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A practical model for predicting road traffic carbon dioxide emissions using Inductive Loop Detector data

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ABSTRACT

Local Government Authorities (LGAs) are typically responsible for roads outside a country's strategic road network. LGAs play a key role therefore in facilitating the reduction of emissions from road traffic in urban areas, 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 balance capturing the impact on emissions of vehicle dynamics (e.g. due to congestion) against in-use practicality. 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 GPS driving patterns (1 Hz 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. 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 categorisation 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 proxy real-world values.

1. Introduction

The world's population is increasingly urbanised (UNFPA, 2007). 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 (i.e. a LGA is responsible for all local roads inside its area of administration), 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 (Smit, 2006; Smit et al., 2010), which means LGAs must engage in emissions modelling. However, LGAs' resources are scarce (Lowndes and McCaughie, 2013). A brief review of the involvement of LGAs in the emissions modelling process is provided in the remainder of this section. For a more detailed review of this subject the reader is directed to work published by Grote et al. (2016a).

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List of abbreviations

AF	Accuracy Factor
AIRE	Analysis of Instantaneous Road Emissions
ALOTPV	Average Loop Occupancy Time Per Vehicle
APE	Absolute Percentage Error
CAN bus	Controller Area Network bus
cc	cubic centimetre
CO_2	Carbon Dioxide
COPERT	Computer Programme to calculate Emissions from Road Transport
CV	Cross Validation
DfT	UK government's Department for Transport
DV	Dummy Variable
EF	Emission Factor
EM	Emissions Model
HBEFA	Handbook of Emission Factors for Road Transport
HCSE	Heteroscedastic-Consistent Standard Error
HDV	Heavy Duty Vehicle
HGV	Heavy Goods Vehicle (a sub-category of HDV)
IEM	Instantaneous Emissions Model
ILD	Inductive Loop Detector
ITS	Intelligent Transport Systems
IV	Interaction Variable
LDV	Light Duty Vehicle
LGA	Local Government Authority
LGV	Light Goods Vehicle (a sub-category of LDV)
LOOCV	Leave-One-Out Cross Validation
MAF	Mean Accuracy Factor
MAPE	Mean Absolute Percentage Error
MLP	Multilayer Perceptron neural network
MLR	Multiple Linear Regression
MOVES	Motor Vehicle Emission Simulator
NAEI	UK's National Atmospheric Emissions Inventory
PEMLA	Practical Emissions Model for Local Authorities
PEMS	Portable Emissions Measurement System
PHEM	Passenger car and Heavy duty Emissions Model
r	Pearson linear correlation coefficient
R^2	Coefficient of determination
RTM	Road Traffic Model
SAF	Speed-specific Adjustment Factor
SCOOT	Split, Cycle and Offset Optimization Technique
SD	Standard Deviation
SDR	Speed Detection Radar
TEE-KCF	Traffic Energy and Emissions – Kinematic Correction Factor
TRL	UK's Transport Research Laboratory
TRL EFs 2009	TRL Emission Factors 2009 average speed emissions model
TRL/NAEI EM	TRL EFs 2009, with average speed emission functions weighted by each vehicle category's fraction of national VKMs in UK urban areas according to the NAEI national fleet model
U07	SCOOT system message
UTC	Urban Traffic Control
VERSIT+	Verkeers Situatie
VKM	Vehicle-Kilometre

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 (Grote et al., 2016a). In general, more complex models are more accurate representations of the real-world than less complex models (Smit et al., 2006). However, more complex models require more detailed input data (Smit et al., 2010), which are more susceptible to errors. Optimal model complexity occurs at the point beyond which the decreasing accuracy of input data begins to offset any accuracy gains through increasing model complexity (Alonso, 1968; Ramos et al., 2011; Smit et al., 2010).

EMs range in complexity, and are (briefly) reviewed here in accordance with the classification framework published in Grote et al. (2016a) and Smit et al. (2010). Specific examples of EMs (abbreviated titles are expanded in the List of Abbreviations section provided at the beginning of the article) are included to illustrate each EM type. 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, often classified as urban, rural or motorway (e.g. the UK national Greenhouse Gas Inventory EFs). Average Speed EMs calculate vehicle category-specific EFs as a function of traffic average speed (e.g. COPERT, TRL EFs 2009). Traffic Situation EMs correlate vehicle category-specific EFs with a range of defined traffic situations characterised by road type and a qualitative description of traffic conditions (e.g. HBEFA). Traffic Variable EMs calculate vehicle category-specific EFs as a function of variables that describe the traffic as a whole, such as traffic average speed or traffic density (e.g. TEE-KCF). Cycle Variable EMs calculate EFs for individual vehicles based on variables derived from driving patterns (fine-grained time series of speed points), such as number of stops per km or maximum acceleration (e.g. VERSIT+ [1]). Modal EMs calculate EFs for individual vehicles based on vehicle or engine operating modes, with the latest generation performing at temporal resolutions of 1 Hz typically termed Instantaneous EMs (IEMs) (e.g. MOVES, PHEM).

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[2] (RTM) outputs, Speed Detection Radar (SDR) traffic classifier systems, or vehicle telematics data available from Intelligent Transport Systems (ITS) (Grote et al., 2016a). UTC systems are particularly appealing because their operation is based on vehicle detection by Inductive Loop

[1] VERSIT+ was originally a Cycle Variable EM, but following major changes in 2009 is now better described as a Modal EM (Ligterink and De Lange, 2009).

[2] The term Road Traffic Model (RTM) is used to describe any software application that models the movement of vehicles on road networks. RTMs can be classified according to scale, ranging from macro-RTMs which consider the movement of traffic as an aggregated whole, through to micro-RTMs which simulate the detailed movements of individual vehicles (Grote et al., 2016a).

Detectors (ILDs) buried under the road surface at strategic network points, and the data generated by these ILDs can be considered a 'free' by-product of the traffic control system, meaning collection does not entail additional expenditure (Marsden et al., 2001; Reynolds and Broderick, 2000).

Individual vehicle driving patterns are available from sources such as in-vehicle GPS devices or the outputs of micro-RTMs widely used by transport planners. However, whilst obtaining individual vehicle driving patterns allows more detailed EMs (Cycle Variable and Modal EMs) to be used, compared to collecting traffic variables, collecting driving patterns for each and every vehicle in a network is a process involving high resource consumption (Grote et al., 2016a). Unlike traffic variables, they lack ready availability because they are seldom used in traffic engineering to describe network performance (Song et al., 2015). Additionally, driving patterns generated by RTMs have been found to be of questionable accuracy (Song et al., 2012, 2013). Recent research by Samaras et al. (2017) demonstrated that the coupling of micro-RTM outputs with an IEM has powerful potential for studying road traffic emissions in urban areas. However, simulations were somewhat limited in scale, being calibrated for passenger cars using a 1.6 km segment of an arterial corridor in Turin, Italy.

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 EMs). Use of Average Speed EMs is already widespread, which has been attributed to the easy availability of traffic average speed data (Smit et al., 2008b). Examples of work in the area of estimating network-level emissions using Average Speed EMs include studies by Nejadkoorki et al. (2008) and Fu et al. (2017). However, it is well known that Average Speed EMs (and Aggregate EMs) do not account well for the influence on emissions of congestion (Boulter et al., 2012; Int Panis et al., 2006; Ramos et al., 2011), which increases emissions through increased vehicle stop-start events, i.e. through congestion's effect on vehicle dynamics (Barth and Boriboonsomsin, 2008; Madireddy et al., 2011; Smit et al., 2008a). In fact, the term congestion was used as a proxy for vehicle dynamics in this study, because the principal concern was capturing as much as practical within resource constraints of the influence of vehicle dynamics on emissions, regardless of whether or not they are labelled as congestion (Grote et al., 2016a).

Based on the review of LGA involvement in the emissions modelling process, a two-part hypothesis was formulated. Part (1) is that 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 (in addition to traffic average speed) other traffic variables (e.g. traffic density (vehicles/km) or traffic average delay rate (seconds/vehicle·km)) as quantifiable measures of congestion, with only a small associated increase in complexity. In other words, as suggested by Grote et al. (2016a), Traffic Variable EMs potentially represent optimal model complexity for LGAs, offering improved account for congestion with a small increase in complexity over Average Speed EMs. Part (2) is that ILDs were identified as a readily available source of traffic variables, where collection does not entail additional expenditure of LGAs' limited resources (refer to Section 2.4 for examples of traffic variables that can be routinely collected from ILDs), and repurposing these data for use as inputs to the emissions modelling process would therefore represent an efficient use of those resources. Additionally, part (2) is supported by a survey of British LGAs which concluded that ILDs installed as part of UTC systems represented one of the most convenient sources for LGAs to collect data for use as EM inputs (Grote et al., 2016b). The two-part hypothesis formed the basis of this study. The general approach taken was to investigate the prediction of network-level CO_2 emissions based on traffic variables derived from ILD data.

The EM developed during the investigation, termed the Practical EM for Local Authorities (PEMLA), is a new Traffic Variable EM based on inputs generated from ILD data. The officially recognised EM recommended by the UK government's Department for Transport (DfT) for use in road traffic emissions analyses is the Transport Research Laboratory (TRL) Emissions Factors 2009 (TRL EFs 2009) Average Speed EM[3] (Boulter et al., 2009; Brown, 2016). PEMLA was therefore compared to this official EM with the expectation that augmentation by the addition of other traffic variable inputs to supplement traffic average speed (which is the only input to TRL EFs 2009) could potentially enhance accuracy through improved account for congestion. The method used to develop PEMLA is described in Section 2. The results of PEMLA's development are detailed in Section 3, consisting of the functional form of the model and a table of model parameters. Also presented in Section 3 are the results from the assessment of PEMLA in comparison to other EMs. Results are discussed in Section 4, followed by conclusions presented in Section 5.

2. Method

2.1. Method overview

A schematic overview of the method selected for the study is provided in Fig. 1. A more detailed description of each part of the method is provided in Sections 2.2–2.7.

2.2. Vehicle categories

EMs in Europe typically have highly disaggregated vehicle categories that, at the finest detail, distinguish between compliance with different European Emission Standards (e.g. the UK National Atmospheric Emissions Inventory (NAEI) distinguishes over 200

[3] The research was conducted during a time when the officially recommended EM for CO_2 was TRL EFs 2009. Subsequent to the work, the UK government has recently (2016) begun the process of migrating the officially recommended EM to COPERT, which is also an Average Speed EM similar to TRL EFs 2009.

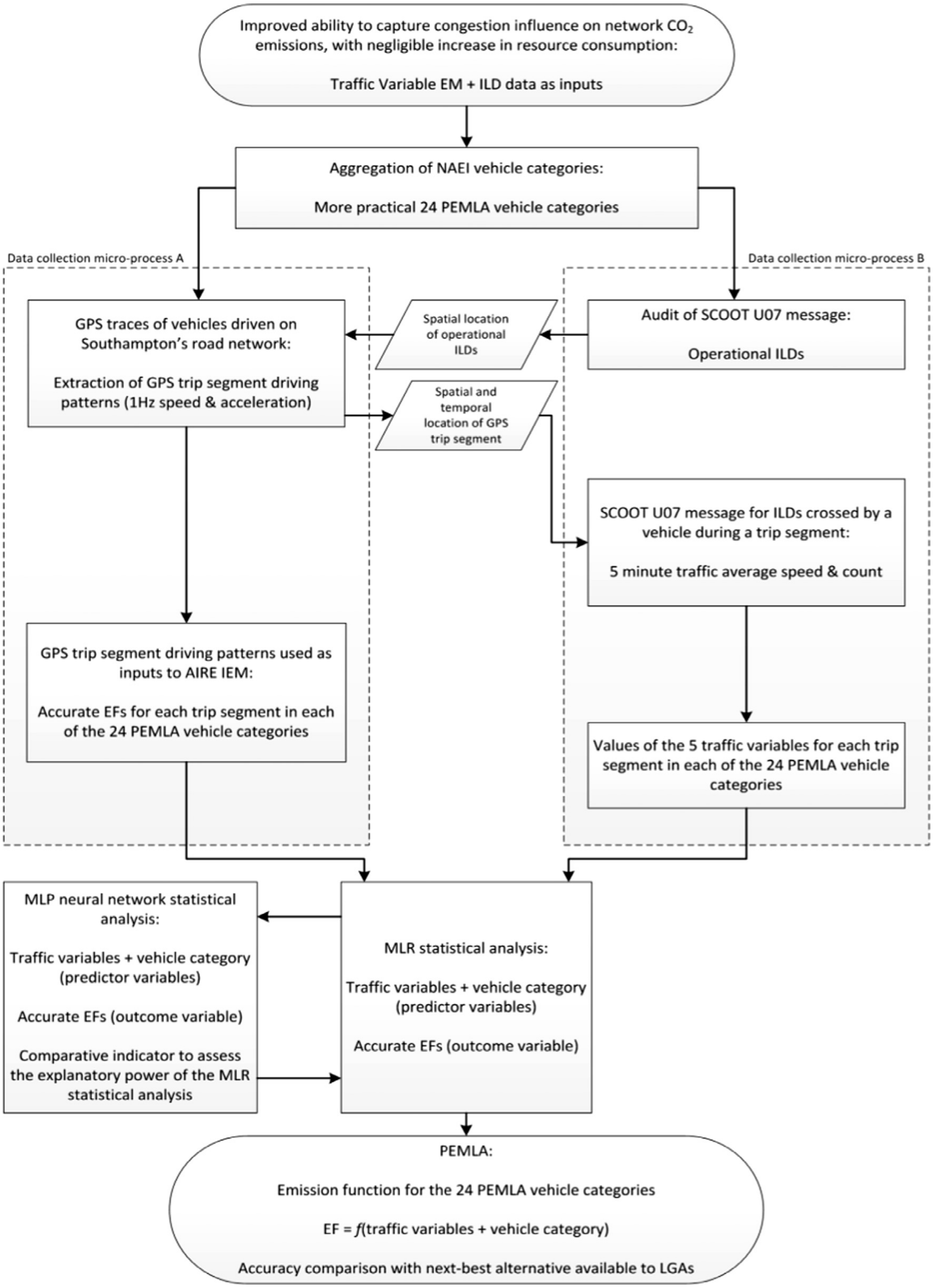

Fig. 1. Flow chart showing an overview of the study method. NAEI is the UK's National Atmospheric Emissions Inventory. Micro-process A shows calculation of accurate vehicle EFs (refer to Section 2.3). Micro-process B shows calculation of traffic variables (refer to Section 2.4). ILD is Inductive Loop Detector. SCOOT is Split, Cycle and Offset Optimization Technique, an Urban Traffic Control (UTC) system. SCOOT U07 message (refer to Section 2.4) contains data returned by each ILD in the UTC system. AIRE is Analysis of Instantaneous Road Emissions, an Instantaneous Emissions Model (IEM). MLR is Multiple Linear Regression. MLP is Multilayer Perceptron.

vehicle categories). For reasons of practicality, a reduced number of vehicle categories were sought. This was achieved by analysing the contribution to a composite traffic EF (EF_T, refer to Table 1 notes) made by each of the NAEI categories at various traffic average speeds. The analysis was conducted using the TRL EFs 2009 Average Speed EM, the UK's officially recommended EM (Boulter et al., 2009), with average speed emission functions for each vehicle category weighted by a category's fraction of total national vehicle-kilometres (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) 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)

Table 1
PEMLA vehicle categories and closest corresponding AIRE vehicle categories.

PEMLA vehicle category	Percent of VKMs[a]	NAEI vehicle category within the PEMLA vehicle category making greatest contribution[b] to EF_T[c]	Closest corresponding AIRE[d] category (x SAF[e] where applicable)
Cat. 01: Car, Gasoline, < 1400 cc[f], Pre-Euro[g] 5	8.0	Car, Gasoline, < 1400 cc, Euro 4	Car, Gasoline, < 1400 cc, Euro 4
Cat. 02: Car, Gasoline, < 1400 cc, Euro 5	6.5	Car, Gasoline, < 1400 cc, Euro 5	(Car, Gasoline, < 1400 cc, Euro 4) x Euro 5 SAF
Cat. 03: Car, Gasoline, < 1400 cc, Euro 6	3.6	Car, Gasoline, < 1400 cc, Euro 6	(Car, Gasoline, < 1400 cc, Euro 4) x Euro 6 SAF
Cat. 04: Car, Gasoline, 1400–2000 cc, Pre-Euro 5	8.5	Car, Gasoline, 1400–2000 cc, Euro 4	Car, Gasoline, 1400–2000 cc, Euro 4
Cat. 05: Car, Gasoline, 1400–2000 cc, Euro 5	6.9	Car, Gasoline, 1400–2000 cc, Euro 5	(Car, Gasoline, 1400–2000 cc, Euro 4) x Euro 5 SAF
Cat. 06: Car, Gasoline, 1400–2000 cc, Euro 6	3.8	Car, Gasoline, 1400–2000 cc, Euro 6	(Car, Gasoline, 1400–2000 cc, Euro 4) x Euro 6 SAF
Cat. 07: Car, Gasoline, > 2000 cc, Pre-Euro 5	2.4	Car, Gasoline, > 2000 cc, Euro 4	Car, Gasoline, > 2000 cc, Euro 4
Cat. 08: Car, Gasoline, > 2000 cc, Euro 5	1.9	Car, Gasoline, > 2000 cc, Euro 5	(Car, Gasoline, > 2000 cc, Euro 4) x Euro 5 SAF
Cat. 09: Car, Gasoline, > 2000 cc, Euro 6	1.1	Car, Gasoline, > 2000 cc, Euro 6	(Car, Gasoline, > 2000 cc, Euro 4) x Euro 6 SAF
Cat. 10: Car, Diesel, < 2000 cc, Pre-Euro 5	8.8	Car, Diesel, 1400–2000 cc, Euro 4	Car, Diesel, 1400–2000 cc, Euro 4
Cat. 11: Car, Diesel, < 2000 cc, Euro 5	12.1	Car, Diesel, 1400–2000 cc, Euro 5	(Car, Diesel, 1400–2000 cc, Euro 4) x Euro 5 SAF
Cat. 12: Car, Diesel, < 2000 cc, Euro 6	6.8	Car, Diesel, 1400–2000 cc, Euro 6	(Car, Diesel, 1400–2000 cc, Euro 4) x Euro 6 SAF
Cat. 13: Car, Diesel, > 2000 cc, Pre-Euro 5	3.7	Car, Diesel, > 2000 cc, Euro 4	Car, Diesel, > 2000 cc, Euro 4
Cat. 14: Car, Diesel, > 2000 cc, Euro 5	5.1	Car, Diesel, > 2000 cc, Euro 5	(Car, Diesel, > 2000 cc, Euro 4) x Euro 5 SAF
Cat. 15: Car, Diesel, > 2000 cc, Euro 6	2.9	Car, Diesel, > 2000 cc, Euro 6	(Car, Diesel, > 2000 cc, Euro 4) x Euro 6 SAF
Cat. 16: LGV[h], Gasoline, All	0.3	LGV, Gasoline, All Weights, Euro 4	LGV, Gasoline, All Weights, Euro 4
Cat. 17: LGV, Diesel, All Weights, Pre-Euro 5	3.3	LGV, Diesel, All Weights, Euro 4	LGV, Diesel, All Weights, Euro 4
Cat. 18: LGV, Diesel, All Weights, Euro 5	7.4	LGV, Diesel, All Weights, Euro 5	(LGV, Diesel, All Weights, Euro 4) x Euro 5 SAF
Cat. 19: LGV, Diesel, All Weights, Euro 6	2.3	LGV, Diesel, All Weights, Euro 6	(LGV, Diesel, All Weights, Euro 4) x Euro 6 SAF
Cat. 20: HGV[i], Rigid[j], All	1.7	HGV, Rigid, 28–32 t, Euro VI	(HGV, Rigid, 28–32 t, Euro V) x Euro VI SAF
Cat. 21: HGV, Artic[k], All	0.4	HGV, Artic, 40–50 t, Euro VI	(HGV, Artic, 40–50 t, Euro V) x Euro VI SAF
Cat. 22: Bus, All	1.0	Bus, Standard, 15–18 t, Euro V	Bus, Single Deck, Euro V
Cat. 23: Coach, All	0.4	Coach, Euro V	Coach, Euro V
Cat. 24: Two-Wheel, All	1.2	na	na

na = not applicable.
[a] Percent of VKMs is the NAEI national fleet model percentage of total urban VKMs for England outside London in 2016 (NAEI, 2014).
[b] 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 (DfT, 2011a).
[c] EF_T is a composite EF for the traffic (gCO_2/VKM_T), where VKM_T is vehicle-kilometre for the traffic.
[d] AIRE is Analysis of Instantaneous Road Emissions, an IEM produced by SIAS Limited and Transport for Scotland.
[e] SAF is Speed-specific Adjustment Factor (refer to Section 2.3 for explanation).
[f] cc is engine capacity in cubic centimetres.
[g] Euro shows compliance with relevant European Emission Standards: Arabic numerals for Light Duty Vehicles (LDVs); and roman numerals for Heavy Duty Vehicles (HDVs).
[h,i] LGV is Light Goods Vehicle (in general < 3.5 tonnes gross vehicle mass); HGV is Heavy Goods Vehicle.
[j,k] Rigid is a rigid HGV; Artic is an articulated HGV.

(EPA, 2015). NAEI categories were aggregated into PEMLA categories whilst ensuring that no PEMLA category contributed more than 10% to the EF_T at any speed. The limit of 10% was selected as a convenient figure that ensured the aggregation process did not produce a category that made a dominating contribution to the composite EF_T, whilst also resulting in a practical number of categories in accordance with the target, i.e. 24 PEMLA vehicle categories (first column in Table 1).

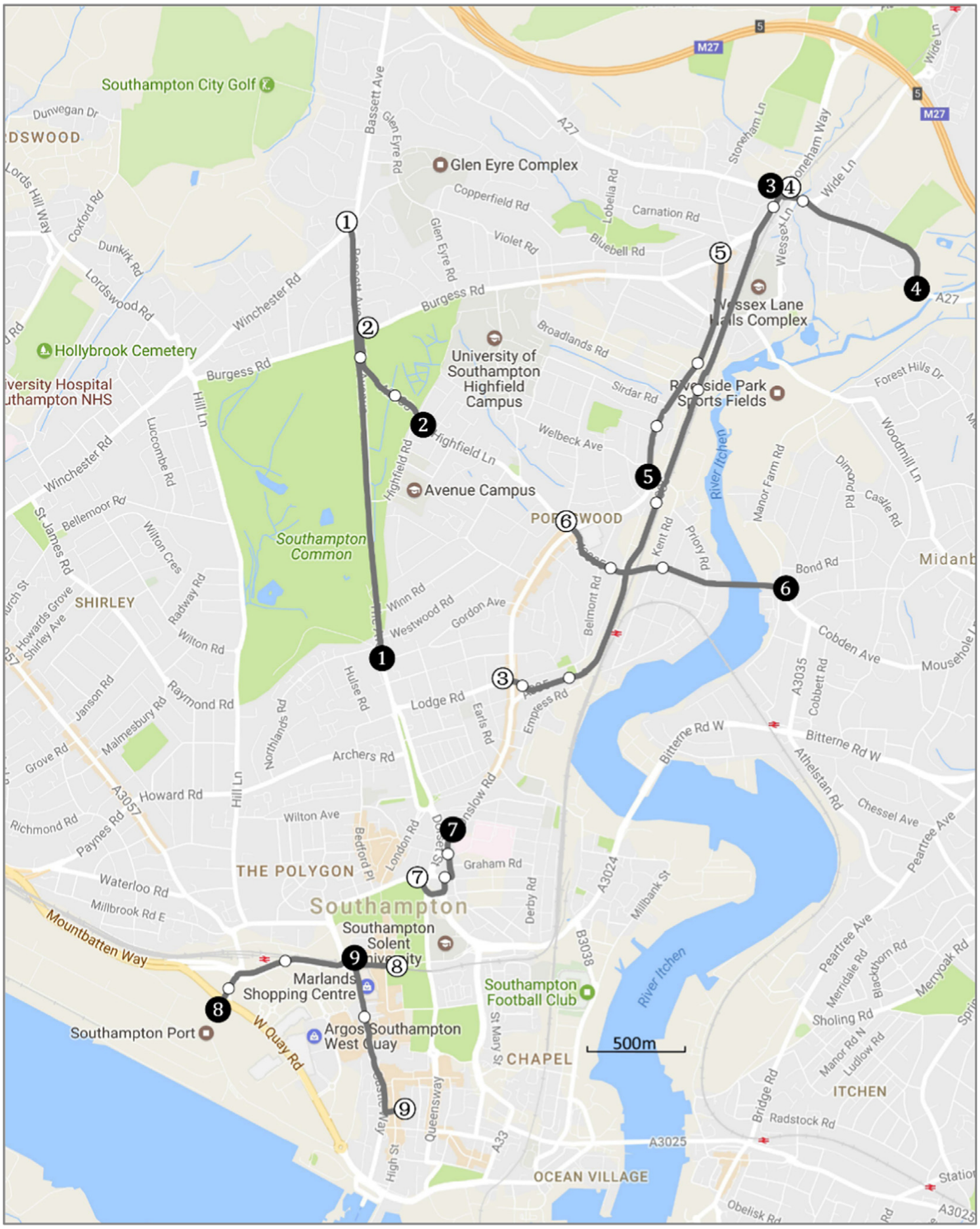

Fig. 2. Map of example trip segments collected in Southampton. GPS traces of trip segments performed by vehicles are shown by thick grey lines. Plain white circles show the positions of Inductive Loop Detectors (ILDs) crossed by vehicles during trip segments. Numbered black circles indicate the start of trip segments, and numbered white circles indicate the end of trip segments. Scale bar indicates a distance of 500 m. Base map obtained from Google Maps.

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	0.731	1.494	1.358	0.925
	Median	0.614	1.218	0.982	0.865
Average trip segment duration (s)	Mean	185	213	183	129
	Median	164	191	151	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.

2.3. Proxy real-world emission factors calculation

Southampton, a city on the South coast of the UK with a population of *circa* 255,000, was used as the testbed for the study. 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. Example trip segments are shown in Fig. 2. 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 the ambition was to ensure spatial features (i.e. intersections and operational ILDs) were captured and distance snippet extraction was a more practical method of achieving this.

Drivers (numbers shown in Table 2) were recruited from contacts at institutions across Southampton. The GPS devices used for recording vehicle movement were BT-Q1000X GPS Travel Recorders manufactured by Qstarz, which have specified accuracies of 3 m for position data and 0.1 m/s (0.36 km/h) for speed data. These devices are hand-held loggers that have been used successfully for recording travel data in previous studies (e.g. NuStats, 2011, 2013). 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 recorded by the logger was the variable of interest, meaning the positional accuracy of waypoints was less important.

Even with PEMLA vehicle categories reduced to 24, finding sufficient volunteer drivers in each of the 24 categories willing to carry GPS loggers and then collecting at least 100 trip segment samples (approximate minimum sample size necessary for reliable MLR analysis) from those drivers for each category, would have made volunteer driver recruitment impractical within the study's resource constraints. Therefore, for trip segment collection, based on the fact that it was vehicle movement (rather than emissions) that was collected by the GPS loggers, PEMLA vehicle categories were grouped into four more-aggregate categories defined by broadly similar power-to-mass characteristics. 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. The four aggregate categories were: Bus; HDV (except Bus); LDV; and Two-Wheel (Table 2); with buses seen as requiring a category separate from other HDVs due to the effect of their specialist multi-stop operation on vehicle dynamics.

Each trip segment produced a driving pattern that constituted second-by-second vehicle speed (m/s) recorded by the logger (an example of a speed-time profile for a GPS trip segment driving pattern is shown in Fig. 3), from which vehicle acceleration (m/s^2) was computed as the change in second-by-second speed, i.e. a driving pattern constituted instantaneous vehicle speed and acceleration at 1 Hz resolution. Instantaneous speed and acceleration distributions for the combined 514 trip segment driving patterns are shown in Figs. 4 and 5. The driving patterns (except Two-Wheel) were used as inputs to an IEM to calculate an accurate[4] 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).

In the absence of a practical method to collect real-world emissions measurements (i.e. it was logistically impractical within the resource constraints of the research to fit Portable Emissions Measurement System (PEMS) equipment to vehicles in all 24 PEMLA

[4] The term "accurate EF" is used throughout this article to describe EFs calculated by the IEM employed in the research (which was AIRE as detailed in the next paragraph). It is acknowledged that this is not use of "accurate" in the strict sense, in that true real-world EFs are unknown. However, "accurate" is used in the sense that AIRE (as an IEM) will produce more accurate outputs than either TRL/NAEI EM or PEMLA (as an Average Speed EM and a Traffic Variable EM, respectively). Where "accurate EF" is used to describe AIRE outputs, this should be taken to mean proxy rather than true real-world EFs.

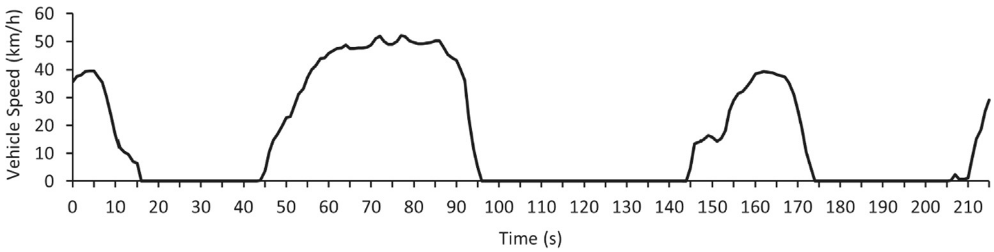

Fig. 3. Example speed-time profile for a GPS trip segment driving pattern. The trip segment driving pattern was collected from a GPS logger carried in a vehicle in the LDV category. Shown as Trip Segment 8 in Fig. 2.

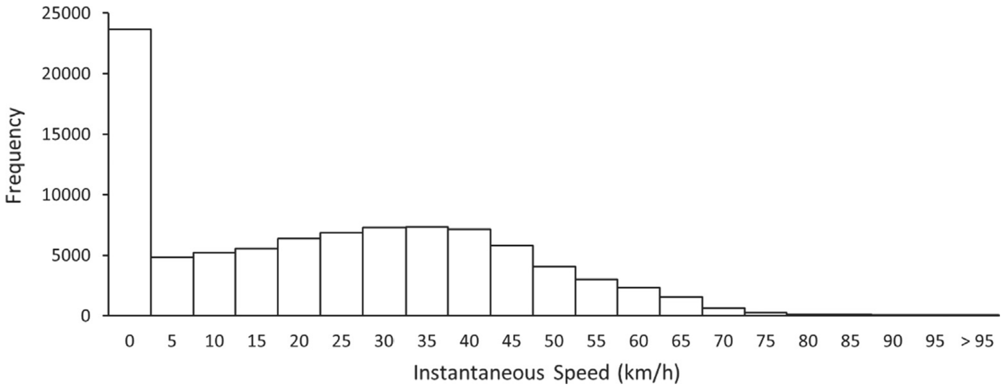

Fig. 4. Frequency distribution of second-by-second speed data for the 514 trip segment driving patterns. Total of 92,254 GPS records (28,501 for Bus; 24,209 for HDV; 25,164 for LDV; and 14,380 for two-wheel) for the combined 514 trip segment driving patterns. Horizontal axis label indicates the upper limit of the speed bin. Speed bins are: lower limit < speed ≤ upper limit.

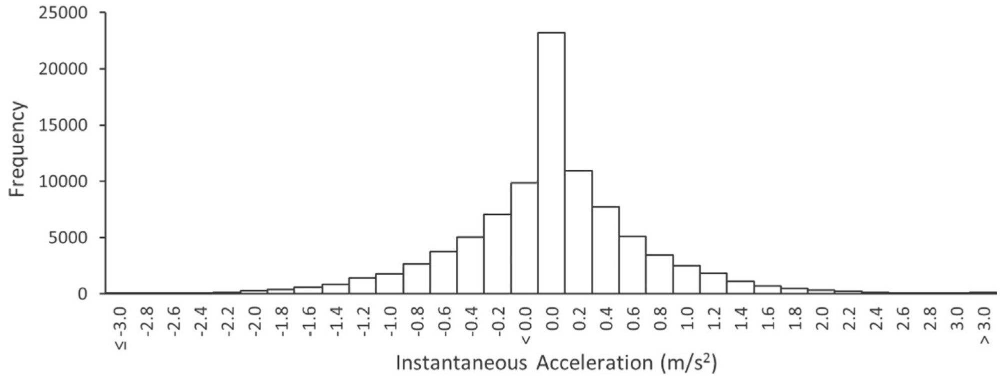

Fig. 5. Frequency distribution of second-by-second acceleration data for the 514 trip segment driving patterns. Total of 92,254 GPS records (28,501 for Bus; 24,209 for HDV; 25,164 for LDV; and 14,380 for two-wheel) for the combined 514 trip segment driving patterns. Horizontal axis label indicates the upper limit of the acceleration bin. Acceleration bins are: lower limit < acceleration ≤ upper limit; except for the acceleration bin labelled 0.0 which records the frequency of observations where acceleration was 0 m/s^2.

categories), the outputs from the IEM were used as a proxy for real-world EFs. A hierarchical approach was adopted to select a suitable IEM for this process. Arguably, the foremost examples of the latest generation of IEMs are MOVES, VERSIT+ and PHEM (Wyatt et al., 2014). However, none of these EMs were feasible for reasons such as study resource constraints or applicability to UK roads. The next-best option was considered to be Analysis of Instantaneous Road Emissions (AIRE), specifically AIRE v1.0 (build ID 1.0.24115.0) produced in June 2011 (the latest version available). It is acknowledged that the development and validation of AIRE is not documented in detail in an accessible document. However, the original development of AIRE was achieved using outputs from PHEM, a more detailed IEM based on engine speed and power (Hausberger et al., 2009). Additionally, AIRE was originally developed specifically for use on UK roads, was independently validated by the Transport Research Laboratory (TRL, a well-respected UK transport research institution), is an IEM featuring vehicle categories disaggregated according to Euro Standard, is supported by Transport Scotland (the national transport agency for Scotland, UK) on whose behalf it was developed, and is distributed freely by the manufacturers (SIAS Limited) (Transport Scotland, 2011). Therefore, the assumption that AIRE outputs were the best available option to serve as proxies for real-world EFs was thought to be reasonable. If more resources were available, PHEM has potential to be a more accurate and up-to-date replacement for AIRE in the methodology to construct PEMLA.

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 (third column in Table 1). The resulting TRL/NAEI EM category was then matched to the closest corresponding AIRE category (fourth column in 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/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/V Standard using the TRL/NAEI EM, with vehicle average speed (as calculated from its GPS driving pattern) as input. For example, to calculate the SAF for a Category 02 vehicle (Car, Gasoline, < 1400 cc, Euro 5) performing a trip segment with a vehicle average speed of 31 km/h, the relevant EFs from TRL/NAEI EM are 144 and 129 gCO_2/VKM for Euro 4 and Euro 5 compliant vehicles, respectively, giving a SAF of 129/144 = 0.896.

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 (Smit et al., 2008b).

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, it has been suggested that this method is more accurate than using traffic average speed as input because it captures the deviation of vehicle average speeds from the average for the traffic (Smit et al., 2008b).

2.4. 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 (Bretherton et al., 2011). The SCOOT system database is accessed via numerous different messages. For this research, ILD data were provided by the U07 message, which is a bespoke SCOOT message developed by the University of Southampton. Although this message is specialist in nature, it is routinely available from any SCOOT system. The U07 message returns values from each ILD for: estimated traffic average speed (km/h and mph) over a 5 min interval based on a relationship derived between Average Loop Occupancy Time Per Vehicle (ALOTPV) and vehicle speed; traffic flow based on vehicle count in a 5 min interval (vehicles/5 min); and the percentage of a 5 min interval for which an ILD was occupied (%). Detailed explanations of the development and contents of the U07 message, including derivation of the ALOTPV and vehicle speed relationship, are available in Cherrett et al. (2001, 2002).

Numerous traffic variables could potentially have been selected for investigation as predictor variables. A comprehensive study detailing the many different possible traffic variables can be found in Smit (2006). However, it was beyond study resources to investigate all possible traffic variables, and several 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 selection criterion of previous use in emissions predictions. Due to the important requirement for PEMLA to be practical for LGAs to use within their scarce resources, two further key selection criteria were: familiarity to LGAs (i.e. widely used in traffic engineering to describe traffic performance); and easily available for routine collection by LGAs. Finally, as the study was concerned with including congestion influence, a fourth key selection criterion was the ability to act as congestion indicators. Using the four criteria in combination, five traffic 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 $(km/h)^2$.

The 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. Hence, an averaging process for the data from all the ILDs a vehicle crossed during a trip segment was employed, which involved traffic variable values being sampled at 1 min 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 min) and sampling (1 min) 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 min 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. Essentially therefore, the traffic variable averaging process calculated a weighted average of the ILD data that applied to a given trip segment.

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 (Boddy et al., 2005). Other factors that affect ILD accuracy include vehicle chassis height, vehicle metallic content, and ILD responsiveness (Boddy et al., 2005; Cherrett et al., 2002; Lee and Coifman, 2012). Additionally, ILDs can be either single-loop or double-loop installations, with single-loop being the most common (Cherrett et al., 2001; Coifman and Kim, 2009; Li, 2009) 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. However, from the perspective of the motivation for this study, overriding concerns about any potential inaccuracies was the fact that it is ILD data to which LGAs (with their limited resources) have ready and inexpensive access as a 'free' by-product of UTC systems, particularly data from single-loop ILDs as the most commonly installed configuration. The ability of single-loop ILD data (with their inherent inaccuracies) to predict network-level CO_2 emissions was seen therefore as a worthwhile subject for investigation.

ILD data collection implicitly assumed 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.

2.5. Statistical analysis

An appropriate method for exploring relationships between predictor and outcome variables is Multiple Linear Regression (MLR) (Field, 2009), 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 (Sewak and Singh, 2015). 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 (Agirre-Basurko et al., 2006; Gaudart et al., 2004).

However, MLR analysis results are easier to interpret and utilise than those of MLP analysis (IBM, 2013). 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 and recommended for LGA use. A full description of this analysis is available in Grote (2017). However, for brevity, this article is limited to describing the final PEMLA version.

All 24 vehicle categories were analysed together, with vehicle category included as a predictor variable alongside the original five traffic variables. 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 also added to the original five 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 trip segments involving vehicles from that category the value of each of the IVs corresponded to the value of each of the traffic variables; and for trip segments involving 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 trip segments involving Category 01 vehicles, but was zero for trip segments 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 a 30 mph limit and 1 indicated a 40 mph limit. For time of day (DV-Time Period), 0 indicated an off-peak period and 1 indicated a 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.

2.6. Model assessment

PEMLA predictions were compared with those from two well-established EMs. It is acknowledged that this was model comparison rather than true validation. However, true validation (i.e. comparison with independent real-world emissions measurements) was not possible within study resources due to the inherent difficulties associated with collection of a comprehensive set of such data (e.g. impractical to fit PEMS equipment to vehicles in all categories, refer to Section 2.3). That said, positive results when compared with well-established EMs would give confidence in PEMLA.

The first EM for comparison was AIRE, which involved splitting trip segment samples into those used for PEMLA calibration, and those reserved for assessment. Trip segment samples were limited in number, meaning both calibration and assessment 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 assessment is made over multiple, different splits of the samples, with Leave-One-Out (LOO) being the most classical, exhaustive data-splitting CV procedure (Arlot and Celisse, 2010). In LOOCV each case (i.e. trip segment) is left out of the PEMLA 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 with the EF from AIRE as an assessment. The differences between predicted and AIRE EFs for all cases as they are excluded in turn is used to assess the overall PEMLA model calibrated including all cases. For each case, an Accuracy Factor (AF) and an Absolute Percentage Error (APE) were calculated using Eqs. (1) and (2).

$$\mathrm{AF} = \frac{\text{Predicted EF when Case excluded from PEMLA calibration}}{\text{EF from AIRE}} \tag{1}$$

$$\mathrm{APE} = \frac{|\text{Predicted EF when case excluded from PEMLA calibration} - \text{EF from AIRE}|}{\text{EF from AIRE}} \times 100\% \tag{2}$$

The second EM for comparison was the TRL/NAEI EM, with GPS vehicle average speeds (as opposed to ILD traffic average speeds) used as inputs, which has been suggested as a more accurate method for applying an Average Speed EM (Smit et al., 2008b) (refer to Section 2.3). For each case, an AF and an APE were calculated using Eqs. (3) and (4).

$$\mathrm{AF} = \frac{\text{Predicted EF}}{\text{EF from TRL/NAEI (vehicle average speed)}} \tag{3}$$

$$\mathrm{APE} = \frac{|\text{Predicted EF - EF from TRL/NAEI (vechicle average speed)}|}{\text{EF from TRL/NAEI (vehicle average speed)}} \times 100\% \tag{4}$$

Fifty three trip segments in the Bus category (Category 22) were collected from a bus being operated with PEMS equipment on-board. Hence, these cases did have PEMS data available, from which real-world EFs were calculated. The PEMS data were collected during a different project conducted by the University of Southampton investigating bus emissions (particularly oxides of nitrogen). The PEMS equipment used 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 during February 2016 (vehicle details in Table 3). During testing, two passenger seats were removed to accommodate the installation of the PEMS equipment (refer to Fig. 6). 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. Measurements were recorded at a frequency of 10 Hz. Additionally, the experimental installation was validated by comparison of fuel flow (g/s) outputs from the PEMS (calculated by the PEMS using the carbon balance method) with those from the engine control unit obtained via the Controller Area Network (CAN) bus.

Comparison of PEMLA predicted EFs with 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 Eqs. (5) and (6).

$$\mathrm{AF} = \frac{\text{Predicted EF}}{\text{EF from PEMS}} \tag{5}$$

$$\mathrm{APE} = \frac{|\text{Predicted EF - EF from PEMS}|}{\text{EF from PEMS}} \times 100\% \tag{6}$$

2.7. Predictive accuracy comparison

The predictive accuracy of PEMLA was assessed in comparison to that of TRL/NAEI EM, which is the next-best alternative EM available to UK LGAs. For this comparison, EFs from AIRE were (again) used as a proxy for real-world EFs. For each case, an AF and an APE were calculated using Eqs. (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-

Table 3
Vehicle characteristics for the bus used for PEMS data collection.

Characteristic	Test vehicle
Registration plate	SK63 KNB
Registration date	29th November 2013
Fuel type	Diesel
Engine capacity	4461 cubic centimetres
Euro Standard compliance	Euro V
Revenue weight[a]	13,139 kg
TRL/NAEI EM vehicle category	Bus, Midi, < 15 tonnes, Euro V
PEMLA vehicle category	Bus, All
Maximum passenger load[b]	37 seated plus 31 standing: Total = 4420 kg
Payload during test[c]	6 passengers, 34 bags of grit (25 kg each), PEMS equipment: Total = 1360 kg

[a] Revenue weight is defined by the UK Department for Transport as the maximum gross weight of a vehicle.
[b] Vehicle loads are calculated assuming an average passenger mass of 65 kg, which was the assumption used in the development of TRL EFs 2009 Average Speed EM (Barlow, 2009).
[c] Mass of the PEMS equipment (including batteries) minus the mass of the 2 seats removed is 120 kg.

Fig. 6. PEMS equipment installation on the test bus.

for-like comparison because ILD data (plus access density) were used as PEMLA inputs.

$$\mathrm{AF} = \frac{\text{Predicted EF}}{\text{EF from AIRE}} \tag{7}$$

$$\mathrm{APE} = \frac{|\text{Predicted EF - EF from AIRE}|}{\text{EF from AIRE}} \times 100\% \tag{8}$$

3. 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 4. Full details of diagnostic testing to examine compliance with MLR assumptions are available in the work by Grote (2017) previously mentioned in Section 2.5. The MLR assumption of homoscedasticity (tested with Breusch-Pagan and Koenker tests) was violated, but this was overcome using a Heteroscedastic-Consistent Standard Error (HCSE) estimator in the MLR analysis (Hayes and Cai, 2007). Additionally, a natural 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 Eq. (9). To apply PEMLA in practice to a particular segment of the road network, Eq. (9) would be used, along with the parameters in Table 4 and measured segment-specific values for the traffic variables (Traffic Average Speed, Traffic Average Delay Rate and Access Density Cubed) and the DVs (Road Type by Speed Limit and Time Period), from which PEMLA would predict an EF (gCO_2/VKM) for each vehicle category. The category-specific EFs can then be combined into a composite EF_T (gCO_2/VKM) for the traffic on the segment once the fraction of VKMs for vehicles in each PEMLA category is established (e.g. by assuming the segment-specific fleet-mix is in accordance with the NAEI national fleet model or by measuring the segment-specific fleet-mix using a local survey). Total emissions for the segment (gCO_2) would then be calculated by multiplying total segment-specific VKMs by EF_T. The results of the assessment of PEMLA are shown in Table 5, along with the results of the comparison of the predictive accuracy of PEMLA with that of TRL/NAEI EM.

$$\text{Predicted EF}\,(gCO_2/\mathrm{VKM}) = e^{f(\text{predictor variables})} \tag{9}$$

4. Discussion of results

Table 4 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 40 mph speed limit. In UK urban areas, 40 mph limits tend to apply to arterial roads, whereas 30 mph limits tend to apply to collector and local roads. Arterial roads usually have greater segregation from potential hazards, i.e. pedestrians, other road users, access to residential and retail premises, priority at intersections, and priority for green traffic signals. This segregation is designed to give smoother traffic flow, i.e.

it decreases stop-start events for vehicles and therefore decreases emissions. Hence, a negative Road Type DV coefficient was expected.

Some IV predictor variable coefficients in Table 4 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 (Ramos et al., 2011). 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 on EFs outweighed the effect of the traffic variables, and when in combination it was therefore vehicle category that dominated and determined the sign of the coefficient. In relation to the EF represented by the constant in PEMLA ($e^{5.9485}$ = 383 gCO_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 07–09) 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.

Table 4
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]	4×10^{-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[*]
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[*]

(continued on next page)

Table 4 (*continued*)

Predictor variable	Model coeff.	Std. error of model coeff.	Standardised model coeff. β[a]	t-Statistic
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. $R^2 = 0.93$, where Adjusted R^2 is an estimate of what R^2 would be if the model was based on analysis of the entire population rather than just a sample from the population.
For comparison, equivalent MLP neural network analysis resulted in $R^2 = 0.93$ (i.e. the same as the MLR analysis) indicating it is unlikely that there are relationships between predictor and outcome variables that are undetected by the (more constrained) MLR analysis (refer to Section 2.5).
na = not applicable.

* Indicates t-statistic is significant at 0.05 level.

[a] Standardised 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 01–19 are LDVs (for further category details, refer to Table 1).

[d] TraffAvSpd is traffic average speed (km/h).

[e] TraffAvDlyRt is traffic average delay rate (s/vehicle·km).

[f] AccDensCubd is access density cubed $(\text{intersections/km})^3$.

[g] Categories 20, 21 and 23 are HDVs except Buses (for further category details, refer to Table 1).

[h] Category 22 is Buses.

[i] Category 24 is Two-Wheel vehicles.

[j] DV is Dummy Variable.

Assessment by LOOCV (i.e. model comparison with AIRE) produced good agreement (MAF = 1.02 and MAPE = 16% in Table 5). For reference, in their meta-analysis of road traffic EM validation, Smit et al. (2010) found that mean prediction errors for CO_2 were generally within a factor of 1.3 of observed values. Model comparison with TRL/NAEI EM (using GPS vehicle average speeds as inputs) produced reasonable agreement (MAF = 1.21 and MAPE = 26% in Table 5). 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 (Smit et al., 2008b) (refer to Section 2.3), 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.

Table 5
Mean accuracy factors and mean absolute percentage errors from assessment and predictive accuracy comparison of PEMLA.

Process		n	MAF[a] (SD[b])	MAPE[c] (SD)
Assessment 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, computed as the arithmetic mean of the AFs calculated for all the trip segments.

[b] SD is standard deviation.

[c] MAPE is Mean Absolute Percentage Error, computed as the arithmetic mean of the APEs calculated for all the trip segments.

[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 = 4 km/h, whereas minimum speed for emission function = 6 km/h).

PEMLA performed poorly in partial validation with PEMS EFs (MAF = 2.21 and MAPE = 121% in Table 5). Three potential reasons for this are: (1) PEMLA Category 22 'Bus, All' 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 kg) and compliant with a modern Euro Standard (Euro V); (2) comparison of the EFs used as real-world proxies 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 sample size for PEMS validation is small (53 cases compared to 3205 cases for the model comparison methods), and drawn from only one vehicle category (Category 22).

In predictive accuracy comparison with the next-best alternative EM (TRL/NAEI EM), when using the same source for inputs (i.e. ILD data) PEMLA has a MAF that outperforms TRL/NAEI EM. MAF values in Table 5 suggest that on average (i.e. when applied to a whole network or substantially large parts of a network in accordance with PEMLA's design purpose) 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 5 suggest that on average PEMLA will be in error by 16% and TRL/NAEI EM by 22%. However, it is important to acknowledge that this predictive accuracy comparison is likely to be favourable to PEMLA because PEMLA was developed based on EFs from AIRE, to which the accuracies of PEMLA and TRL/NAEI EM were then compared (refer to Section 2.7). That said, the close correspondence of PEMLA with AIRE during the predictive accuracy comparison can be seen as a benefit for PEMLA because (by virtue of being an IEM) AIRE is likely to be a more accurate representation of the real-world than TRL/NAEI EM.

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 accurate emissions for the purposes of calibration, assessment (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 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 assessment 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 (Barlow and Boulter, 2009). Conversely, as stated in Section 2.6 the PEMS equipment was serviced prior to installation, calibrated both before and after each measurement period, and validated by comparison of fuel flow (g/s) outputs with those from the engine control unit. Therefore, there was 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.

Due to its Southampton-specific development, transferability of PEMLA requires assessment 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 categorisations and fleet compositions (Grote et al., 2016a). A further consideration is that ILDs may be superseded by other methods of traffic detection such as magnetometers, radar detectors, CCTV sensors, or vehicle telematics data available from ITS technologies (e.g. in-vehicle Bluetooth, GPS, mobile telephony or Wi-Fi devices (Grote et al., 2016a)). However, any detection system that can provide LGAs with data similar to those obtained from ILDs (i.e. traffic average speed and count of vehicles passing specified locations) would be likely to be able to provide the required data for application of PEMLA to estimation of network-scale CO_2 emissions. Additionally, PEMLA's applicability 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.

5. 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. PEMLA outperformed the next-best alternative (TRL/NAEI EM) in accuracy comparison and is better able to capture the influence of congestion on emissions. At the same time, PEMLA involves only a small increase in complexity compared to TRL/NAEI EM and therefore its implementation will remain practical within LGAs' limited resources. It was not possible within the resource constraints of the study to conduct a detailed analysis of the in-use resource requirements for the implementation of PEMLA in practice compared to those necessary for TRL/NAEI EM. However, the facts that PEMLA is essentially a set of emission functions that can be easily encoded into a spreadsheet model format similar to the TRL/NAEI EM average speed emission functions that have already been encoded into a spreadsheet model format by the DfT for use by LGAs (DfT, 2011a, 2011b), and that PEMLA inputs are based on ILD data (also collected in a spreadsheet format) to which LGAs already have easy and inexpensive access, indicate that PEMLA and TRL/NAEI EM would use similar resources to implement. PEMLA is assessed therefore as being closer to optimal complexity for LGAs than the well-established Average Speed EM alternative.

However, an important caveat is that the accuracy comparison process (refer to Section 2.7) was likely to favour PEMLA because PEMLA was developed based on AIRE, to which the accuracies of PEMLA and TRL/NAEI EM were then compared; although the close correspondence of PEMLA with AIRE was seen as a positive for PEMLA because (by virtue of being an IEM) AIRE is likely to be a more accurate representation of the real-world than TRL/NAEI EM. Additionally, PEMLA's outperformance of the next-best alternative is only in the context of the highly specific accuracy comparison performed during the research, and further work is required to establish if this outperformance can be generalised.

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 fuelled (e.g. electric, natural gas, hydrogen) still appears to be some years (decades?) away. In the meantime modelling emissions from conventionally fuelled vehicles remains a necessity, and PEMLA is a practical option to fulfil this requirement.

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