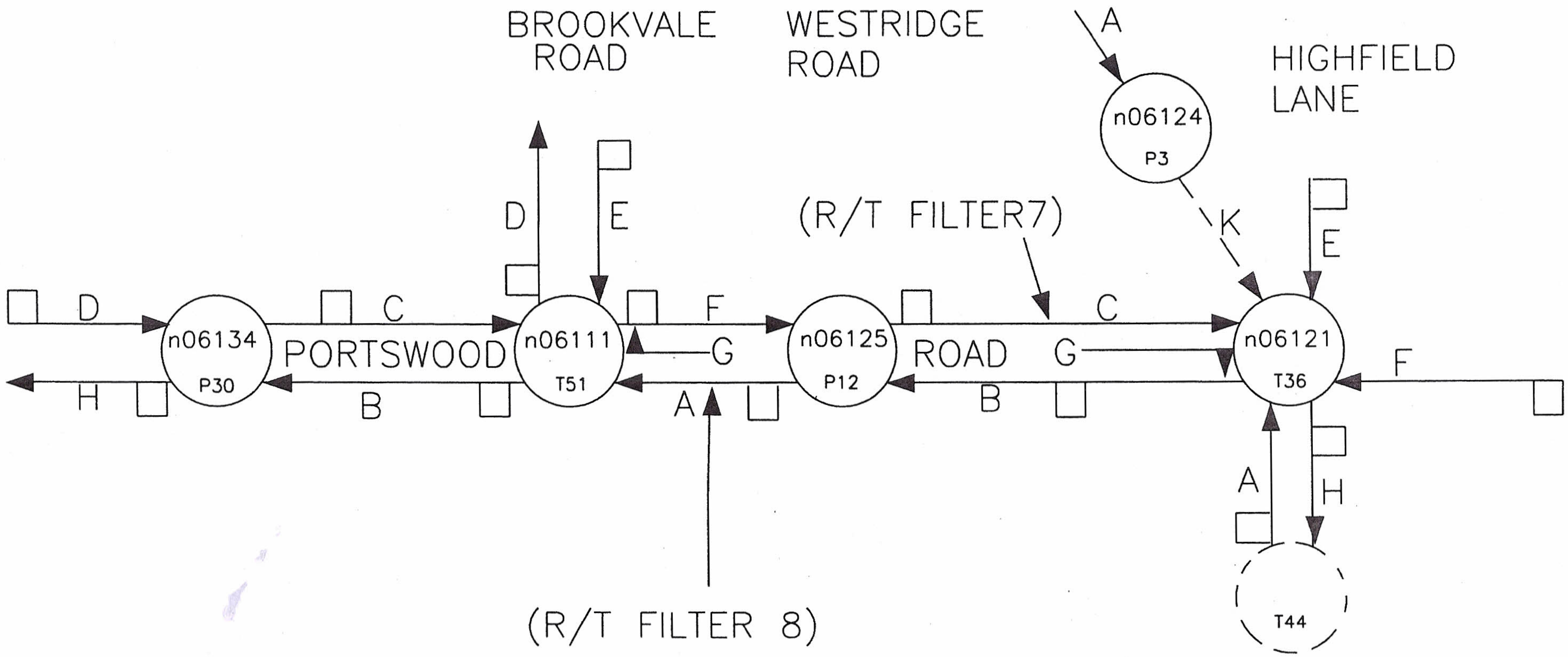

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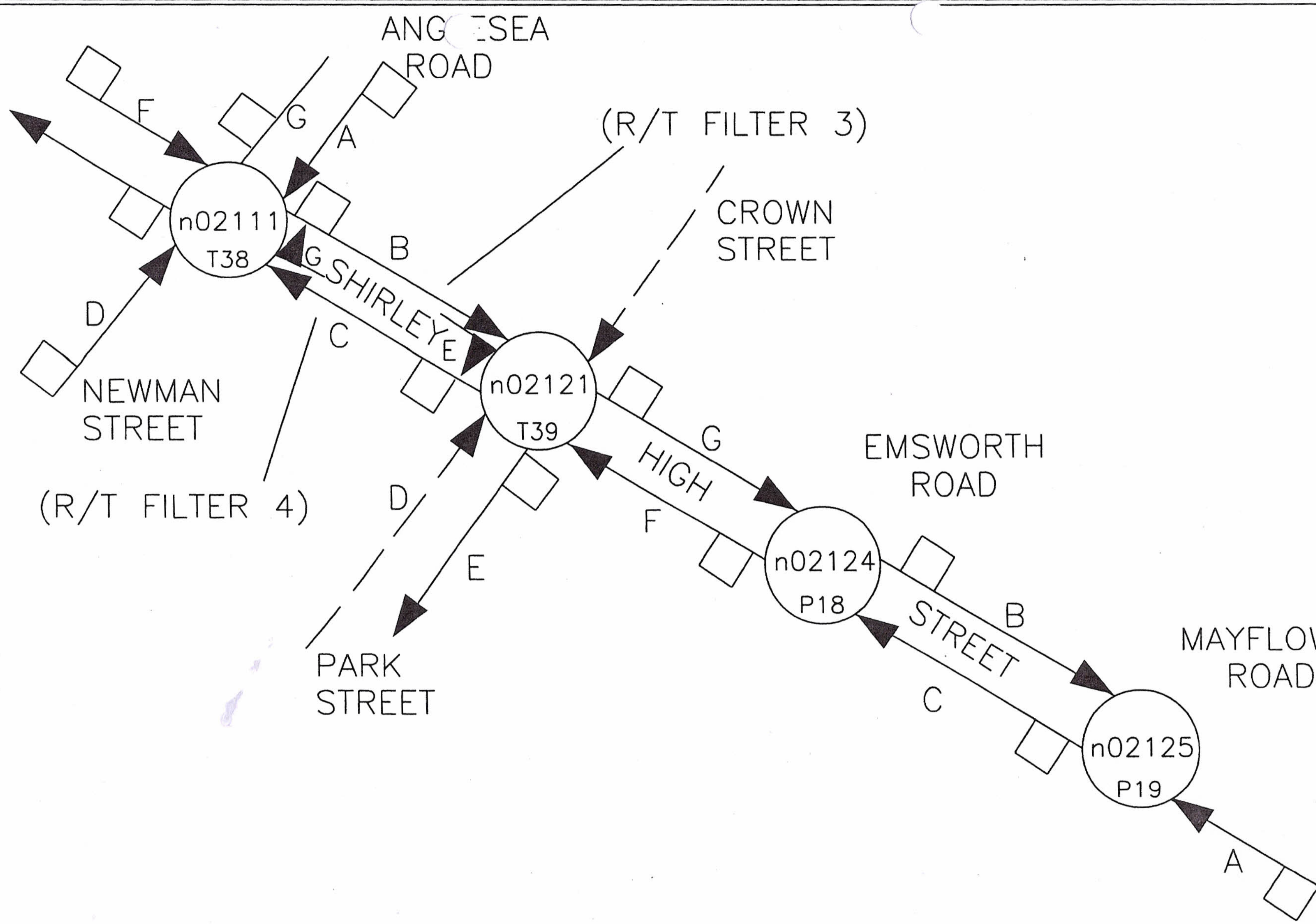

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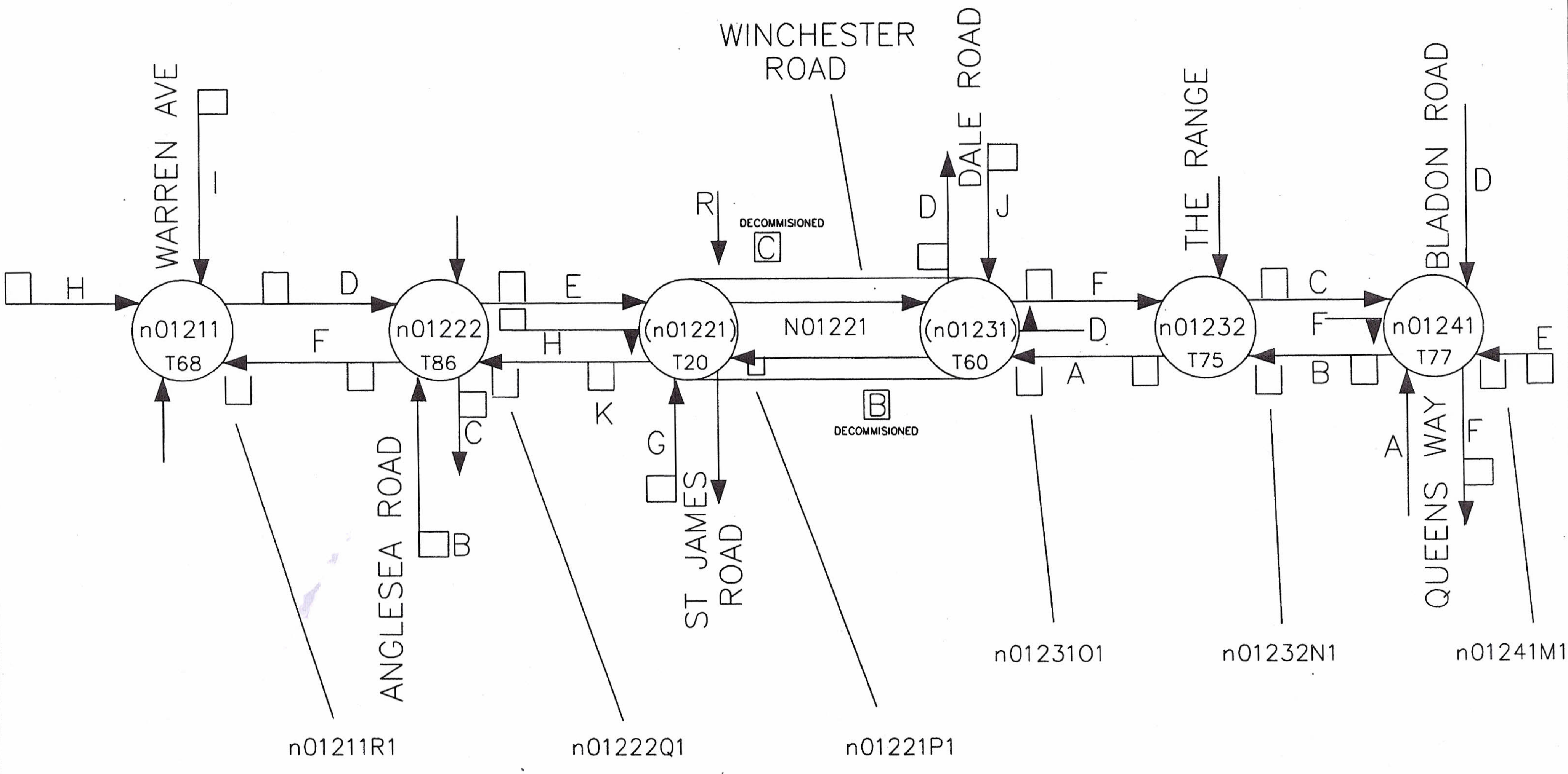

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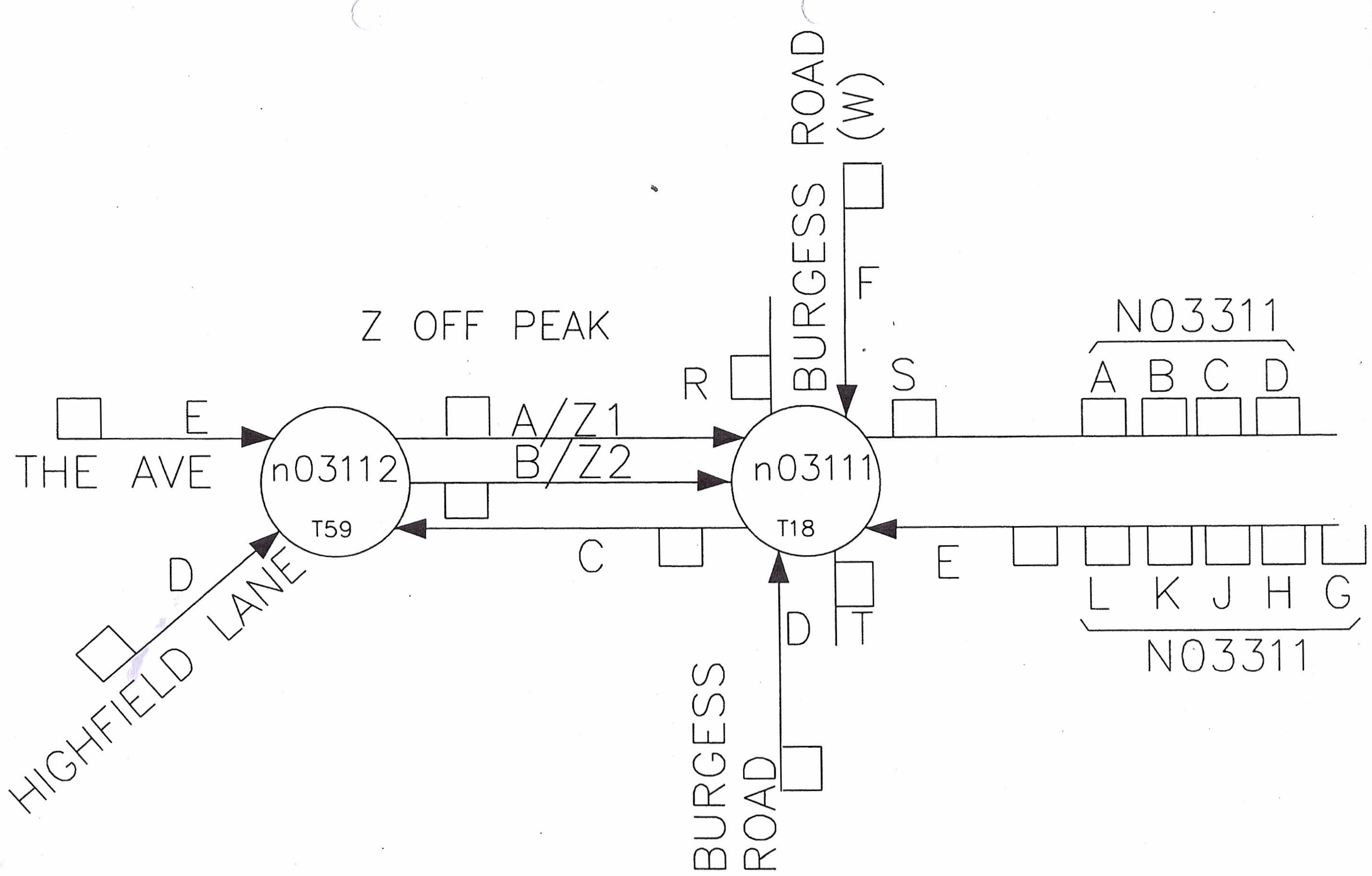

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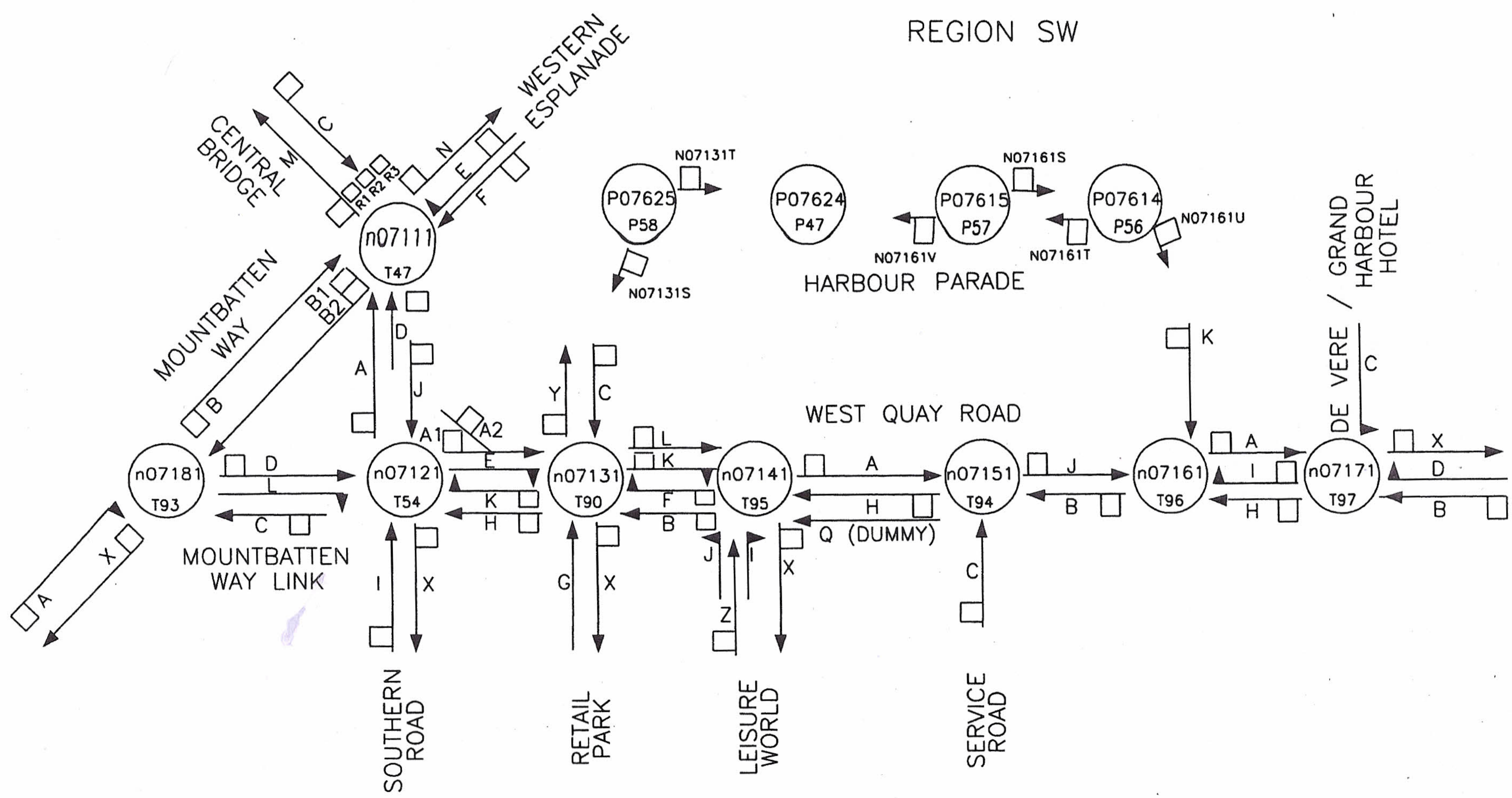

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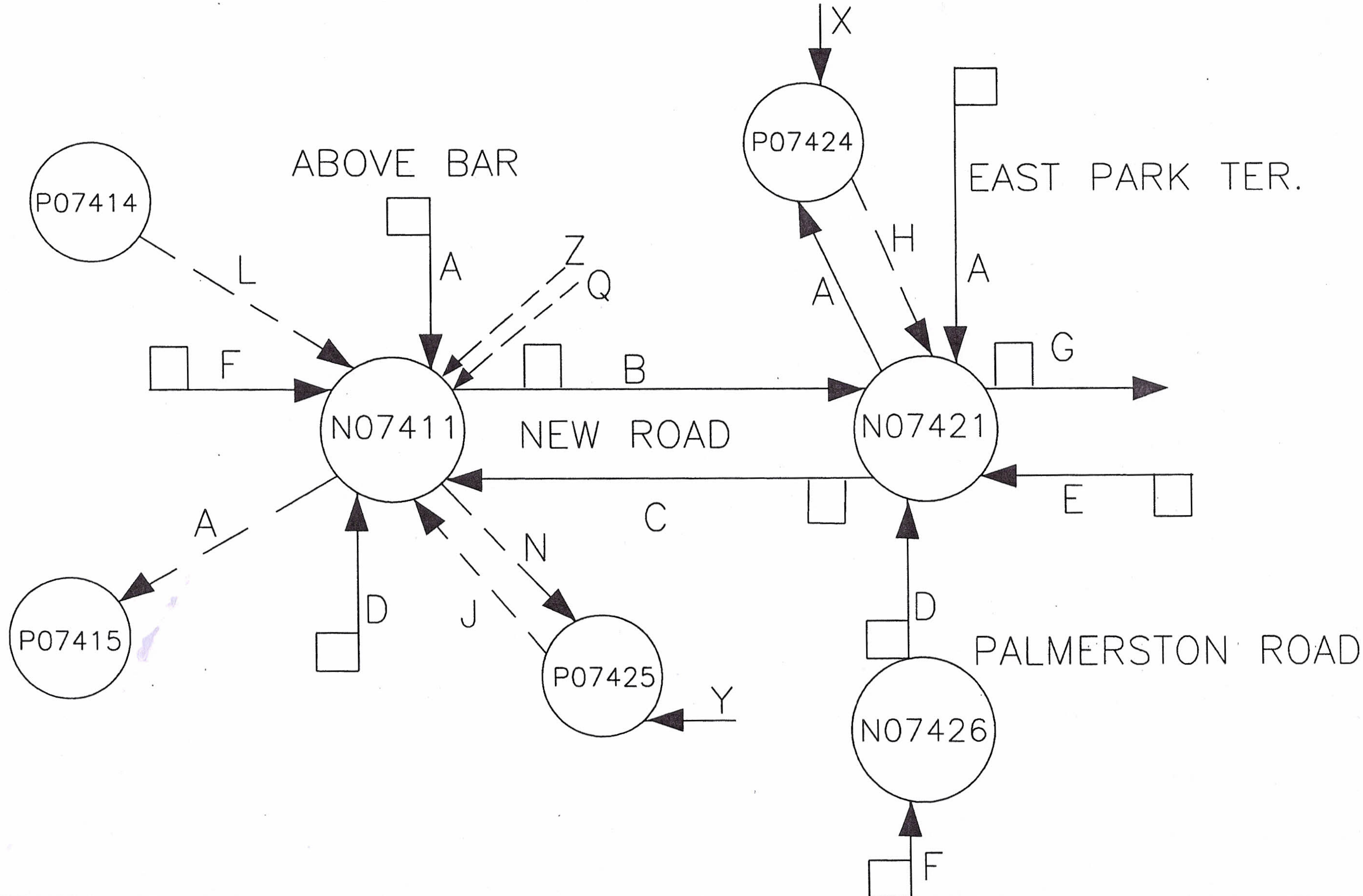

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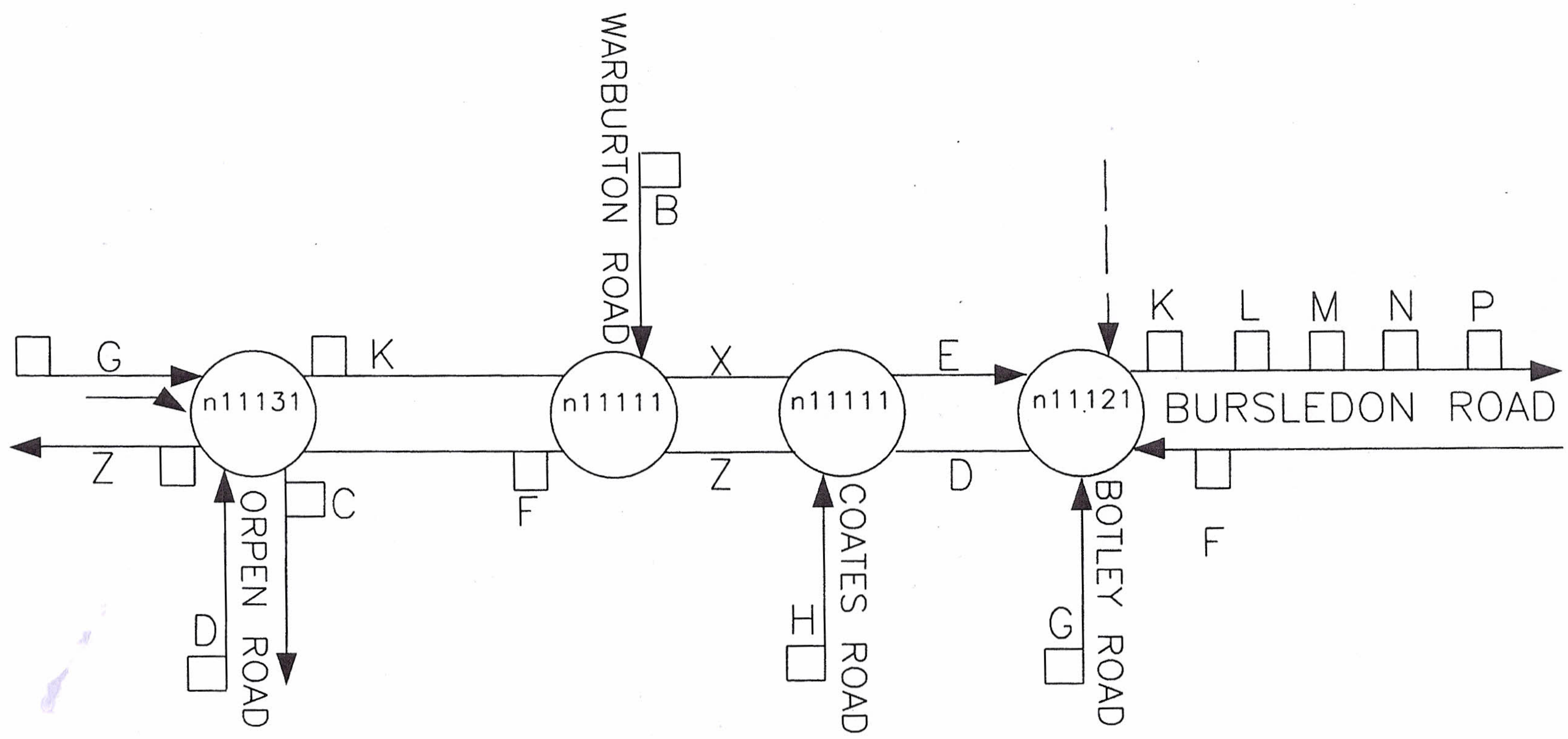
SOUTHAMPTON SO14 7PR

SOUTHAMPTON UTC

REGION RSX

SOUTHAMPTON CITY

Picture No:



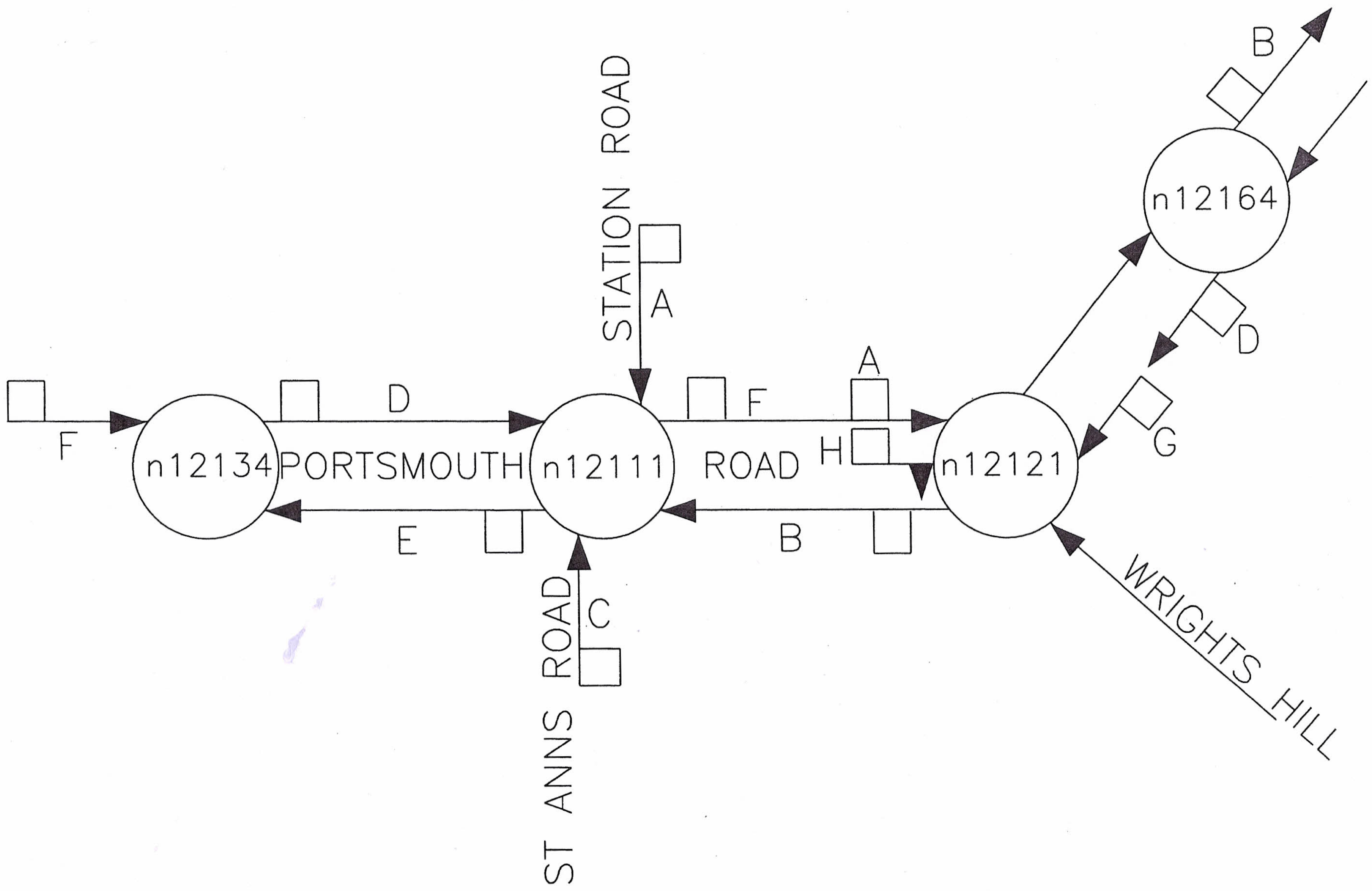
TRAFFIC SYSTEMS
R G ANDERSON
MARLAND HOUSE
CIVIC CENTRE ROAD
SOUTHAMPTON SO14 7PR

SOUTHAMPTON UTC

REGION SY

SOUTHAMPTON CITY

Picture No:R 18



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