UNIVERSITY OF SOUTHAMPTON

FACULTY OF ENGINEERING AND PHYSICAL SCIENCES

Civil, Maritime and Environmental Engineering

Potential of Wireless Power Transfer for Dynamic Charging of Electric Vehicles

by

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ABSTRACT

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POTENTIAL OF WIRELESS POWER TRANSFER FOR DYNAMIC CHARGING OF ELECTRIC VEHICLES

Luke Hutchinson

Wireless Power Transfer (WPT) offers a viable means of charging Electric Vehicles (EV)'s whilst in a dynamic state, mitigating issues concerning vehicle range, the size of on-board energy storage and the network distribution of static based charging systems. Such charge while driving technology has the capability to accelerate EV market penetration through increasing user convenience, reducing EV costs and increasing driving range indefinitely, dependent upon sufficient charging infrastructure. While much work has taken place to assess the potential of WPT under both static and dynamic situations at technical levels, the real world aspects of such a scenario has received limited investigation. The current gap in knowledge was not technologically driven, instead, it was an implementation issue in understanding how systems would be deployed and utilised within the road network.

It became evident that a series of modelling tools were required in which studies could quantify the optimisation of deployment scenarios, environmental and user benefits, as well as the detailed interaction of users within the traffic network. A series of traffic and energy models are produced that have demonstrated for the first time how the specific WPT road layout will affect driver journey times, as well as the detailed vehicle interactions with one another and the charging system. This has shown realistic values for both EV energy consumption as well as energy that can be transferred to the vehicle from dynamic WPT charging systems. A series of mathematical models are presented that can be used to determine likely vehicle speeds, energy consumption, energy transfer and emission values given a users specific WPT charging configuration; importantly, without the need for further detailed microscopic simulation work. Finally, the tools developed in this thesis were applied to a macroscopic study to begin to understand the level of WPT route equipment that may be required at the Strategic Route Network (SRN) level to provide a feasible charging system.

A greater understanding has been gained to the current potential of WPT systems, and whilst WPT technology has been shown to be technically possible for the dynamic charging of EVs, it cannot be assumed. Such scenarios require extensive analysis before physical deployment of infrastructure, the issues explored within this thesis and the tools developed as a result of such can be used to undertake this analysis and optimisation.

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Academic Thesis: Declaration Of Authorship

I, Luke Hutchinson, 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.

Potential of Wireless Power Transfer for Dynamic Charging of Electric Vehicles

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;
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Definitions and Abbreviations

AADF	Annual Average Daily Flows
AAPI	Aimsun Application Programming Interface
AC	Alternating Current
AFV	Alternative Fuel Vehicle
AIMSUN	Advanced Interactive Microscopic Simulation for Urban and Non-urban networks
ANOVA	Analysis of Variance
ANPR	Automatic Number Plate Recognition
API	Application Programming Interface
BEV	Battery Electric Vehicle
BSI	British Standards Institution
CBA	Cost Benefit Analysis
CNG	Compressed Natural Gas
CD	Car Diesel
CE	Car Electric
CP	Car Petrol
CO_2	Carbon Dioxide
CO_2e	Carbon Dioxide equivalent
CSV	Comma Separated Values
DC	Direct Current
DD	Double D
DDQ	Double D Quadrature
DEFRA	Department for Environment, Food and Rural Affairs
DfT	Department for Transport
DNO	Distribution Network Operator
DSRC	Dedicated Short Range Communication
DWPT	Dynamic Wireless Power Transfer
EM	Electromagnetic
EU	European Union
EV	Electric Vehicle
EVSE	Electric Vehicle Supply Equipment
FCEV	Fuel Cell Electric Vehicle
FOD	Foreign Object Detection
G2V	Grid to Vehicle
GLM	General Linear Model

GUI	Graphical User Interface
HAD	Heavy Goods Vehicle Articulated Diesel
HAE	Heavy Goods Vehicle Articulated Electric
HGV	Heavy Goods Vehicle
HEV	Hybrid Electric Vehicle
HRD	Heavy Goods Vehicle Rigid Diesel
HRE	Heavy Goods Vehicle Rigid Electric
ICE	Internal Combustion Engine
ICEV	Internal Combustion Engine Vehicle
ICT	Information and Communications Technology
IEC	International Electrotechnical Commission
IET	Institution of Engineering and Technology
IPT	Inductive Power Transfer
ISO	International Organization for Standardization
ITS	Intelligent Transport Systems
KAIST	Korea Advanced Institute of Science and Technology
LFP	Lithium Iron Phosphate
LD	Light Goods Vehicle Diesel
LE	Light Goods Vehicle Electric
LGV	Light Goods Vehicle
Li-Ion	Lithium Ion
LOD	Live Object Detection
LPG	Liquid Petroleum Gas
MATSim	Multi Agent Transportation Simulation
MIDAS	Motorway Incident Detection and Automatic Signalling
MITSIM	MIcroscopic Traffic SIMulator
Ni-MH	Nickel-Metal-Hydride
NCA	Lithium Nickel Cobalt Aluminium Oxide
NCM	Lithium Nickel Manganese Cobalt Oxide
NO2	Nitrogen Dioxide
NO_x	Nitrogen Oxide
OBU	On Board Unit
OD	Origin-Destination
OECD	Organisation for Economic Co-operation and Development
OLEV	On-Line Electric Vehicle
OSM	Open Street Map

PARAMIC	PARAllel MICroscopic
PESTEL	Political Economic Social Technological Environmental Legal
PHEV	Plug-in Hybrid Electric Vehicle
PM	Particulate Matter
PTV	Planung Transport Verkehr
RCD	Residual Current Device
RIPT	Resonant Inductive Power Transfer
RMC	Resonant Magnetic Coupling
RWD	Real Wheel Drive
RSU	Road Side Unit
SAE	Society of Automotive Engineers
SOC	State of Charge
SRN	Strategic Road Network
SUMO	Simulation of Urban Mobility
TSS	Transport Simulation Systems
UBIS	User Battery Interface Style
VOC	Volatile Organic Compounds
V2G	Vehicle to Grid
V2I	Vehicle to Infrastructure
V2V	Vehicle to Vehicle
VECTO	Vehicle Energy Consumption calculation TOol
VISSIM	Traffic in cities (German translation) SIMulation model
WPT	Wireless Power Transfer

Chapter 1 Introduction

Wireless Power Transfer (WPT) is an emerging, and potentially enabling, charging technology that is capable of orchestrating a dramatic shift to the way in which we perceive Electric Vehicles (EV)s, as well as the way in which they are utilised. Whilst much is understood about WPT charging systems at the technological level. There is however a need for a traffic modelling framework capable of considering WPT charging systems; so as to help guide the development and deployment of such systems from a traffic perspective. This chapter presents the context of this research and its motivations, research aim, objectives, contributions and structure of the thesis.

1.1 Context

The growth in global population, energy consumption and the continuing depletion of natural resources has inevitably led to a number of social, economic and environmental issues (Tietenberg & Lewis, 2016). The transportation sector shares many of these current challenges; the growth in population, car ownership, parking requirements as well as continually high levels of personal mobility and transport emissions are all significant (Rodrigue, et al., 2017). The UK's transport sector is currently responsible for 27% of the country's total emission count, in recent years this sector has overtaken energy supply, 24% (Office for National Statistics, 2017); similar emission proportions are seen on a global scale across other Organisation for Economic Co-operation and Development (OECD) countries. The Royal College of Physicians (2016; 2018) estimate the health impacts of air pollutants are costing the UK economy some £22.6 billion a year. The Committee on the Medical Effects of Air Pollutants (2018) predict that the long-term exposure to man-made air pollution in the UK shortens lifespans equivalent of 28,000 to 36,000 lives annually. Recent European Union (EU) legislation aims to "Halve the use of 'conventionally-fuelled' cars in urban transport by 2030; phase them out in cities by 2050; achieve essentially Carbon Dioxide (CO_2) free city logistics in major urban centres by 2030" (European Commission, 2016).

The increasing awareness of energy conservation and environmental protection has seen policymakers and car manufacturers generate a shift towards Intelligent Transport Systems (ITS) and Alternative Fuel Vehicles (AFVs); such vehicles are a necessary solution to meet the required low-carbon future (Carrington, 2016). An AFV utilises an alternative fuel source or is not solely reliant on a petroleum product, examples include; Battery Electric Vehicles (BEV), Plug-in Hybrid Vehicles (PHEV), Hybrid Electric Vehicles (HEV), Fuel Cell Electric Vehicles (FCEV) as well as vehicles using Liquid Petroleum Gas (LPG), Compressed Natural Gas (CNG) and biofuels. There has been mixed success amongst AFVs (The Society of Motor Manufacturers and Traders, 2019), some fuels are not viable due to economic or availability factors, some require further technological development and others are not capable of meeting the continually reducing emission targets. The electrification of road transport provides a viable means of reducing fossil fuel consumption and environmental pollution, hence the recent advancements in EV design and performance (U.S. Department of Energy, 2019). Alongside technology development, governmental policy reform, vehicle subsidisation and eased taxation policies have accelerated the market uptake and penetration of EV's (Business, Energy and Industrial Strategy Committee, 2018). This is evident in many OECD countries, Norway currently has the largest EV market share at 31.2% (Norwegian Road Federation, 2019) and intends to ban fossil fuelled vehicles within the next decade (Staufenberg, 2016). It is evident that EVs have the ability to significantly reduce the transport industry's reliance on fossil fuels, lower transport related CO_2 emissions and improve air quality within cities; helping to address the prior social, economic and environmental issues. Yet, three key barriers hamper the mass adoption of EVs; price, range and ease of charging (Lee & Clark, 2018).

To meet global emission standards, a 100% year on year growth of EVs is required; something which is not attainable at current adoption rates (International Energy Agency, 2019). Whilst EVs have zero carbon emissions at point of use, there are numerous negatives. Energy storage capacity is a growing concern as the modern world continues to distance itself from fossil fuel derived energy sources (Covert, et al., 2016), advancements in energy storage is also necessary to resolve many of the supply reliability issues of renewable technologies (U.S. Department of Energy, 2019). The on-board battery storage of EV's also follows this trend, the lack of battery capacity and energy density advancements poses to hamper the continued development and market take-up of EV's. The battery is the most expensive component of an EV (Bullard, 2019), without major breakthroughs in energy storage capacity, it is unlikely that EV range will significantly increase or that vehicle costs will decrease. The high costs and poor specific energy densities of batteries compared to fossil fuels results in a less than ideal scenario. EV's require frequent charging to maintain a sufficient range and with long charge times or potential material breakdown that occurs during fast charging, battery charging technology has restricted EV development. With no significant advancements in battery technology forecasted within the foreseeable future (Bullis, 2015) (Temple, 2019) this has resulted in substantial research into alternative charging methods as well as the reinforcement of the current charging network with the installation of charging points at residential properties, workplaces, service stations, city centres and many other points of interest (Transport & Environment, 2018). Whilst these charging points are made up of both standard and fast charging technologies, the requirement for the vehicle to be stationary for the given charging time is still an issue. The refuelling time of a typical Internal Combustion Engine (ICE) vehicle (ICEV) is just a few minutes, whilst BEVs require recharging times of several hours or between 20-40 minutes on a fast charging station to reach an 80% charge (Zap Map, 2020). The limited range capabilities of EVs results in greater recharging frequencies, hence reducing such vehicles general usability and convenience, and ultimately market take-up. In addition, there are still conductive energy losses within the plug-in charging system resulting in an overall efficiency of 86% (Forward, et al., 2013). Further, the high-power transfer, human handling and the ability for the user to forget to plug in/out are not ideal factors.

An alternative solution is to utilise inductive charging technology. Wireless Power Transfer technology, a form of inductive charging, is capable of mitigating the issues of plug in charging. The EV is parked over a coil that inductively transfers electrical energy to a receiver coil positioned on the vehicle. Yet, this static process does little to mitigate the issues concerning frequent EV charging and the requirement of a large battery capacity on the vehicle.

The ability to use WPT in a dynamic state, whilst the vehicle is driven, has the possibility to increase driving range indefinitely; dependent upon sufficient charging infrastructure. When compared to other conductive based dynamic charging systems, such as overhead gantries or track based systems, WPT negates the need for intrusive gantry infrastructure and vehicle pantographs, and generally offers the greatest flexibility between vehicle classifications. WPT studies have shown that battery capacities can be reduced to just 20% (Musavi & Eberle, 2014) when optimising both vehicle and WPT infrastructure design in parallel; thus eliminating issues concerning both heavy and expensive battery packs. This reduction in on-board battery storage will consequently reduce EV costs whilst increasing energy efficiency through lightweighting (Heuss, et al., 2012) (Berylls Strategy Advisors, 2016). Inevitably, energy losses result in a reduction of system efficiency over that of conductive systems; however, research has shown that WPT systems can achieve efficiencies greater than 90% through directing power to the electric motor rather than the battery (Qualcomm, 2019). Yet, such technology still remains in its infancy; both static and dynamic forms of WPT are susceptible to introduced errors such as coil misalignment and current transformation.

There are a number of organisations developing both static and dynamic WPT solutions, some of which are market ready and many more still under laboratory development. The most notable work concerning WPT includes systems developed by Korea Advanced Institute of Science and Technology (KAIST), Bombardier and Qualcomm. Through continual development KAIST have deployed a 100 kW WPT system with a transfer efficiency off 85% over a 20cm air gap with misalignment tolerances of up to 20cm (Suh & Cho, 2017); reducing the air gap sees transfer efficiencies greater than 90% but regulations mandate a minimum vehicle ground clearance in many cases. Such systems have shown the competency of the technology but widespread deployment has not yet come to fruition; deployment scenarios, application areas, traffic dynamics and standardisation issues have hampered this (Hutchinson, et al., 2019).

1.2 Motivation of Study

Dynamic charging of an EV, be it through inductive or conductive means, is a new and potentially trend shifting concept. The way in which people perceive EVs, their associated range anxiety, their existing charging behaviour, as well as their driving behaviour will all shift given such dynamic charging systems. Not least there will be a dramatic change to the way in which energy is transferred throughout the transport system. WPT is one of numerous emerging, and potentially enabling technologies that can facilitate dynamic charging.

Whilst much is understood at the technological and laboratory levels, current research is lacking in the analysis of the traffic element. Research gaps exist in the way in which systems should be deployed, how they may be utilised by drivers, the likely implications of such systems to other road users as well as unknowns around the potential power needs and environmental benefits of such systems.

Thus, there is a significant need to investigate WPT systems at the traffic level; capturing both detailed vehicle interaction, as well as higher level analysis of the Strategic Route Network (SRN).

1.3 Research Aim and Objectives

The current state of WPT technology development is heavily focused on technological advancement, focussing on technical demonstrators and quantifying precise power transfer potentials. It is clear however that little analysis has been carried out relating to the consequences of moving from test-bed to real life situations.

The following research questions are explored within this thesis:

- What are the main barriers to integrating WPT systems into the road network?
- What are the detailed energy implications of a dynamic WPT charging system?
- What are the implications for policy makers going forward?

1.3.1 Research Aim

The aim of this thesis therefore is to investigate the issues related with transitioning Dynamic Wireless Power Transfer systems for Electric Vehicles from technical demonstrators to full scale deployments.

1.3.2 Research Objectives

To address this aim, it is anticipated that contributions to knowledge will need to be made in four core areas of research:

- To understand and quantify the current technical potential of WPT systems
- To develop a series of modelling tools that assess the detailed traffic and energy aspects of WPT charging systems
- To quantify the energy transfer potential of WPT in real-life situations
- To understand the level of WPT infrastructure required to provide a feasible system

1.4 Thesis Outline

The thesis is organised into nine chapters; following the introduction, the remaining chapters are introduced below.

Chapter 2: Wireless Power Transfer Review

A technological review that assesses EV fundamentals, conductive and inductive charging processes, WPT infrastructure requirements, state-of-the-art WPT systems, influential parameters, and international standards.

Chapter 3: Traffic Modelling Review

A modelling review that first identifies the model requirements specification, before assessing various traffic simulation packages, driving and charging behaviour, as well as analysing various traffic and energy modelling techniques from literature.

Chapter 4: Research Methodology

Outlines and justifies the methods that were applied to the research.

Chapter 5: Traffic Modelling

Details the development of a realistic microscopic modelling environment in which a variety of scenarios and WPT influential factors can be simulated.

Chapter 6: Energy Modelling

Assesses the energy component of the WPT situation, considers and develops significant models for estimating energy consumption, energy transfer and emission production.

Chapter 7: Microscopic Simulation

Documents the calibration and validation of both traffic and energy models, undertakes exploratory data analysis, and concludes with formulating a series of mathematical equations based upon the microscopic simulation work.

Chapter 8: Macroscopic Model

Scales the prior microscopic work to a macroscopic case study, assessing both the traffic and energy impact of the WPT situation at the SRN level. Documents the results obtained from macroscopic simulation work; in terms of the amount of WPT infrastructure required for varying scenarios.

Chapter 9: Conclusions

Final conclusions are drawn against the initial aim and objectives, including the direction of future work, associated limitations, policy implications, and highlighting the contributions of this research.

Chapter 2 Wireless Power Transfer Review

2.1 Introduction

As introduced in the prior chapter, WPT offers the ability to charge EVs dynamically, thus reducing their reliance upon existing static based charging systems and generally increasing user convenience and EV range. Yet, questions exist as to how WPT systems can be transitioned from technical demonstrators to full scale deployment. Given such a research aim, it is first important to understand the current capabilities and future potential of such technology.

This review first presents the fundamentals of current EV battery technology, both conductive and inductive charging techniques, as well as the magnetic coupling theory of the WPT situation. Before which, dynamic WPT is assessed in terms of infrastructure requirements, state of the art, maturity of the technology, relevant international standards, as well as current barriers in deployment. Through such analysis a wider situation awareness will be facilitated and an understanding gained if issues are technological driven or otherwise based.

2.2 Electric Vehicle Fundamentals

An EV consists of three major power sub-systems; an electric battery, an electric motor and a controller that controls the motor power supply and ultimately vehicle speed and direction. Until 2010, the lack of EV technology capability has resulted in the market domination of ICE vehicles. However, recent advancements in EV technology, notably motor design and Lithium Ion (Li-Ion) batteries, have seen market penetration and take-up of numerous EV's. The increasing awareness of energy conservation and environmental protection has seen policymakers generate a shift towards low carbon vehicles, further accelerating the market penetration of EV's (Business, Energy and Industrial Strategy Committee, 2018). Norway has been able to accelerate their take up of EV's, substantial subsidy and taxation policies have resulted in a 29% EV market share (International Energy Agency, 2019) and the plan to ban fossil fuelled vehicles within the next decade (Staufenberg, 2016).

The recent rise in EV ownership and the increasing travel distance of commuters (Office for National Statistics, 2014) has led to further demand being placed upon battery storage technology and the charging network to support EV's. The battery is one of the most expensive components of an EV; without major breakthroughs in energy storage capacity, it is unlikely that EV range will significantly increase. Therefore, to compensate for the lack of EV range, the charging network has been the subject of much investment with the installation of charging points at residential properties, workplaces, service stations, city centres and many other points of interest. Whilst these charging points are made up of both standard and rapid charging technologies, the requirement for the vehicle to be stationary for the given charging time is still an issue. Dynamic WPT provides a viable means to utilise EV in-motion charging and infinitely increasing EV range.

2.2.1 Current Electric Vehicle Batteries

Energy storage capacity is a growing concern as the modern world continues to distance itself from fossil fuel derived energy sources (Covert, et al., 2016), advancements in energy storage are necessary to resolve many of the supply reliability issues of renewable technologies (U.S. Department of Energy, 2019). The on-board battery storage of EV's also follows this trend, therefore the lack of battery capacity and energy density advancements has the potential to restrict the continued development and market take-up of EV's. Energy storage breakthroughs are also an essential component for the development cycle of low carbon technologies and the continual progression to lower carbon vehicles (Automotive Councils UK, 2017).

Table 1 - Properties of EV and PHEV Batteries (Husain, 2011)

Battery Type	Specific Energy (Wh/kg)	Specific Power (W/kg)	Energy Efficiency (%)	Cycle Life
Lead-Acid	35-50	150-400	80	500-1000
Nickel-Cadmium	30-50	100-150	75	1000-2000
Nickel-Metal-Hydride	60-80	200-400	70	1000
Aluminium-Air	200-300	100	<50	N/A
Zinc-Air	100-220	30-80	60	500
Sodium-Sulphur	150-240	230	85	1000
Sodium-Nickel-Chloride	90-120	130-160	80	1000
Li-Polymer	150-200	350	N/A	1000
Li-Ion	90-160	200-350	>90	>1000

Properties of EVs and PHEVs are summarised in Table 1. Li-Ion traction batteries are now commonplace in most EV's (Lu, et al., 2013) (Hannan, et al., 2017), due to their high energy density to volume (Wh/l) and mass ratios (Wh/kg), such batteries also have good power densities, very little or no memory effect, long lifespan, low self-discharge and fast charge times when compared to other battery types, notably Lead Acid and Nickel-Metal-Hydride (Ni-MH) (Wakihara, 2001). However, Li-ion batteries are sensitive to high temperatures that reduce battery performance and risk cell ignition; they are also expensive to manufacture (Scrosati & Garche, 2010) (Bloomberg NEF, 2019). In order to maximise battery life, Li-Ion traction batteries should not be fully depleted or subjected to deep discharge cycles (Husain, 2011) therefore the State of Charge (SOC) of the battery must be constantly monitored and managed appropriately.

There are a number of EV battery technologies under development (see Table 1) but whilst Li-Ion batteries have a lower specific energy, their high specific power, energy efficiency and cycle life mean that they are the most suitable technology for traction batteries (Husain, 2011) (Hannan, et al., 2017). Costs of EV batteries are within the region of $156 per kWh (BloombergNEF, 2019) but continue to decrease as technology and economies of scale develop, this represents an 87% fall compared to $1100 per kWh in 2010. In addition, the power to mass ratio of traction batteries, typically 60-96 Wh/kg (Burke, 2007), is poor when compared to other fossil fuel sources. Much research has been undertaken to develop solid-state battery technology (Luntz, et al., 2015), which has the potential to significantly increase storage capacity whilst reducing costs. Yet, such technology appears to be at least five years away from mass production (Visnic, 2019). Yet, the average EV range is ~100 miles, doubling this distance still leaves a considerable gap between the ranges of ICE vehicles achieving in excess of 600 miles per tank. For freight vehicle applications, this is not an option due to the great volume and mass requirements for traction batteries to achieve even a reasonable range.

Unlike ICE vehicles, EV's are much more flexible in terms of their mechanical configuration (Chan, 2002). Whilst they follow the typical aesthetical form of modern vehicles, due to the lack of mechanical drive components, EV's use wheel driven electric motors and specifically shaped battery packs for optimum vehicle packaging. The majority of battery packs are located on the floor pan of the vehicle to optimise weight distribution, lower the vehicles centre of gravity as well as for mechanical design and safety (Arona, et al., 2016).

2.2.2 Charging Methods for Electric Vehicles

The need for EV charging is fundamental, electrical energy is not generated on-board the vehicle, instead it is generated externally and transferred to the traction batteries during the charging process. There are a number of different forms of EV charging, ultimately the present and future optimised charging network will feature an array of these different chargers that best suit location, charging demand, charging time, electricity supply and cost considerations. It is vital not to underestimate the importance of home charging; the ability to slowly charge the vehicle overnight at the EV owner's residence is both convenient and a cost effective means to refuel the vehicle. Scaling the current levels of home charging to a scenario with the high penetration of EVs may change the feasibility of home charging (Clement-Nyns & Haesen, 2010); population growth, technology capabilities, energy and power availability, attitudes to energy consumption, market structures as well as potential changes in mobility are all factors that could influence charging behaviour.

Charging technologies can be divided into two main groups, conductive and inductive. The former consists of fixed-point plug-in chargers that provide a conductive connection between the vehicle and electricity grid, meanwhile inductive chargers are those that transmit electrical energy wirelessly using an electromagnetic coupling.

2.2.2.1 Conductive Charging

Whilst there are a number of EV charging international standards, EV owners are still overwhelmed by a large array of charging cables, plugs and types of chargers (BEAMA, 2015) (Zap Map, 2019). There are also several classifications of EV charging modes (Falvo, et al., 2014), all of which follow a similar premise. The subsequent outline follows the 'Electric vehicle conductive charging system: General requirements' BS EN 61851-1 standard (British Standards Institution, 2017). Conductive systems can be categorised into Alternating Current (AC) and Direct Current (DC) chargers. AC systems utilise an on-board vehicle charger to rectify the AC to DC for battery charging, while DC chargers rectify the AC power supply to DC within the Electric Vehicle Supply Equipment (EVSE) before supplying it to the vehicle. The BS EN 61851-1 standard specifies four types of EV charging mode:

Mode 1 (AC) - Non-dedicated circuit and socket outlet:

The most basic form of vehicle charging; a charging cable connects the vehicle to standard household electrical sockets. Maximum current and power transfer is 13A and 3 kW respectively for UK domestic 230V 3-pin plug applications (Zap Map, 2020). This charging mode is not recommended for use due to the lack of control equipment; whilst 3-pin plugs are fused, there is no in-line Residual Current Device (RCD) to provide protection. Hence, within the UK, home chargers are now restricted to at least Mode 2 due to safety concerns (BEAMA, 2015).

Mode 2 (AC) - Non-dedicated circuit and socket outlet, cable incorporated RCD:

A Mode 2 charger features an in cable control box and a RCD to protect the system and user. The control box ensures a protective earth conductive connection before the charging is commenced; it also monitors the battery and charging process. For domestic applications, a UK 3-pin plug is utilised and maximum current and power transfer is still limited to 13A and 3 kW respectively. Many EV manufacturers limit residential Mode 2 charging power at 1.4 kW to 2.3 kW (6A to 10A) for safety reasons. Maximum current and power can be increased to 32A and 7.4 kW for industrial applications when utilising industrial connectors (Bicheno, 2011). Whilst this charging mode features control equipment and RCD protection, it is only recommended for occasional use, as a back-up charging method when no dedicated charger is available, or for vehicles with limited charging requirements, such a PHEVs (BEAMA, 2015).

Mode 3 (AC) - Dedicated EV charging system, dedicated outlet:

Whilst Mode 1 and Mode 2 utilise existing domestic, and industrial connectors, Mode 3 features dedicated EVSE. Tethered cables are typically used, especially for domestic use, with specific EV connectors or for non-tethered applications dedicated EV sockets are provided (Zap Map, 2020). Domestic applications (single phase) are typically 3.7 kW (16A) or 7.4 kW (32A). Commercial and public EVSE (three phase) are often capable of supplying higher power transfer limits to reduce charge time (Bicheno, 2011). Modes 1-3 all supply AC to the vehicles on-board charger to convert to DC for battery charging, hence charge time remains limited by the capabilities of the on-board charger, regardless of AC power supply limits. Due to additional communication lines between the vehicle and EVSE, Mode 3 has potential for smart charging capabilities in the future.

Mode 4 (DC) - Dedicated EV charging system, dedicated outlet:

On-board vehicle chargers are constrained by volume, mass and cost; Mode 4 systems use a larger external charger that rectifies the AC power supply to DC before supplying it to the vehicle. Such rapid chargers bypass the on-board charger and are capable of power transfers in excess of 100kW, greatly reducing charge times. Such chargers are constrained to commercial depots and public locations because of power supply requirements and high capital costs (BEAMA, 2015). Due to the high power transfer, tethered cables are used and similar control, protection and communication measures found in Mode 3 EVSE are again present. Typically, Mode 4 chargers are used to provide rapid on-route top-up charging. Tesla Motors use a 120 kW DC charging system within their Supercharger (rapid charging) network, built exclusively for Tesla owners; however, this has led to a parallel charging infrastructure being built which is not an ideal scenario (Rajagopalan, et al., 2013).

The time it takes to charge an EV battery is dependent upon a number of factors; EVSE, charging mode (on-board or external charger), efficiency of charging equipment, battery size, battery temperature, as well as the battery level before charging commences. Table 2 provides typical charge times of a 24 kWh battery being charged to 80%.

Whilst there are a number of different charging modes, there are also numerous EV connectors both standardised and manufacturer proprietary versions, such as Tesla’s version (Rajagopalan, et al., 2013). The most common versions are Type 1 and Type 2 connectors standardised under International Electrotechnical Commission (IEC) 62196; Type 1 is more popular in United States of America, while European countries mostly use Type 2 connectors. Apart from the standard electrical plugs, 3-pin and commando, all other types utilise signal lines for communication between the vehicle and power supply for safety.

Table 2 - Charge Time of a 24 kWh Battery to 80% Capacity (BEAMA, 2015)

Current	Maximum Power Output	Charge Time	Input Voltage	Maximum Current	Charging Mode
AC	2.3 kW	8hrs 20mins	230 1-phase AC	10	2 / 3
	3 kW	6hrs 30mins	230 1-phase AC	13	2 / 3
	3.7 kW	5hrs 15mins	230 1-phase AC	16	2 / 3
	7.4 kW	2hrs 35mins	230 1-phase AC	32	2 / 3
	14.5 kW	1hr 20mins	400 3-phase AC	21	3
	22 kW	55mins	400 3-phase AC	32	3
	43 kW	30mins	400 3-phase AC	63	3
DC	20 kW	1hr	400 3-phase AC	40	4
	50 kW	25mins	400 3-phase AC	100	4
	100 kW	15mins	400 3-phase AC	200	4

It is important to note that these conductive charging systems do have associated energy losses, Sears, Roberts and Glitman (2014) identified that average charge efficiency was 85.7% when considering off peak, smart charging and different forms of charging equipment and modes. This is further reinforced by work undertaken by Forward, Glitman and Roberts (2013), who found an average efficiency of 86.4%, and Valøen and Shoesmith (2007) who identified that between 10-20% of energy is lost in charging and discharging an EV traction battery.

With respect to dynamic conductive charging systems, Siemens and Scania have trialled catenary overhead power systems, electrical power is transferred through pantographs fitted to trucks (Scania Group, 2014; 2020). Although a conductive charging system, it is a potential solution for the high-power transfer needed for long-distance freight. Yet, requires intrusive charging infrastructure such as gantries, and raises safety issues over high voltage lines above incompletely segregated carriageway. Further, a pantograph designed for Heavy Goods Vehicle (HGV) applications would not be suitable for cars to use because of the height of the system. Alternatively, a segmented conductive strip placed within the road and respective inverted pantograph from the vehicle could be used. Alstom in partnership with Volvo are adapting their tram and rail based systems to develop an Aesthetic Power Supply system that can be fitted to the road (Alstom, 2020; Volvo, 2018). Such a road system would be less intrusive to retrofit, and would not require large overhead gantries as seen with the Siemens and Scania systems.

2.2.2.2 Inductive Charging

There are two main forms of WPT, near field and far field. The latter is commonly used in signal broadcasting as power levels are very low but energy transfer distances are very far. Near field is capable of higher power levels, but is limited to transferring energy to just a single wavelength from the transmitter; power rapidly decays proportionally to transfer distance (Qiu, et al., 2013). Inductive Power Transfer (IPT), a form of near field WPT, utilises an inductive coupling between two magnetic fields generated by wound coils. Unlike far field, near field power transfer is non-radiative so the transferred energy remains within close proximity to the transmitter reducing issues concerning human exposure to the energy and magnetic fields (International Commission on Non-Ionizing Radiation Protection, 2010). In order to increase the power transfer, efficiency and range, coupled magnetic resonance is utilised in EV applications (Sabki & Tan, 2014). Such WPT charging technology use two resonant circuits that resonate the coils at the same frequency in order to maximise energy transfer through a Resonant Magnetic Coupling (RMC) (Gil & Taiber, 2013). Resonant coupling was initially pioneered by Nikola Tesla but his early experiments were only successful for very low power signal applications (Wheeler, 1943). Advancements in electronic components has enabled further development of Resonant Inductive Power Transfer (RIPT) technology.

A further inductive charging method is the On-Line Electric Vehicle (OLEV) system, generally a similar process to RIPT but has greater potential for higher power transfer whilst using a lower resonant frequency (Musavi & Eberle, 2014). Rather than a single transmitter pad, the coil is spread out longitudinally over the roadway enabling power transfer to occur at multiple locations along the extended coil track. Of all the WPT technologies available, RIPT (most often referred to as WPT in literature) and OLEV appear the most promising for EV applications (Musavi & Eberle, 2014). Whilst they are separate entities, the same basic inductive principles apply, with the key difference being the sizing configuration of the coils, see Figure 1.

A static system will see the driver park their vehicle over a ground based charging pad to receive a wireless charge to their EV. This sealed system has greater safety benefits over conductive type chargers and removes much of the inconvenience associated with continually plugging and unplugging an EV. Technically, the system rectifies the grid AC supply to DC before converting the DC power to a high frequency AC. The high frequency AC is required to power the transmitter coil located underneath the vehicle, this generates an alternating magnetic field that induces a corresponding AC voltage within the receiving coil located on the vehicle (Li & Mi, 2015). A further AC to DC rectification process is undertaken and the DC power is used to charge the traction battery or transferred directly to the power train in dynamic WPT applications. The shape and design of the two magnetic couplers, the transmitter and receiver coils, have a great influence on transfer efficiency.

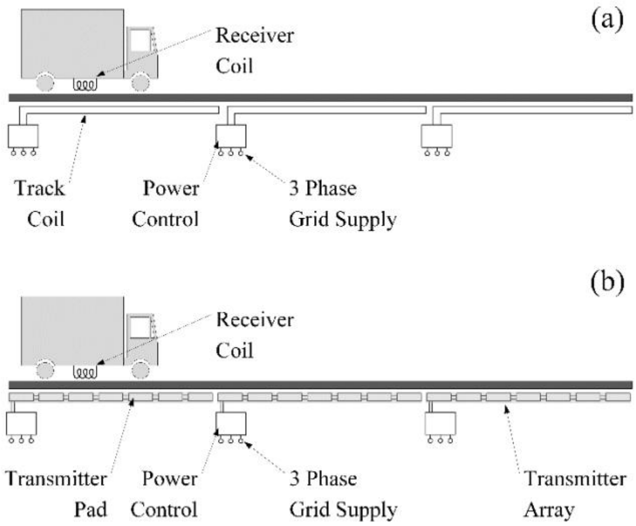


Figure 1 – Two Forms of Wireless Power Transfer
(a) On-Line Electric Vehicle (OLEV), (b) Resonant Inductive Power Transfer (RIPT)

Whilst forms of WPT substantially reduce electrical safety concerns and simplify the charging process, when compared to plug in conductive systems, interoperability is still an issue. Transmitter and receiver pads must be coupled to maximise efficiency, therefore a specific operating frequency must be standardised in addition to pad design and size. Further, WPT systems are vulnerable to operational errors that will significantly decrease energy transfer efficiency, most notable lateral or longitudinal misalignment (Qualcomm, 2019). Due to the lack of cables, data communication between the vehicle and charger must now also be wireless using Dedicated Short Range Communication (DSRC) or other wireless network protocols such as Bluetooth or Wi-Fi. The subsequent sections outline the magnetic coupling design as well as the dynamic WPT process.

2.2.3 Magnetic Coupling

The pad design is the most important factor in ensuring a high efficiency magnetic coupling between the transmitter and receiver coils. The coil design will dictate the shape of the magnetic field, thus the misalignment tolerance, leakage flux and magnetic radiation are all parameters affected by coil design (Choi, et al., 2015). For static WPT the magnetic structure follows the form of a lumped pad whilst dynamic WPT often use an OLEV track (looped coil) type system for economic reasons. A further refinement to the track based system is to segregate the tracks into smaller loops, which in effect become a series of pads that are controlled separately. The issue with large tracks is that the receiver coil will only cover a specific region of the track that reduces the coupling efficiency and the track will emit an exposed Electromagnetic (EM) field across its energised length (Covic & Boys, 2013).

The structure of a magnetic pad is the culmination of a coil, ferromagnetic material and a shielding layer. Due to the high frequencies involved in WPT systems, Litz wire is typically used for the coil to compensate for high AC resistance caused by the skin effect (Miller, et al., 2012). The ferrite material is used to strengthen, guide and shape the magnetic flux. Pad magnetic structures can either be single-sided or double-sided; flux is present on both sides of double-sided pads, while only one side on single-sided pads, see Figure 2. Li and Mi (2015) note that double-sided pads have high shielding losses due to the requirement of shielding the EV chassis from the EM field. Therefore, single-sided pads require much less shielding due to the majority of the flux is positioned on a single-side and only minor shielding of leakage flux is necessary.

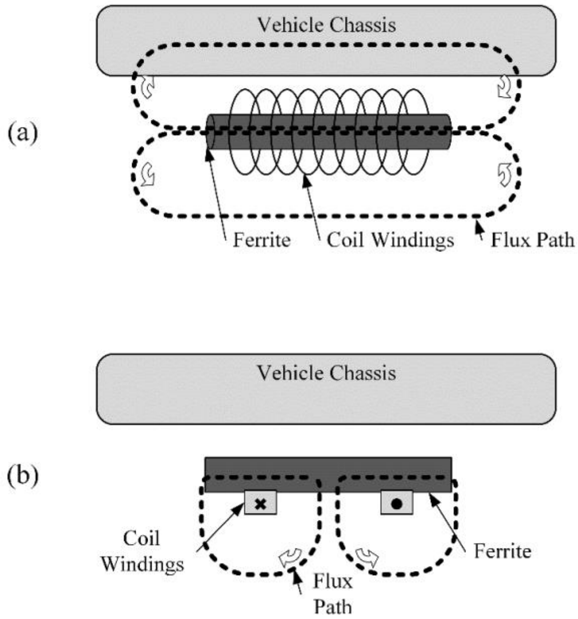


Figure 2 – Main Flux Path of Double-Sided and Single-Sided Pads *(Li & Mi, 2015)*
(a) Double-Sided Pad, (b) Single-Sided Pad

There are a number of different single-sided pad designs, both circular and rectangular, that are designed to enhance, often exclusively, energy transfer, misalignment tolerance and air gap transfer distance. Much work concerning the development of circular pad design and optimising ferrite layout has been undertaken by Budhia, Covic and Boys (2011). However, a rectangular pad developed by the University of Auckland (Boys & Covic, 2012) has been found to significantly improve the magnetic coupling and misalignment tolerance when compared to a circular design of equal material cost. Whilst this rectangular Double D (DD) type coil has a good misalignment tolerance in the y direction (longitudinal) the addition of independent quadrature coil significantly increases misalignment in the x direction (lateral) (Boys & Covic, 2012). The resultant Double D Quadrature (DDQ) pad is capable of air gaps in excess of 30cm and when receiving energy from a DD transmitter pad the effective charge zone is five times larger than a circular type pad (Li & Mi, 2015), yet is more complex and expensive than other pad designs. A high coupling efficiency and quality factor enable high transfer efficiencies; in order to increase the quality factor, a high frequency is typically used, as opposed to increasing the coil structure (Li & Mi, 2015).

2.3 Dynamic Wireless Power Transfer

Whilst the static WPT technology discussed previously offers a wireless form of EV charging, it does little to rectify the problems associated with the vehicle remaining stationary for the duration of the charging process. Therefore, dynamic WPT is an ideal solution to this and provides a theoretically infinite EV range, dependent upon the supporting charging infrastructure (Maglaras, et al., 2015). The dynamic energy transfer process is similar to a static system but a number of changes are required to both the vehicle and infrastructure to support this.

As the vehicle approaches the embedded road coils it will initiate communication between itself and the roadside signal transmitter to initiate an electronic handshake. A Road Side Unit (RSU) controls a series of charging zones, each consisting of an array of charging coils. An equipped vehicle, fitted with a receiver coil and On Board Unit (OBU), will initiate a wireless communication between its OBU and the RSU to regulate power transfer. The purpose of this control communication is to optimise the transfer process, maintaining a high efficiency, and to ensure that coils are energised and de-energised when appropriate. Gil, Sauras-Perez and Taiber (2014) evaluate both communication requirements, and the various communication technologies available.

In a dynamic WPT process, rather than a single transmitter coil, the magnetic field is generated over a number of consecutive coils that power up as the vehicle passes over them. The length and frequency of these coils vary dependent upon the application, example systems are discussed within Section 2.3.2. Dependent upon vehicle speed this inevitably results in very short periods of time that the coils will be interacting, hence technology with a high power transfer must be used (Gil & Taiber, 2013). The possibility, as well as the impact, of coil misalignment is also greatened in a dynamic state. Dynamic WPT systems should be designed to cope with misalignment, this can be achieved through vehicle automated alignment, driver training, driver aides, road markings, coil size or coil magnetic design; various measures can be taken dependent upon cost efficiency and application scenario.

Further considerations include the magnetic field exposure to humans and the damaging affects this exposure could have public health. There is little evidence to support the impact of EM fields upon human health, International Commission on Non-Ionizing Radiation Protection (2010) state that exposure to EM field has the potential to induce current and energy absorption in human tissue. They specify the maximum exposure limits as 200mA/m2 at 100kHz and a magnetic flux density of 27μT which appears to be conservative compared to the Institute of Electrical and Electronic Engineers (2019) guidelines that specify a flux density of 205μT. Whilst the EV can incorporate active (electrical) and passive (material) shielding to reduce vehicle occupant radiation exposure, the magnetic field could pose a risk to other nearby motorists and pedestrians using the roadway if radiation exceeds stated limits. The deployment of such technology into pedestrian free areas such as motorways will negate this risk and active monitoring systems that detect and terminate the charging process when other vehicles are too close is one solution for unshielded vehicles (Scania Group, 2014). Hui, Zhong, and Lee (2014) suggest that human exposure limits will be the limiting factor when considering the maximum power transfer capabilities of WPT systems, yet exposure limits impose limiting factors on coils and system design not necessarily power levels. With appropriate design and compensation for shielding, a system can be designed to transfer hundreds of kW's safely.

To increase dynamic WPT efficiency, possibly to the same levels as static systems, rather than using the electrical energy to charge the battery, the energy should be transferred directly to the powertrain via an ultra or supercapacitor (Covic & Boys, 2013), negating any charging and discharging losses of the EV battery. As long as power transfer is sufficient, the vehicle will enter and leave the charging zone with the same SOC; however, its range has effectively been extended as no energy from the traction battery has been used to propel the vehicle over the duration of the WPT system. Thus, dynamic WPT avoids such battery losses resulting in a system that is more efficient than static charging methods.

It is evident that the EV charging method has an impact on EV design, on-board energy storage, vehicle mass, travel range and recharging dwell time, dynamic WPT offers the opportunity to reduce traction battery size whilst increasing range and removing the reliance on static based charging systems. However, numerous technical aspects must be overcome to validate dynamic WPT technology and to ensure its deployment into the road network.

2.3.1 Dynamic Charging Infrastructure

A number of vehicle and infrastructure based challenges must be overcome for the integration of WPT charging systems; not least the integration of charging pads into the road structure as well as the necessary power electronics and electricity grid reinforcement. A significant proportion of the costs concerning WPT systems concern the installation of the charging pads within the road construction. Stolte (2013) states that Germany are expecting to replace a lot of their existing road infrastructure within the next twenty years, hence are looking towards installing WPT systems to reduce the installation cost but also as a means to future proof their infrastructure. The Forever Open Road project is developing the next generation of roads that are adaptable and modular in their design; communication and WPT systems could be integrated into their design (TRL, et al., 2013).

The embedded coils must meet the same regulations regarding the road they are integrated into. A typical roadway is constructed from a number of aggregate layers; a flexible structure consists of a sub-grade, membrane, sub-base, base course, binder course and a 4cm surface course. In comparison, older rigid style roads feature a concrete section, sometimes with a 4cm tarmac overlay, rather than the base and binder courses. The transmitter coils for WPT are embedded into the base course of newer flexible roads and the sub-base for rigid type roads; this ultimately affects the depth of the pad, with older rigid roads requiring fitment at a lower depth (Naberezhnykh, 2014).

The transfer distance between the transmitter and receiver includes the air gap as well as the distance the pad is buried below the road surface (Chen, et al., 2015); hence, the increased depth of the pad in concrete sections can be problematic. Currently, a 20cm coil gap appears to be sufficient for road installation and vehicle clearance. However, Esguerra (2016) proposes the use of magnetisable concretes that are able to amplify and shape the EM field further complementing the transmitter pads. Further considerations include the robustness of the embedded coils, Gil and Taiber (2013) state the systems should be able to cope with expansion and contraction of the road surface, be sealed units, require no maintenance and should not cause issues with further road maintenance such as resurfacing which occurs periodically every 10-12 years. The resurfacing process is quite aggressive and for an average life of WPT systems being 20 years (Naberezhnykh, 2015), the structure must be capable of withstanding at least one resurfacing process.

Due to the sealed nature of the installation, once installed, the device will not be accessible for further maintenance, servicing or upgrades achieved through technology advancements. The latter point is important in determining at what point of technology development it is appropriate to begin the deployment of such systems. Technology improvements are inevitable, but at what point is the technology efficient and future proof enough to begin installation; systems should be designed for higher power scenarios that may be achievable in the future (Gil & Taiber, 2013). Dynamic WPT designs that embed coils within the road but locate power electronics at the roadside do allow for some level of upgrading and maintenance without the disruption of the road surface. The installation of some WPT infrastructure will ultimately aid the development of such systems and generate advancements in further generations of the technology.

Power demand placed upon the grid should also be considered, the electrification of road transport in addition with WPT systems will create varying power demand patterns on the grid. The high frequency of energising and de-energising road base pads will generate large power spikes and appropriate roadside power electronics are necessary to compensate for this. The location of power electronics for WPT control must be located at least 2m from safety barriers (Naberezhnykh, 2015). The length of coil energised has little effect on power requirements, since coil length will vary by just a few metres; however, energising large sections of the roadway will increase the risk of radiation exposure. The grid already experiences power spikes in the morning (6-9am) and winter evenings (5pm-8pm) (Department for Business, Energy and Industrial Strategy, 2019), these times correlate with traveller commuting and WPT systems will undoubtedly increase the magnitude of electricity demand. Therefore, reinforcement and expansion of the electricity grid, including the expansion of renewables, is essential. Smart charging of vehicles, Grid to Vehicle (G2V), in addition with Vehicle to Grid (V2G) systems are possible future systems that will create additional energy storage and security (Damousis, 2014). The use of roadside energy storage devices, such as batteries, for buffering demand requirements is another possibility, albeit increased energy losses in electrical energy conversion. Whilst electricity demand will increase, a notable reduction in fossil fuel demand will occur in parallel, thus the overall transportation energy system will balance out.

Information and Communication Technology (ICT) is an important component of WPT systems; ICT systems will be responsible for vehicle alignment to the transmitter coils, as well as Vehicle to Infrastructure (V2I) communication and road user charging of the system (Amditis, 2014). The V2I DSRC protocol will be responsible for initiation and monitoring of the charging process, it is recognised that this will need to be an almost real time data communication to ensure efficient alignment and energy transfer is maintained (Damousis, 2014). For road user charging, the amount of energy transfer is necessary in calculating the user cost; however, there is a difference between the energy sent into the transmitter coils to that received by the vehicle (Smiai & Winder, 2015). The type of vehicle, driver behaviour, misalignment, vehicle speed and weather conditions are just some of the factors that will affect the energy transfer and cost of electricity supplied. All energy transformation and transmission are susceptible to energy losses (primarily heat); electricity grids have transmission losses in the region of 3% to 10% of the total load (Ramos, et al., 2008), which are inevitably charged to the end user as would likely be the case for WPT systems. Smiai & Winder (2015) suggest the use of dynamic routing ICT systems to make route choice based upon the EV's current charge and the possible dynamic WPT systems (once installed) between the user's origin and eventual destination.

A major challenge of dynamic WPT is the ability to synchronise the transmitter coils to ensure that they are energised and de-energised at appropriate intervals (Taiber, 2014). The power electronics should ensure that the frequency of this action is fast enough to cope with typical motorway headways of 20m or in some cases much smaller headways; minimum vehicle headways should be within the region of 5 to 10m for the technology capabilities (Theodoropoulos, et al., 2014). It is important that the system is de-energised before a traditional vehicle, without any shielding, passes over the pad due to human exposure to the EM field. Further, the system should be capable of re-energising for a further EV. Siemens and Scania have developed a lorry with active sensors to monitor if other vehicles or pedestrians are too close to the EV for dynamic charging to occur; it will switch the system on/off depending on its environment (Scania Group, 2014).

When considering the first use case, work undertaken by Meijer (2016) using PESTEL analysis suggests that probable scenarios for the deployment of WPT systems are for urban bus routes as well as long and short haul freight corridors. Whereas, urban based deployment for heavy freight, light goods and service vehicles appear less likely. The ideal scenario is for deployment to roadways that see continuous repeatable trips; therefore, initial deployment is likely to concentrate on freight and fleet vehicles that undertake such trips. On motorway links, it would be best practice to install WPT systems on the inside or dedicated lane, for example smart motorways could use the hard shoulder for a dedicated charging lane. The inside lane is the most obvious for HGV applications, and would be best for construction as well as maintenance or repair work as that lane is easier to close off. Further applications could include dynamic charging of freight vehicles travelling at night during reduced levels of vehicle congestion. Night charging incentives could be offered for cheaper electricity that would spread the peak load demand on the grid and reduce vehicle congestion during daytime hours. The deployment of such technology nationwide for all vehicle classes is not feasible and deployment should first be aimed at classes that have the most to gain.

Whilst the technology, standards and efficiencies achievable are still under review, and allowing where possible for evolution of costs over time and fluctuations in exchange rates, provisional financial costs have been proposed. Notably with specific relation to the proposer's system design, project and assumed EV proportion. The Transport Research Laboratory (2016) suggest infrastructure and grid connection costs are in the region of £3.9 million per km, operation costs are £1.2 million per km and electricity costs are £12 million per km for a lifespan of 20 years. Meanwhile, an electric bus fleet feasibility study (Shekhar, et al., 2016) concludes that infrastructure costs are £0.98 million per km for a 12 year lifetime. Finally, the KAIST system saw infrastructure costs of just £0.25 million per km (Huh, et al., 2011). As the technology is still very much underdevelopment, it is understandable that there is such a range in cost and application scenarios. Importantly, the installation and road coverage of WPT system does not need to be the entire route length, many schemes use between a 5 and 15% coverage ratio to route length (Suh & Cho, 2017).

It is important to consider the benefits of WPT charging systems and the monetary saving of CO_2, NOx and Particulate Matter (PM) diversion that EV solutions provide. TRL (2016) suggest that the environmental savings of WPT systems are a 45% reduction in CO_2 and between 35% and 40% reduction in NOx and PM. Over a 20 year lifespan, this equates to monetary values of circa £2 million per km for CO_2 and between £100k and £1 million per km for NOx and PM. These values are dependent upon take up of EV dynamic charging systems and current levels of environmental pollution.

Qualcomm (2016) expect that various 3rd party vehicle based pads will be produced by manufacturers, therefore these receiver designs should all function with a standardised embedded transmitter pad. Smiai & Winder (2015) recognise that standardisation is needed across a number of areas; wireless systems, grid infrastructure, coil alignment, communication protocols as well as power levels and frequencies. Standardisation is also required to specify the fitment location of the receiver pad to the base of the vehicle in order for all manufacturer systems to align themselves with the embedded coils. Specifying fitment to the vehicles centreline would alleviate most of these problems and the road based coils can be embedded to the centreline of the lane. Vehicle manufacturers state that there is only a small amount of space available for vehicle packaging of a receiver pads, typically around $20cm^2$ which is far less than the size required for high power dynamic transfer and necessary misalignment tolerances. However, freight applications have considerably more space available for receiver coils. Differing vehicle air gaps will also prove problematic; freight vehicles will have different ground clearances to private passenger vehicles. The system design must be interoperable; this could be through a pad that lowers from the vehicle body for charging purposes or is through the actual receiver pad design.

The DDQ generation of receiver pads (Boys & Covic, 2012) currently appear to be the most efficient, but were designed for quasi-dynamic applications such as taxi rank charging systems. The quantity of pads required and their higher respective costs, result in them not being a feasible choice for dynamic WPT applications. Instead much longer and simpler coils are required to simplify the system whilst minimising costs. Systems should be capable of high transfer efficiencies with a driver misalignment of up to 15cm (Naberezhnykh, 2015). Covic and Boys (2013) recognise that there is a notable increase in efficiency when using the energy transferred from WPT systems directly for the powertrain motorisation rather than charging the battery. Such a scenario increases efficiency beyond that of static WPT systems and effectively extends the vehicles range as the time it spends over the dynamic WPT system are additional miles gained.

While static WPT offers users both increased convenience and safety over existing plug in charging systems, it does little to negate the necessity of large traction batteries and stationary vehicles for recharging. Dynamic WPT is capable of mitigating such aspects, consequently reducing the emphasis placed upon on-board energy storage solutions and long vehicle dwell times for recharging.

Whilst conductive systems like the road-based track or overhead pantograph systems will likely be segregated systems, dynamic WPT systems can technically be integrated with existing traffic; thus avoiding the need to segregate such infrastructure in a designated lane. Safety issues can be resolved by ensuring the WPT system is not powered up when humans or non-equipped, unprotected cars, are in the vicinity of the coils. Yet, segregation of the system could be used as a benefit of the system, either globally or along certain parts of the route, to benefit users with shorter commutes or similar. This is one option to offset the high initial investment of the technology. However, at low levels of EV proportions or WPT equipped vehicles, there is little justification for segregation of the charging lane. The reduced capacity for other vehicles will likely have a significant impact to existing traffic flow and dynamics.

The following factors are identified as the most influential parameters that affect energy transfer efficiency of a dynamic WPT scenario; such parameters exist within four main categories. It is important to distinguish between what efficiency the system is technically capable of, assuming a perfect driving scenario, and the proportion of error an average driver induces. The wider system network factors are not unique to dynamic WPT applications; many of these power supply infrastructure points would be applicable to other charging applications.

Wider system network:

- Location of charging lanes
- Grid supply capabilities
- Voltage and frequency of power transmission
- Weather conditions

Problems and errors:

- Foreign objects in charging zone
- Proximity of pedestrians or other vehicles that will cause charging to terminate
- Installation and manufacturing errors

Vehicle and infrastructure interaction:

- Air Gap; vehicle ground clearance and depth of embedded coil
- Binder and surface course material; their magnetic properties
- EV design; i.e. mass, traction batteries, motor efficiency, electrical convertors
- Direct power feed to motor or via traction batteries

- Vehicle and embedded coil/loop design and switching speed of primary coils
- V2G/G2V communication capabilities and speed
- Associated power electronics to power primary coils; i.e. inverter designs, cooling systems

Human driving properties:

- Vehicle coil to embedded coil alignment
- Vehicle speed and acceleration
- Elapsed time spent in charging lane

Much work has been undertaken in assessing the viability and scope of WPT technology for EV charging applications within the technological domain by both academia and research institutions. Yet, limited investigation of how such systems will be optimised, deployed and utilised within the traffic network has yet been undertaken. Whilst WPT has been validated as a feasible technology, it is important to assess the latest state-of-the-art systems being developed and deployed by industry.

2.3.2 State-of-the-Art in WPT Systems

There are a number of organisations developing both static and dynamic WPT solutions, some of which are market ready and many more are research projects still under laboratory development. The most notable work concerning WPT includes systems developed by Korea Advanced Institute of Science and Technology (KAIST), Bombardier and WiTricity/Qualcomm.

Other systems include; the Oak Ridge National Laboratory has undertaken notable work concerning WPT systems, having achieved a relatively high 95% efficiency of a 20 kW WPT system over a 16cm air gap (Onar, et al., 2016). However, these were laboratory based experiments with no real world demonstration having been undertaken as yet. Utah State University have developed and demonstrated static systems of up to 25 kW with laboratory efficiencies greater than 90% achieved (Morris, 2015). Further, the CIRCE Victoria project saw the development of a 50 kW static and dynamic test track, achieving 92% efficiency for static WPT and 83% for dynamic WPT (CIRCE, 2017). Whilst these WPT efficiencies generally appear high, Barrett (2013) states that conductive charging is usually 1 to 2% more efficient than WPT systems, however if the WPT system is used in a dynamic state (directly powering the motors) it is more efficient. It is important to note, laboratory testing is vastly different to real world testing where other factors and scaling of the system will ultimately affect efficiencies stated.

KAIST/Dongwon:

According to TRL, KAIST/Dongwon OLEV have developed the most market ready dynamic WPT solution (TRL, 2015) (Bateman, et al., 2018). Their OLEV project has been in progress since 2009 and has seen the development of five generations of OLEV systems (Suh & Cho, 2017). KAIST's first generation OLEV system was capable of a 3 kW power transfer over a 1cm air gap, misalignment tolerance was just 3mm with a transfer efficiency of 80% (Choi, et al., 2015). Continual development has resulted in a real world system capable of transferring power levels of 100 kW over a 20cm air gap. Through development of both the power rail track and on-board receiver pad, misalignment tolerances have been increased to 20cm with an efficiency of 83%. Reducing the air gap sees transfer efficiency greater than 90% but regulations mandate a minimum vehicle ground clearance in many cases (Rovito, 2014). Yet, all of the KAIST systems appear to have a low misalignment tolerance and poor interoperability between the OLEV system and other WPT systems (Bateman, et al., 2018).

Various generations of the OLEV technology have been trialled since 2010, systems have been implemented at four sites across South Korea (Jang, 2018). This includes an OLEV trolley in Seoul Grand Park, a shuttle bus at the KAIST campus in Daejeon, a much larger public bus service in Gumi City (Rovito, 2014) and a further site in Sejong. Whilst the shuttle bus service has a minor route of just 3.76km segregated from other road vehicles, the public bus service in Gumi has a length of 35km with numerous charging zones and is integrated with other road vehicles (TRL, 2015). All of the KAIST OLEV generation meet the specified human exposure EM field emission limits regulated by International Commission on Non-Ionizing Radiation Protection (2010).

The Gumi City buses receive a full charge before leaving the depot, and then opportunistic charging via the OLEV systems is used to maintain sufficient energy to complete the route. By implementing charging zones at key areas, such as around bus stop locations, takes advantage of the slower transit speeds witnessed when a bus is decelerating and accelerating. The system is also capable of static wireless charging, both at the bus depot and when the bus passengers are boarding and alighting. However, the systems primarily use static WPT based charging rather than dynamic. The power rails remain switched off until an OLEV compatible vehicle approaches, the rails then power up once the bus is overhead. A directional indicator is used by the driver to accurately align the power rail and bus receiver pad to maximise energy transfer. Due to the high power transfer and opportunistic charging process, battery capacity is five times less than a non-WPT enabled electric bus system. Further, as only accelerating regions, junctions, bus stops and depot bays require OLEV charging systems, infrastructure costs are less than £0.32 million per km, including power electronics and embedded power rails (Huh, et al., 2011).

Bombardier PRIMOVE:

The approach taken by Bombardier and Scania with their PRIMOVE program is to concentrate on sustainable mobility through several key areas; wireless charging, traction batteries and propulsion systems, across both road and rail transportation modes (Bombardier, 2017). Their WPT system was developed as a dynamic system for catenary-less trams but then turned into a high power static WPT system for buses as the business case and exploitation route for this implementation was more near-market. Their system focuses more on static based charging rather than dynamic; they have been able to achieve higher power transfers for static systems when compared to dynamic systems.

Further road trials and installed commercial systems include a number of bus routes in Belgium, Germany and Scandinavia; charging stations are located at bus stops, end of the line stops and bus depots. Buses receive a full charge before leaving the bus depot and opportunistic top-up charging is carried out when the bus is stationary at any of the charged bus stops. Due to the short dwell times, the WPT system has a high power rating of 200 kW with reported efficiencies greater than 90% according to Bombardier (2017). Whilst PRIMOVE primarily concentrates on static based systems, Bombardiers WPT system was tested during the Flanders' DRIVE research project and trials have been undertaken in Mannheim for a truck based 200 kW dynamic charging system, as well as a tram based system. Bombardier also developed a Z-Mover for static WPT, the transmitter pad will lift up to meet the receiver coil when a compatible vehicle is parked above the pad. This effectively reduces the air gap to an optimised distance in order to increase efficiency, whilst allowing fitment to various types of vehicles with both small and large ground clearances.

WiTricity/Qualcomm:

WiTricity have a market ready static WPT system aimed at car manufacturers and Tier 1 suppliers, the system was originally developed at Massachusetts Institute of Technology. The scalable WiTricity system is capable of transferring power from 3.6 kW to 11 kW at efficiencies greater than 90% (WiTricity, 2020). The system integrates Foreign Object Detection (FOD) and Live Object Detection (LOD) for monitoring the charging environment for both metallic objects (FOD) and humans or animals (LOD). WiTricity recently acquired Qualcomm Halo in 2019 to accelerate their WPT development. Initially a research project, Qualcomm originally purchased the Halo IPT project in 2011 from the University of Auckland and Arup who first developed the project over the twenty years prior to this (Qualcomm, 2011). Prior to acquisition from WiTricity, Qualcomm alongside the FABRIC project demonstrated a WPT on a 4x25m segmented test track with speeds up to 60mph, but with limited power transfer of up to 20 kW (Percebon, 2017). Qualcomm had stated that they were keen for, and continually assisted, policymakers in standardising WPT technology to ensure interoperability between manufacturers and vehicles (Qualcomm, 2019). Qualcomm (2016) stated that a standardised transmitter pad or track should be mandated and various 3rd party vehicle receiver coils must be designed to support such transmitters.

Without such standards, issues concerning interoperability between vehicles and varying charging infrastructure will hamper the take-up and potential of WPT systems. Each of the systems proposed by KAIST, Bombardier and WiTricity/Qualcomm are functional and effective in their own designs, but are either not compatible with one another or severely affect the efficiencies of the overall system. Standardising infrastructure electronics will provide manufacturers with the necessary reference specification to develop their systems for, without the risk of incompatible systems as seen with the wide array of conductive plug types and charging stations.

2.3.3 International Standards of Electric Vehicles and Associated Technologies

There are a number of organisations currently working on the standardisation of WPT systems and associated technologies; this includes the global organisations International Organisation for Standardisation (ISO) and International Electrotechnical Commission (IEC) as well as the American based organisation Society of Automotive Engineers (SAE). The main reason for standardisation of WPT systems is for interoperability and safety; standards should not stifle competition or restrict the development of WPT technology but provide a reference system to manufacturers (Woronowicz, 2014). At present, manufacturers typically produce dynamic or static based systems as individual entities rather than a single coherent system. Table 3 contains standards relevant to WPT systems and other associated technologies; it should be noted that not all standards are finalised and many are still under development.

Leading standards are currently ISO 19363, IEC 61980 and SAE J2954. The ISO 19363 standard covers EV architecture, WPT, safety and interoperability aspects. The IEC 61980 standard series consists of several parts that cover the general system, EV and infrastructure communication system as well as inductive wireless power transfer requirements. Whilst the SAE J2954 covers similar aspects to the other standards, it is specific in its power range and application, up to 11 kW static WPT systems; higher power and dynamic systems may be considered in future revisions (Society of Automotive Engineers, 2019). Standards should specify the minimum performance, safety criteria, technology evaluation and common WPT charging system approach. Whilst not mandatory like regulations, standards remove difficulties in developing technologies or bringing new technologies to market through standardising relevant aspects, ultimately accelerating the rate of market penetration and technology growth. Standards will assist and create growth of WPT technologies, as they have done and continue to do for EV’s (Pereirinha & Trovão, 2011).

Table 3 - Wireless Charging and Relevant Technology Standards

Standard	Topic
ISO 19363	Electrically propelled road vehicles – magnetic field wireless power transfer – safety and interoperability requirements
ISO 15118	Road vehicles – vehicle to grid communication interface
ISO 17409	Connection to external electric power supply
ISO 12405	Li-Ion battery system – performance testing and safety performance
ISO 6469	Electrically propelled road vehicles – safety specifications
IEC 61980	Electric vehicle wireless power transfer (WPT) systems
IEC 62840	Electric vehicle battery swap system
IEC 61851	Electric vehicle conductive charging system
SAE J2954	Wireless charging of electric and plug-in hybrid vehicles
SAE 1772	Electric vehicle and plug in hybrid electric vehicle conductive charge coupler
SAE J1773	Electric vehicle inductively coupled charging
SAE J2836/6	Use cases for wireless charging communication for plug-in electric vehicles
SAE J2847/6	Communication between wireless charged vehicles and wireless EV chargers
SAE J2931/6	Signalling communication for wirelessly charged electric vehicles
BS EN 61851-1	Electric vehicle conductive charging system: general requirements

Future WPT systems should be capable of matching the efficiency benchmark set by conductive systems, >85% according to SAE J1772 standard (Society of Automotive Engineers, 2017) (Miller & Jones, 2013). Standardisation of the system architecture, operating frequency, coil alignment tolerances and efficiencies are essential to ensure interoperability. Whilst coil design can vary per vehicle, the embedded coil and infrastructure architecture should be standardised for manufacturers to develop their own vehicle based systems that are optimised against the infrastructure system. Whilst work is continuing in this area, the current maturity of technology and technical complexity are the main barriers to standardisation, yet the standards are still in advance of the market that continues to shape and develop such standards (Marengo, 2015). However, standardisation is now paramount to ensure that the infrastructure system design is standardised, allowing manufacturers to optimise their systems to the infrastructure and to ensure that the technology reaches the point of market deployment. Until system architectures are finalised, from the operating frequency to the shape of the magnetic coupling, road based trials and eventual deployment are hindered.

The most important factors that should be developed into current standards are:

- System frequency
- Human exposure safety criteria
- Location of the coil to the centreline of the vehicle and lane
- Driver assistance systems to maximise vehicle lane alignment.
- Interoperability between static and dynamic WPT systems
- Bi-directional energy transfer capabilities to maximise the scope for both V2G and G2V possibilities

2.4 Chapter Conclusions

EV's have the ability to significantly reduce the transport industry's reliance on fossil fuels, lower transport related CO_2 emissions and improve air quality within cities. It is evident by the literature reviewed that WPT systems are capable of increasing EV market penetration, increasing vehicle range, reducing EV costs, as well as reducing transport energy consumption through reduction in traction battery mass and higher electricity transfer efficiencies. Whilst static WPT systems increase user safety and convenience, dynamic WPT systems are capable of achieving higher efficiencies when making transferred power exclusively available for the EV motors, thus removing energy losses that occur when transferring energy in and out of a traction battery.

From literature reviewed; (i) it is clear that plug-in or static WPT charging within home environments will still play a key component within the entire charging infrastructure; it provides both a convenient and low cost method of EV charging. (ii) Standardisation is necessary in all areas concerning WPT systems, most important is the need to standardise the road based transmitter design. Without the necessary standardisation, system architectures cannot be developed and implemented without fear of interoperability issues between countries or indeed systems. (iii) The most likely scenario for WPT deployment are interurban freight corridors where repeatable trips are expected. Whilst these are good initial deployment locations, the technology should be scalable to enable the eventual wider capture of private and smaller class vehicles.

It was identified that existing WPT research focused more on the technological aspect, as opposed to how such systems would realistically be used from a traffic viewpoint. It is clear that the gap in knowledge is not technologically driven; instead, it is an implementation issue. This exists on two distinct levels; issues over standardisation of systems, and a lack of understanding in how systems will be deployed and utilised within the road network. It is the latter point that is the focus of this thesis; how WPT systems will be scaled up to the higher road network level. There is very little evidence at present to clarify how such systems will function within the traffic domain. There are fundamental questions concerning the capability of WPT systems applied to the SRN, the most appropriate first use case of such systems and the eventual formulation of a WPT charging network. For successful deployment, the technologies impact should be maximised with the minimum quantity of infrastructure and technology use. A modelling tool in which potential deployment scenarios can be investigated, and optimised, to bring this to fruition is therefore necessary.

Chapter 3 Traffic Modelling Review

3.1 Introduction

As identified in Chapter 2, the development of a realistic modelling environment is required in which various scenarios, test cases and general scaling of WPT systems can be investigated and optimised. Therefore, this chapter first assesses the modelling requirements to achieve this. Based upon the prior literature review, the model requirements specification contains each influential factor that should be considered when modelling WPT systems. From this, an investigation into the capabilities of existing traffic modelling packages and their suitability to modelling of, and considering, such WPT factors is undertaken. Further, the review investigates the driving and charging behaviour component of this study in an effort to understand the differences that may be present and should be accounted for within the modelling work. Finally, an assessment of different modelling techniques and approaches used related to EV and WPT charging systems in literature is undertaken.

3.2 Model Requirements Specification

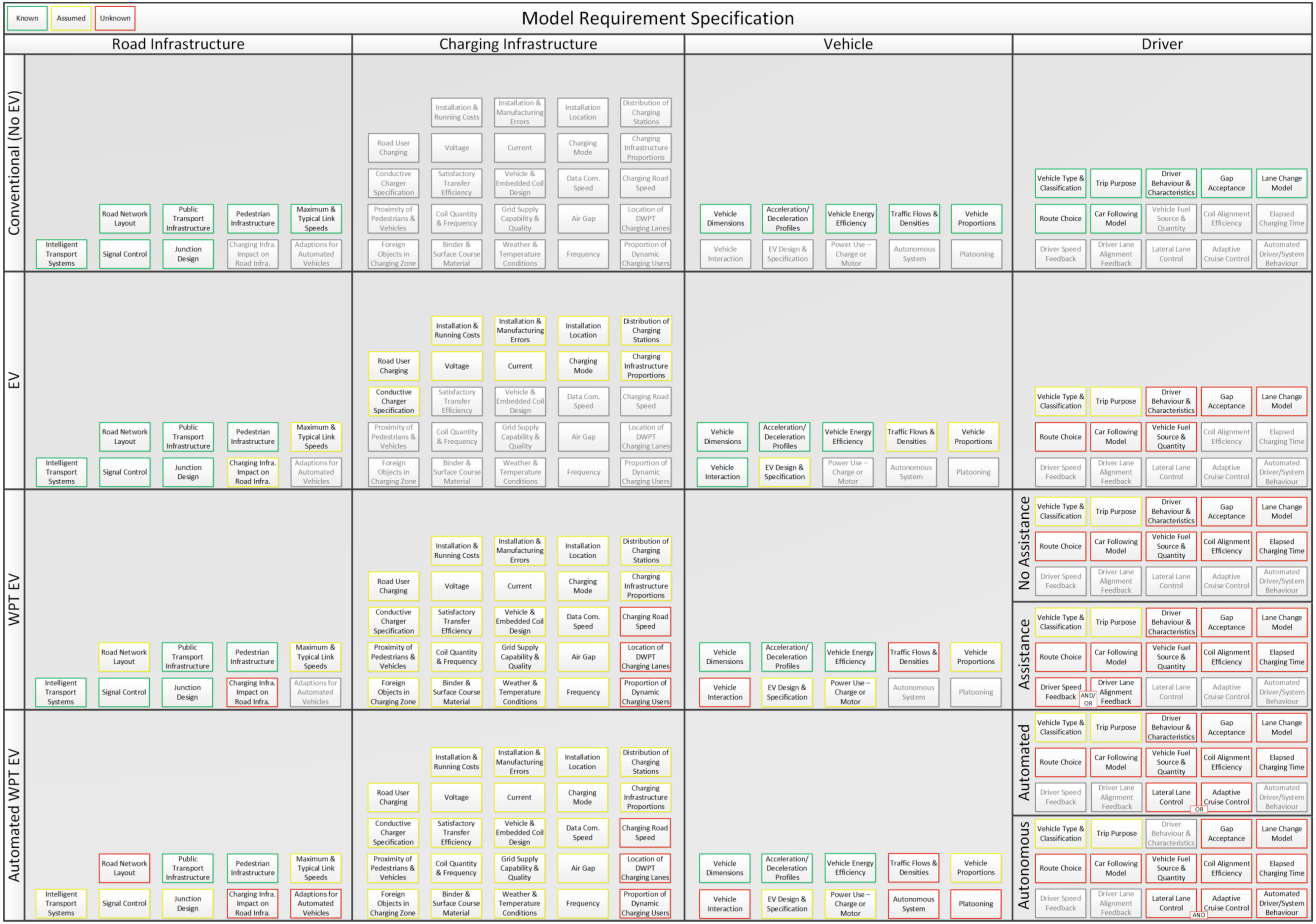
When considering the modelling of dynamic WPT systems, such systems are dependent upon the interaction environment between the driver, vehicle, road and charging infrastructure; achievable energy transfer and system efficiency are reliant upon such aspects. Assessing each component as an individual entity enables the accumulation of influential factors that must be accounted for, under each aspect, within the modelling process.

At this current point in time, the transportation sector is in the midst of a transition away from conventional ICEV's to a higher proportion of EVs, with numerous countries suggesting that they will cease the sale of fossil fuelled vehicles within the next two to three decades (Petroff, 2017). The UK government have recently moved the UK ban of petrol and diesel vehicles forward to 2035 (BBC, 2020). Current trends suggest that the industry is moving towards a solely electrified road transport fleet. In conjunction with this transition, the automation of transport is gaining significant traction (Litman, 2020), therefore it seems plausible/tangible that any modelling work of WPT systems should embrace the current and future trends of the road transport sector. This leads to four distinct vehicle scenarios; conventional ICEV, EV, WPT EV and automated WPT EV. These represent the expected transition pathway of the road transport industry over following decades, the modelling requirements will be influenced depending upon the point in time along this pathway or the particular future scenario under investigation.

It is acknowledged that automation is not autonomous, autonomous travel (according to the SAE (2018) J3016 classification) may not arrive for quite some time, if at all, hence the distinction between automated and autonomous scenarios. Furthermore, in reviewing WPT technology, prototype demonstrators and current research, it is questionable as to whether WPT charging is something that can be viably achieved without automation, or at the least, extensive driver assistance systems. In an era of technology and automation, it may be unrealistic to expect that a primary driving task of the future driver is to maintain lane, and thus coil, alignment in order to facilitate WPT.

The following model requirements specification, shown in Table 4, has been created and extensively developed to summarise the individual factors that need to be accounted for when considering the modelling of WPT charging systems. The four categories are presented alongside the four scenarios with varying levels of EV, WPT and vehicle automation. The subsequent model requirement specification contains each factor that needs to be accounted for across the four scenarios. Depending upon the scenario, such factor values are either known, can be assumed, or are currently unknown; signposted by green, yellow and red indicators respectively. Factors that are not relevant at that scenario level are shown in grey. As scenarios progress, individual factors either become more pertinent or transition to a different state of known, assumed or unknown; whilst their state may not change between scenarios, their corresponding values or criterion will likely change.

Table 4 – Model Requirement Specification



To expand on the model requirements specification, the following subsections further describe the individual factors shown in Table 4.

Road Infrastructure:

First assessing the road infrastructure component, at this current point in time the road network, public transport and pedestrian infrastructure are well established and understood, as are current signal control systems, junction design and ITS schemes. As road transport transitions to a higher electrical dominance, factors such as maximum, and particularly typical, link speeds shift to a state of uncertainty. It has been demonstrated in literature (Rolim, et al., 2012) (Helmbrecht, et al., 2014) that EV drivers have different driving behaviour to that of ICEV's, and the very nature of electric transport results in varied speed/curve profiles, further changing the typical transit speeds that may be experienced. Additional factors also become more pertinent at this EV stage, the impact that the charging infrastructure has upon the road infrastructure includes installation of static charging points at various points of interest. Yet, both link speed and charging impact can be assumed from existing traffic conditions and research. When assessing the WPT EV scenario, the road network layout will inevitably have to change at this stage with the addition of WPT charging systems. This is one of the primary inputs of the modelling process, and aims to identify the necessary changes that such systems warrant. A further area of investigation is the impact charging systems will have on the road infrastructure, an expected output of the modelling process, and thus unknown at this stage. Finally, as the specification moves into the final scenario, automated, further uncertainties again include the road network layout and the adaptions required for automated vehicles. The existing road network has been developed over years of research into how humans drive, such a network optimises itself to the human driver, be it from clear road signage to junction design. Thus, much work concerns itself with adapting the current network to be 'readable' and 'navigable' by automated systems.

Charging Infrastructure:

When considering the charging infrastructure component, charging factors only become relevant at a level above zero EV penetration. Assuming a scenario with no WPT charging systems, EV only, static conductive charging systems form the majority of the influential factors. Much research has been undertaken to understand the various technical specifications: voltage, current, charging modes and charging schemes. The optimisation of a distributed charging network is something that is continually under evaluation, and is something that will vary further with WPT charging systems. This is noticeable with the next scenario, WPT EV, distribution and charging proportions are now unknown. The introduction of WPT charging systems transitions such technology specific factors to within the model, such factors include: coil design, voltage, current and frequency; coil quantity, headways, airgap; transfer efficiencies; grid supply; and installation factors. Due to the infancy of such technology, it is inevitable that there are many unknowns and as such underlying assumptions must be made. Whilst the automation of the WPT charging process does not change the state of any factors, it will however involve different metrics and considerations during the modelling process. Further, it may be possible that a future WPT charging system will require some degree of automation in the vehicle to coil alignment.

Vehicle:

The vehicle component highlights technical factors related to individual vehicle dimensions, mass acceleration/deceleration profiles, energy consumption and emissions, as well higher level traffic flow, densities and proportions; all of which are known to some degree within the base level scenario. Transitioning to a higher EV proportion scenario has the potential to vary the typical traffic flows and densities seen previously, the sheer difference in mechanical design will inherently change acceleration profiles, energy consumption and emission values. Implementing WPT charging systems will further vary the detailed vehicle interaction and traffic conditions; an area in which simulation work should investigate. A larger question over power use is also now evident, it is unclear as to whether WPT charging systems will be capable of providing sufficient power to solely power the vehicle with minimal on-board battery input. Or if in fact, vehicles will be capable of charging and motoring at the same time; with surplus transferred energy being used to charge the battery in parallel with motoring the vehicle. When considering the automated scenario, interaction between vehicles, humans and automated systems has been the topic of much research (Litman, 2020). Automation enables the utilisation of platooning freight vehicles to minimise aerodynamic effects on fuel consumption (Scania, 2018), this leads to further questions over optimum coil headways and whether they should be designed to match existing motorway headways of 20m (Theodoropoulos, et al., 2014), or much closer headways that automation could enable.

Driver:

The final component of the model requirements is the driver, mathematical models are used to represent driver behaviour; specifically car following, gap acceptance and lane change movements. Research has shown that the type of vehicle and fuel source have an influence on driving behaviour (Rolim, et al., 2012) (Helmbrecht, et al., 2014) (Jing, et al., 2016). Whilst this is relatively understood for ICEV's, EV's create much more uncertainty due to the fact that most EV owners are early adopters. Further, the low penetration rate of EVs compared to ICEVs results in the current sample not being representative of the wider population. These differences must be represented within the car following, gap acceptance and lane change models, thus are unknown at the EV scenario. Research has indicated that the use of electric vehicles often results in additional trips, further distorting the previous knowledge surrounding trip purpose (Rolim, et al., 2012) (Haustein & Jensen, 2018). Route choice will also vary, with a limited vehicle range EV drivers will optimise their route choice to include recharging facilities. Introducing WPT charging systems will most likely see users further change their route choice to make use of such systems. In order to calculate the amount of energy transferred to a vehicle using WPT systems, elapsed charging time now becomes relevant, as does the alignment between transmitter and receiver coils. The WPT EV scenario is segregated into two distinct scenarios, with and without assistance systems, the sole difference being some form of driver speed and/or lane alignment feedback. The feedback systems transition to lateral lane and adaptive cruise control when the automated scenario is reached. The final scenario is reserved for fully autonomous (Level 5 - J3016 (Society of Automotive Engineers, 2018)) vehicles, whether or not this proves something technologically obtainable.

The evaluation of influential factors, at varying stages of EV, WPT and vehicle automation, has highlighted some of the key areas that will be further investigated within the modelling work. While varying levels were assessed, it is the EV WPT stage that is of importance within this study. Generally, traffic modelling aspects include journey time, vehicle speeds and flows, while WPT aspects include technology specification, charging location and criteria. In addition to the influential factors previously described, the following points include some basic functionalities that are required from the traffic model. Two domains exist; model and data requirements:

Model:

Track vehicles:	Monitor, read and change individual vehicle information
Charging detection:	Monitor vehicle charging events
Driver behaviour:	Adjustment of car following, lane change and gap acceptance models

Data:

Traffic composition:	Vehicle types, flows and densities
Vehicle parameters:	Vehicle specifications, energy consumption, emission production
WPT parameters:	Energy supply, transfer and system specification

3.3 Evaluation of Traffic Model Packages

There are two main purposes of a traffic model, enveloped by Allsop (2008); firstly to simulate and analyse existing transport systems in use, and secondly to model transport systems that aren't currently constructed, could potentially be expanded or altered. Through applying theoretical modelling techniques, transport infrastructure alterations, development and construction can be simulated to optimise and validate designs before commitment to construction and financial efforts are undertaken (Davidson & Davidson, 2020). Traffic simulation models can be categorised into microscopic and macroscopic levels. Microscopic models use car following and lane change models for simulating detailed road scenarios and can be altered on a vehicle by vehicle basis. Macroscopic models (lower resolution) symbolise an aggregated representation of the wider transport system and characteristics over a larger region, rather than a particular road layout or vehicle. Similarities can be drawn between macroscopic simulation and fluid dynamics (Alexander, 2003); at this simulation level, the flow of traffic is similar to the flow of fluid within a system, maximum vehicle flow rates of roads dictate the overall traffic and vehicle flow across the network. Whereas, microscopic simulation is capable of detailed modelling with each vehicle being governed by its own programmed characteristics and regulations (Bazghandi, 2012), it is because of this individual vehicle modelling that microscopic simulations are regarded as more realistic than macroscopic versions (Ehlert & Rothkrantz, 2001). However, microscopic models require a large amount of behavioural knowledge and are difficult to calibrate precisely.

Traffic models consist of a mathematical structure representing the transport system and behaviour the model is based upon (Papageorgiou, 1998); real world parameters are used to increase the accuracy and correlation of the model to the transport system. Papageorgiou (1998) stresses the importance on empirical validation of traffic models against existing and new traffic flows, without such validation to real world data the model may not be entirely representative. If the base data and underpinning assumptions made during the development of the model are not accurate, this inevitably negates any accuracy of the final model and simulation results. The mathematical model consists of a series of nodes and links that form the network matrix of the transport system; nodes represent the intersections of the traffic whilst links embody the flow of traffic (Allsop, 2008). The nodes also represent the point at which the traffic flows enter and exit the model; origins and destinations of the vehicles. Link parameters such as the maximum vehicle flow, capacity and entering/exiting vehicle quantities govern the link and ultimately constrain the interaction of vehicles between nodes (Astarita, 2002); the importance of the underpinning assumptions and imposed regulations to the model are now seen.

A high level investigation is undertaken to assess the functionality, suitability and potential of a series of microscopic traffic simulation packages with respect to EV and WPT modelling. The appropriate software packages assessed are:

- AIMSUN (Siemens)
- SUMO (Open Source)
- VISSIM (Planung Transport Verkehr (PTV))
- PARAMICs (Quadstone)
- PARAMICs Discovery (Paramics Microsimulation)
- MATSim (Open Source)
- MITSIM (Massachusetts Institute of Technology)

There are a number of open source software packages available, Multi Agent Transportation Simulation (MATSim), Simulation of Urban MObility (SUMO) and a version of MIcroscopic Traffic SIMulator (MITSIM). However, agent based demand modelling software packages, MATSim and MITSIM (Figure 3), are more mathematical function based packages with restricted features and graphical representation, when compared to other software alternatives. MITSIM bases its car following model on an unsymmetrical Gazis, Herman, Rothery (1961) model, incorporating three regimes to determine driver behaviour; free driving, acceleration and emergency deceleration (Olstam & Tapani, 2004).

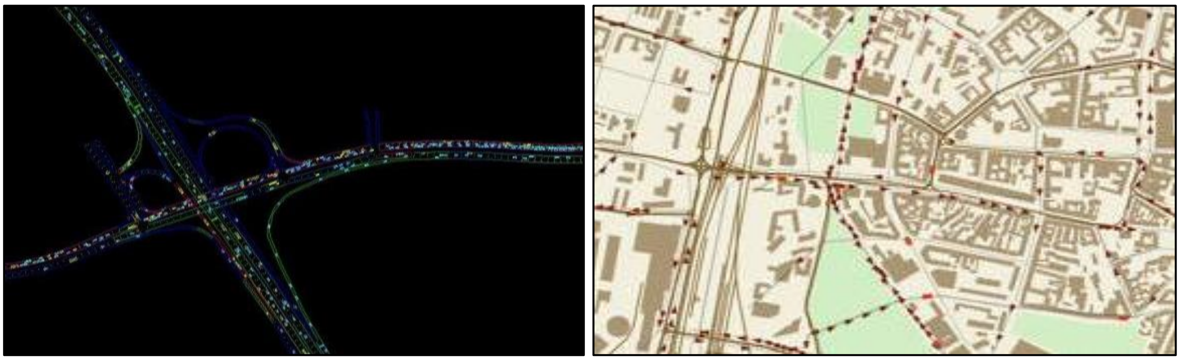


Figure 3 – MITSIM (left) and MATSim (right) (Azevedo, 2015) (MATSim, 2020)

In comparison, SUMO (Figure 4) has greater scope within this project. SUMO is a multi-modal microscopic simulation package designed for simulation of a city wide traffic network (Krajzewicz, et al., 2002). Whilst the basic package may not be the most suitable with respect to the requirements specification, the open source nature of the program allows the user to adjust, adapt and manipulate the software to undertake specific tasks concerning their own requirements. Hence, SUMO is capable of eliminating many post processing efforts that may be required with other less capable software packages. SUMO uses a car following model based upon the safety distance Krauß model (Krauß & Wagner, 1997), which in turn has a strong similarity to the Gipps (1981) model but a simplified version. Again, this component of the program can be changed to suit the users requirements, with the Intelligent Driver Model (IDM) and Wiedemann model being available directly within the software. The open nature of the software places greater emphasis on the user having proficient programming skills in order to capture the programs full potential.

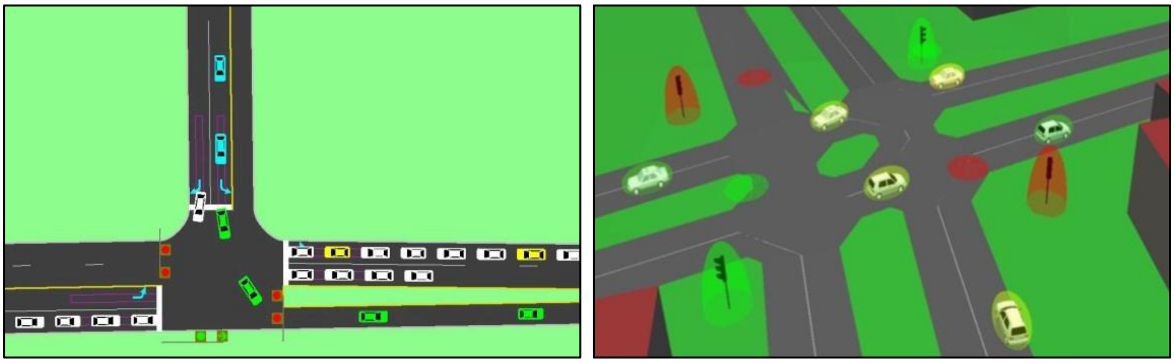


Figure 4 – SUMO (German Aerospace Center, 2016)

The remaining packages assessed are proprietary and incur a cost in their use, similar to SUMO these programs are all multi-modal simulation packages. Traffic in cities (German translation) SIMulation model (VISSIM) is the most widely used and industry leading traffic simulation package (PTV Group, 2020). It is capable of very detailed modelling, including the simulation of Vehicle to Vehicle (V2V) and V2I communication. It features a model based upon the psycho-physical car following, lane change and gap acceptance models proposed by Wiedemann (1974). In addition to the psycho-physical car following model, free and necessary lane changing algorithms, as well as lateral lane behaviour algorithms, culminate to dictate the driver behaviour and realistic vehicle movement. In addition, VISSIM has an API for external programming. It is important to note, the lateral lane behaviour model controls the vehicles lane alignment with respect to slower vehicles or cyclists. It is not capable of varying the lateral lane alignment to represent real driver behaviour as they follow the undulations of the road. Olstam and Tapani (2004) recognise that VISSIM also has a large number of parameters, all of which require calibration to create a realistic simulation. Such parameters are not easily relatable to real world driving factors.

On the other hand, Advanced Interactive Microscopic Simulation for Urban and Non-urban networks (AIMSUN) (Figure 5) is the most capable software upon immediate installation, when negating any development of the open source base software packages. An attribute of AIMSUN is its three tier approach to simulation and its ability to integrate between the three tiers; micro, meso and macroscopic models within a single software package (Casas, et al., 2011). This hybrid approach gives the ability to simulate microscopic and macroscopic simulation simultaneously allowing large areas to be modelled (macroscopic) whilst still retaining the ability to focus on smaller regions in great detail (microscopic). It is a widely used research tool and is a relatively open software that allows for user adjustment to develop specific interfaces and tasks. AIMSUN (2020) state that their microscopic simulator is currently the fastest on the market, it is capable of simulating entire citywide dynamic models beyond real time. The AIMSUN car following model is based upon the Gipps (1981) safety distance model, with lane change and gap acceptance models based on Gipps (1986) model. AIMSUN is the most intuitive package with the least number of parameters that require calibration (but enough to maintain realistic driver behaviour); reducing the calibration work required. Both AIMSUN and VISSIM allow users to define unique vehicle behaviour algorithms. Further, AIMSUN has a substantial API which enables external programs to be developed and interfaced with the simulation package.

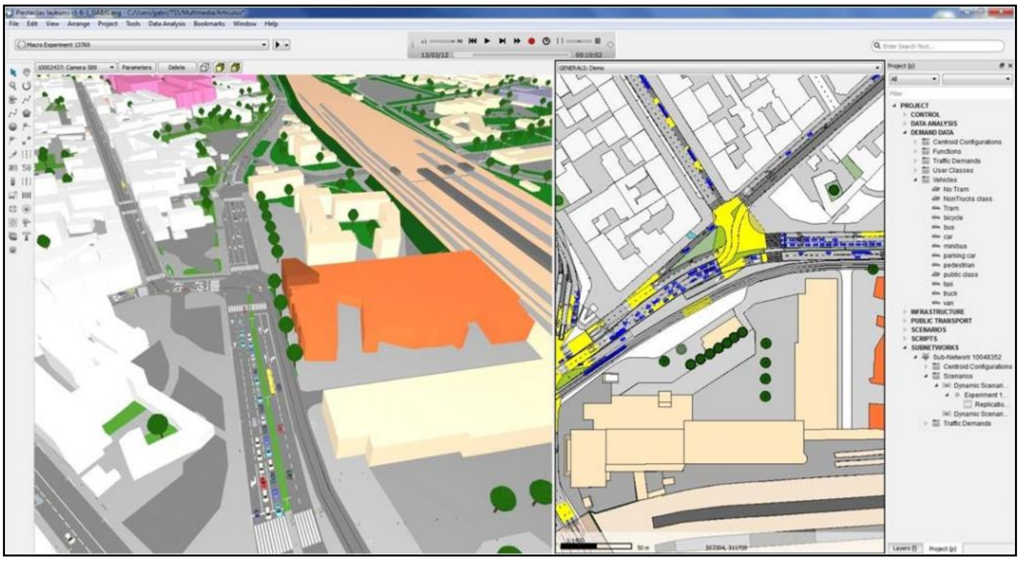


Figure 5 – AIMSUN (2020)

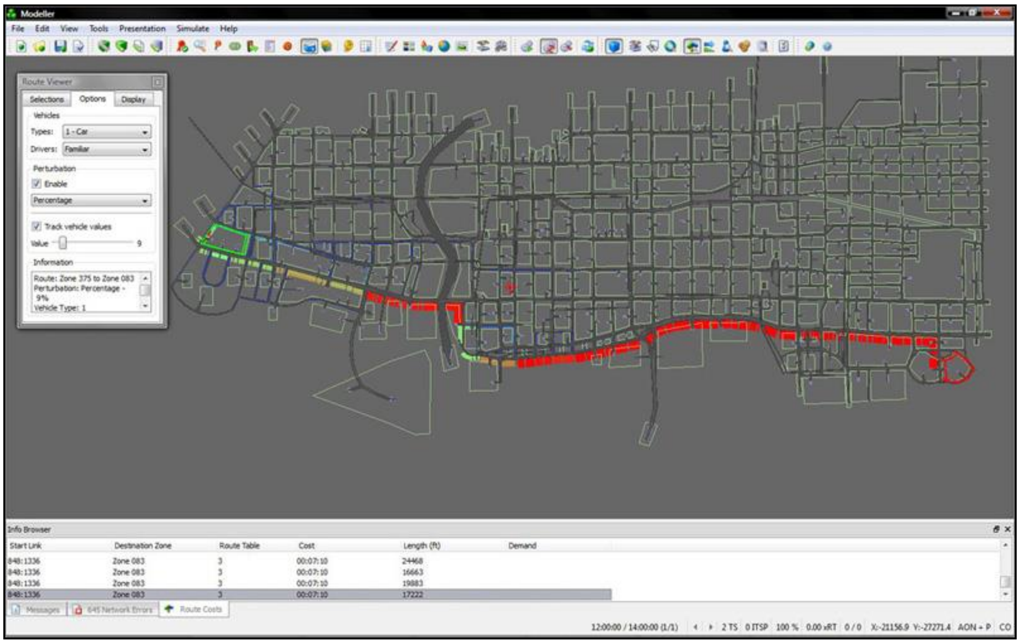


Figure 6 – PARAMICS (Quadstone Paramics, 2020)

Finally, the PARAllel MICroscopic (PARAMIC)s software (Figure 6), both Quadstone's PARAMICs and SIAS/SYSTRA's PARAMICs Discovery, originate from the same PARAMICs project initially established within the 1990's. Hence, these software packages share much of the same basic algorithms and operating software. The psycho-physical car following model developed by Fritzsche (1994) is the basis of the model used within the PARAMICs software. Kotusevski and Hawick (2009) found that Quadstone PARAMICs had the best graphical interface, followed by AIMSUN, when comparing against other simulation packages; libraries of buildings, vehicles and pedestrians compliment the visual simulation. Both PARAMICs software packages offer the ability to adjust simulation values during a live simulation in order to calibrate the model.

The simulation of traffic networks within traffic models provides a validated means of adjusting, testing and analysing such networks theoretically, without commitment to physical testing or construction. All of which are ideal attributes given the current state of WPT development; numerous unanswered questions exist and a tool is needed to ascertain answers theoretically. Microscopic simulation models are capable of capturing individual vehicle movements and interactions around the network, while macroscopic models are more relatable to fluid dynamics with an aggregated approach to vehicle movement. While microscopic models provide greater detail, they also require large quantities of behavioural knowledge and are consequently difficult to calibrate. Microscopic simulations packages use a series of car following, lane change and gap acceptance models to represent driver behaviour. Of which, there are numerous algorithms developed in the aim of providing greater realism and closer representation of driver behaviour.

It is recognised from this overview of relevant traffic simulation packages that there are a large array of capable programs. Yet, they expectantly lack any features specific to EV driver characteristics or WPT charging. Such specific parameters may require post processing in order to compensate for this and to factor them into the simulation process.

To summarise, there are a number of traffic modelling packages available, some of which appear more suitable than others when considering the additional features needed for the WPT situation. In terms of speed, and minimum prior user knowledge, a commercial package was a preferred route, as opposed to open source packages such as Sumo and MATSim. Of which, both VISSIM and AIMSUN are suitable commercial packages that would be more than capable within this study. However, AIMSUN is considered more suitable at this stage because it meets the minimum traffic based requirements, as well as being able to include both behavioural and energy components; either within the package or externally with the use of an API. A further advantage is the better documentation and overall interface available for AIMSUN when compared to VISSIM.

3.4 Traffic Behaviour

It is recognised that a traditional traffic model is not capable of realistically modelling a traffic network featuring a WPT charging system without additional behavioural and energy considerations. The purpose of this section is to assess the driver behaviour component of this study; in particular, the issues over determining likely driver behaviour, how this can be implemented within the model, similar research of differing driving styles and patterns, as well as the necessary modelling assumptions required in order to use the model.

As discussed in Chapter 2, much work has taken place to assess the potential of WPT at technical levels; yet, the behavioural considerations of such a scenario has received little analysis. Such criteria must be first understood, and secondly considered, within a traffic model as they have the potential to vary the detailed vehicle interaction, and quite possibly the viability of WPT systems under particular scenarios. It is not immediately clear if WPT systems will see similar behaviour to conventional vehicles within the network, thus this is the next logically step.

It is already understood that the type of vehicle being driven has an influential effect on driver behaviour; Aghabayk, Sarvi and Young (2015) identify differences in driver behaviour between private vehicles and HGVs. In addition to the type of vehicle, the fuel source of that vehicle is considered to have an influence on driving behaviour. An individual that has made a conscious decision to purchase an ultra/low emission vehicle is likely to have a differing driving style to a driver of a conventional, and higher emission, vehicle. This difference in fuel source imposes different driving styles beyond that of differing speed profiles and acclimation periods (Helmbrecht, et al., 2014). A European study found that the majority of drivers acknowledge that driving an EV changes their driving behaviour; to the extent that they speed less, are less aggressive, and more economic (Rolim, et al., 2012). Travel patterns, route choice and an increase in travel were further changes that occurred through the use of EVs within the study. Generally, EVs have the potential to alter users mobility, driving patterns and styles, energy consumption, and emission generation. These alterations to driver behaviour must be understood in order to compensate for such factors within traffic modelling work; they will inevitably have an effect on underlying car following, lane change and gap acceptance models (Yang, et al., 2014) (Jing, et al., 2016).

The following sub-sections will explore both charging and driver behaviour respectively in an attempt to understand the differences that may be present and should therefore be accounted for within the modelling work.

3.4.1 Charging Behaviour

When considering the differences in user behaviour between ICEVs and EVs, differences not only exist in the way in which the vehicle is driven, but also in the way in which it is used, stored and refuelled. Rolim, Gonçalves, Farias, and Rodrigues (2012) recognise that driving patterns of EV users vary when compared to more conventional ICE vehicles, not least imposed range limitations alter trip distance and the linking of trips, but also the way in which the vehicle is driven and the more general travel patterns. EVs rely on the generation of electrical energy external to the vehicle and a recharging process to transfer this energy to on-board batteries. A number of charging methods already exist, reviewed within Section 2.2.2 – Charging Methods for Electric Vehicles. Home charging inevitably requires off street parking, with only a portion of UK drivers having access to off-street parking (Bates & Leibling, 2012) this often limits the option of an EV, or at least requires different charging behaviour. Access to off-street parking may only reduce, given population growth.

The increasing market penetration of EVs has led to a parallel growth in public charging points to support the EV population; there are over 30,000 charging connectors across nearly 11,000 public locations across the UK (Zap Map, 2020). It is vital not to underestimate the importance of home charging; the ability to slowly charge the vehicle overnight at the EV owner’s residence is both convenient and a cost effective means to refuel the vehicle (Boxwell, 2015). It is unclear at present, the expected proportions of users that will undertake home charging as their primary source of refuelling. All prior research to date has been based on innovators and early adopters; their charging behaviour is not representative of the wider population. This is based on three main factors, the demographics of this early adopter user group do not represent the broader population, currently there is no comprehensive charging network, and home charging is a completely new behaviour. However, scaling the current levels of home charging to a scenario with high penetration of EVs may change the feasibility of home charging. Population growth, technology capabilities, energy and power availability, attitudes to energy consumption, market structures, access to off-street parking as well as potential changes in mobility are all factors that could influence charging behaviour. A recent study found that nearly 60% of EV owners preferred to charge their vehicles overnight using private home based charging (Moon, et al., 2018), thus it was identified that reinforcement of residential power grid infrastructure would often be required to facilitate this. The study conducted by Charilaos and colleagues (2017) investigated charging behaviour and compared the differences between home and out of home charging; they concluded that there is an intrinsic link between charging and travel behaviour.

Whilst there is a gap in knowledge concerning charging behaviour (Tal, et al., 2014), general assumptions can be made with respect to the charging behaviour of EVs. Home charging will play a key component within the entire charging network in both the short and long term. Due to the outright requirement of recharging, there is a tendency for EV owners to charge more than PHEV drivers, yet EVs will not travel as far as PHEVs (Tal, et al., 2014). This insinuates that PHEVs are used more in-line with conventional ICE vehicles as vehicle range is not solely limited by battery capacity. Currently, charging at the workplace is considered the second most important charging location (Tal, et al., 2014). Hu, Dong and Lin (2019) acknowledge that, whilst home charging is still the most significant role in EV use, as public charging infrastructure expands some home charging is shifting to workplace and public charging. However, workplace and public charging further increases existing periods of peak electricity demand, something that overnight home charging opposes.

Nicholas, Hall and Lutsey (2019) demonstrated that vehicles with a shorter range tend to use public charging stations more than vehicles with a higher range. Further, those without access to off-street parking and charging facilities were more reliant upon public charging stations. Thus, the housing structure of the area will play a key component in determining the types of charging infrastructure required, and the charging behaviour of the residents.

Franke and Krems (2013) propose that users can be categorised into high and low User Battery Interface Style (UBIS) groups. Those with a lower UBIS will make less of an input to understanding battery charging requirements and will not optimise resources through minimising their number of charging events. Whereas, those with a higher UBIS will determine battery recharging based on charge level and travel requirements in order to optimise their charging behaviour. Further, Franke and Krems (2013) theorise that a low UBIS user will have a reduced range utilisation due to their lower awareness concerning the vehicles SOC and capability when compared to a high UBIS user. While charging is a necessity for EV owners, it is assumed that owners of PHEV's will choose to charge their vehicle as much as possible in order to maximise their vehicle utility (Tal, et al., 2014). Hu, Dong and Lin (2019) propose a modelling framework using a cumulative prospect theory to describe the charging behaviour of EV drivers. It was identified that drivers with a higher degree of risk would charge their vehicles to a lower SOC. On average, drivers would recharge their EV at 41% SOC.

The introduction of smart charging, where flexible loads such as EV charging occurs at times when there is an abundant supply on the grid, has the potential to smooth peak electricity demand and harness the potential of renewables (O'Connor, 2016). Such a scenario will see a low UBIS as beneficial due to the more frequent connection to the grid, thus charging can commence and cease dependent upon baseload electricity supply. Whilst smart charging is considered a one-way energy transfer, Vehicle to Grid (V2G) applications would see a two-way process that harnesses EVs as flexible additional energy sources to aid the baseload electricity supply (Ul-Haq, et al., 2013). Yet, the energy losses of transferring energy in and out of a traction battery may hamper the feasibility of such V2G applications.

Time of use electricity rates encourage users to make behavioural changes to move their energy consumption to periods outside of peak demand. Varying the cost of electricity dependent upon the time of day, and hence grid electricity demand, has seen to be effective in encouraging users to undertake more off-peak charging (U.S. Department of Energy, 2014). Using energy meter data from the San Diego region, Kim (2019) found that EV charging created a twin peak load curve; with an initial peak occurring between 6 and 8pm and a further peak at midnight when the lower cost of electricity began. They concluded that the financial rate structure of the electricity plan has a significant impact on charge times and general behaviour. The growth of the EV market will ultimately influence charging behaviour, as more vehicles require electrical energy it is essential that the charging infrastructure expands in advance of this demand to ensure adequate supply.

While conventional plug-in charging rates are capable of being derived from current use rates, WPT charging rates are much more of an unknown. A study conducted by Chen and colleagues (2017) modelled the charging requirements of both static charging infrastructure and dynamic WPT charging infrastructure along a long traffic corridor, with the purpose of examining the competitiveness of charging lanes. Assuming drivers would minimise their travel costs, including travel and charging time, as well as charging costs, they found that EV drivers would favour charging lanes over charging stations. They also found that if commercialised, charging lanes appear more profitable than charging stations. The vehicles SOC will be a key factor in the driver choosing whether or not to use the WPT charging systems. A driver with a low SOC will be more likely to use the WPT system than a driver with a high SOC, given the same trip and variables. Yet, further aspects will again influence the driver's choice to use a WPT system, such as access to off road charging, the rate of pay, and route choice.

Currently, WPT is being portrayed to the public as static WPT charging solutions; no longer is there the need to plug in your EV, simply park over the charging pad. Whilst this improves convenience and safety, it does not take advantage of the greater benefits achievable with dynamic WPT. With standardisation permitting, the same vehicle coil will be capable of being used for both static and dynamic charging purposes, transmitter coils will inevitably vary to increase efficiency depending upon charging state. Thus, there are two individual charging states, static and dynamic, the public use proportions of which are both unknown. Technology deployment and market penetration rates are further unknowns, such factors will also alter plug-in charging behaviour dependent upon the growth of WPT charging systems. How and when dynamic WPT solutions are deployed, as well as the deployment locations will all affect user take-up rates and have the ability to alter route choice. In addition, further unknowns exist around the perceived utility cost of travelling on dynamic WPT roads, or indeed the time cost of travelling at a slower speed, or changing routes to take advantage of WPT charging.

Therefore, future WPT user proportions are an unknown factor. A range of user proportions should be modelled to account for a variety of possible future scenarios, as well as assessing the effect that such proportions may have on the viability of WPT charging infrastructure. For example, many WPT scenarios will require a certain user proportion to be feasible.

3.4.2 Driver Behaviour

When assessing driver behaviour, an individual's driving characteristics, route attributes, vehicle variables and charging station specifications are the main explanatory variables that affect EV drivers' route choice and charging methods (Yang, et al., 2015). EV drivers do not follow the typical driving characteristics of ICEV owners, not least due to the differences in route choice considering the necessity of charging stations (Jing, et al., 2016). EV owners also have a tendency to drive more economically, due to the conscious decision to prioritise energy conservation through their selection of an AFV (Rolim, et al., 2012) (Kolbenstvedt, 2015). These differences in route choice and traveller behaviour, when compared to conventional ICEVs, mean that modelling scenarios must be adapted to meet these different characteristics. The route assignment of EV users will vary when compared to ICEVs due to vehicle range, energy conservation and perceived cost. In order to reduce greenhouse gas emissions Norway, like many other governments, have subsidised EV's through taxation policies (Norwegian Road Federation, 2019) and provided wider user benefits such as free travel within congestion zones, toll roads, bus lanes and city parking (Holtsmark & Sckonhoft, 2014). Yet, this results in further changes to route choice and traveller behaviour that must be compensated for within modelling work.

In a small scale, long term study conducted by Rolim, Gonçalves, Farias and Rodrigues (2012), after an initial acclimation period, drivers were found to adapt well to EV's; early issues concerning functionality and charging infrastructure were overcome. Further, users acknowledged that the EV has an effect on their everyday routines; they travelled more, used different roads, were less likely to speed, less aggressive, and adopted a more economic driving style. It is well recognised that the transition from an ICEV to an EV involves an initial acclimation period or learning phase to adapt to the vehicle (Rolim, et al., 2012) (Vilimek, et al., 2012) (Labeye, et al., 2016). There are a number of unique parameters associated to EVs; for example, the limited vehicle range, the lack of vehicle noise at low speeds (Cocron & Krems, 2013) and regenerative braking functionality (Cocron, et al., 2013).

Regenerative braking is an efficient means of recovering energy and improving a vehicles energy efficiency (Cocron, et al., 2013); energy is recovered when the vehicle decelerates, either through letting the car decelerate naturally or braking. Whilst the acceleration and deceleration profiles will vary for EV's when compared to ICEVs, the regenerative braking function lends itself to a new single foot driving style that is typically adopted by EV drivers (Labeye, et al., 2016). The greater deceleration when compared to coasting in conventional ICEVs reduces the extent of which braking is required by the driver; hence varies driving patterns. Unlike conventional ICEVs and their progressive torque curves, the constant torque characteristics of electric motors allow for maximum acceleration independent of the motors speed. Considering constant torque and regenerative braking, such functions allow for very direct responsiveness to acceleration and deceleration, longitudinal vehicle dynamics, when compared to conventional ICEVs (Helmbrecht, et al., 2014). As part of the MINI E field trials a study assessed EV behavioural patterns, it was identified that average speeds did not differ largely between electric and ICE vehicles after vehicle acclimation; though smoother acceleration profiles were seen with EVs (Helmbrecht, et al., 2014).

A further study comparing traditional ICEVs to EV drivers identified that most EV drivers are male, highly educated, have high incomes, and typically have multiple cars in their household (Haustein & Jensen, 2018). Within their study, almost half of EV users reported that they had changed their activity patterns because of the EV; typically planning longer trips more carefully or sometimes not undertaking such trips. The study focused on the demographics, mobility patterns and attitude differences between ICEV and EV drivers, all of which will influence driver behaviour.

Unlike electric and ICE vehicles, PHEVs have two methods of propulsion; pure electric or an auxiliary ICE that can be used with or without electrical assistance. Thus, the vehicle can be utilised in a series of different powertrain states; further blurring the characteristics and behaviour of the driver. In pure electric mode, driver behaviour may be similar to an EV driver but the auxiliary ICE will vary such driving patterns as the vehicle can easily be refuelled using conventional fossil fuels. Once electricity has been depleted, driving behaviour may then be similar to an ICE vehicle.

The most likely scenarios for dynamic WPT deployment are urban bus routes or bus rapid transit systems, and freight corridors where repeatable trips are expected. Therefore, driver behaviour may already vary from private car drivers as initial deployment strategies are targeting bus and HGV applications; a completely different vehicle class. Some work has been undertaken to assess the differences in driving behaviour of HGV drivers (Aghabayk, et al., 2015). Vepsäläinen (2017) found that when comparing driving behaviour between electric and diesel buses, the electric bus was typically driven more aggressively and faster on average; such differences observed were because of the low noise feedback of the EV and higher power available at low speeds.

Within the UK, vehicles travel on the left-hand side of the carriageway, slower vehicles generally move over to nearside lanes when available. Introducing WPT charging lanes may influence the availability of such lanes or reduce the frequency of drivers moving into such lanes, similar to not all users utilising bus lanes when outside of operating hours. Multiple lane carriageways allow faster vehicles to overtake slower vehicles through changing lanes, within the UK such manoeuvres are carried out on the offside of the slower vehicle. Yet, it is not understood if users of a WPT charging lane will move out of a dedicated charging lane to pass a slower vehicle. The perceived utility of maintaining a higher transit speed, at the expense of terminating the charging process is unknown. It is quite possible that dynamic charging systems will have a maximum speed limit cap to facilitate energy transfer, thus such charging lanes will consist of slower moving vehicles. Equally, a minimum speed seems plausible to stop vehicles going so slow that people walk out in between them, and thus close to highly powered coils; this is more a concern in urban locations.

Lateral lane alignment is a unique parameter of the dynamic WPT process as it will ultimately affect the transfer efficiency between the road infrastructure and vehicle (Qualcomm, 2019). The alignment of both the transmitter and receiver coils is an important component of maximising transfer efficiency; this is more achievable when considering a static scenario as opposed to dynamic situations. The ability for a driver to track their vehicle to the middle of a highway lane has been assessed in a study undertaken by TRL (Naberezhnykh, et al., 2014). It was recognised that drivers lateral lane alignment deviates at ±0.15m with drivers showing a tendency to drive slightly to the left of the lane centre by 0.108m. Drivers spent less than 14% of the driving duration within

±0.05m of the lane centre. Further analysis is required within this area, driver aides, feedback systems and differing levels of automation are possible methods to improve lateral lane, and coil, alignment. As increasing levels of ITS are integrated into vehicles and road infrastructure, this will make such scenarios more achievable.

The vehicle's SOC will influence driving behaviour, through both route choice, average transit speeds, acceleration and deceleration rates, as well as vehicle headways. All of which have an influence on energy consumption, and thus can be varied to give better or worse energy consumption given the vehicle's SOC. For example, if the vehicle is fully charged and the trip distance is very little compared to the vehicle range, energy consumption is not a primary concern, thus the vehicle can be driven less economically. Vice versa, if the SOC is nearing depletion, then the driver may change their driving behaviour and route choice to optimise energy consumption; transferring to an eco-driving state.

With respect to existing attempts of modelling EV driver behaviour. Yeap and Tran (2019) investigated the relationship between the battery discharge rate of an EV and different driving parameters; specifically, SOC, vehicle speed, throttle position, brake pressure and motor speed. The study observed that there is a link between the five parameters and the ability to estimate battery discharge rate through a regression model. Whilst the study investigated such aspects and their influence on battery discharge, the study used data from a single instrumented EV travelling a control route, and focused more on the impacts of driver behaviour rather than what that behaviour is. Chen, Sun, Li and Shi (2019) also investigated the relationship between driving behaviour and energy consumption, they trained a neural network with data from one hundred EVs over the course of a year. Their study again focused more on the impacts of behaviour as opposed to the types of behaviour.

Vatanparvar and colleagues (2019) proposed a novel approach to driver behaviour modelling using and consequently training an artificial neural network with historical behaviour data, recent reactions to driving conditions and average speeds of the route. A battery dependent behaviour was developed that is capable of considering the state of the EV and vary driving behaviour dependent upon such factors. However, such a model was trained based upon just three different drivers and their respective driving behaviour. Whilst, it is capable of learning their behaviour with minimal estimation error (12%), it is solely based upon the three driver's specific behaviour. Thus, will not represent the wider population nor does it investigate the type of EV behaviour traits that should be compensated within traffic models.

He, Huang, Yang and Tang (2017) proposed a car following model that considers EV driving behaviour in a network featuring WPT charging lanes. Yet, was based upon a large number of assumptions and specific driving behaviour. It did not investigate the type of behaviour that would be witnessed, and instead stated what the EV driver will do. Li and colleagues (2018) proposed a vehicle behaviour model for EVs based upon the Intelligent Driver Model (IDM). The results indicated that vehicles with a low SOC had a higher longitudinal crash risk due the EV drivers randomness and incompliance. Yet, such a model only assessed the longitudinal safety and did not consider the lane change behaviour, how EV drivers would enter and exit the charging lane. Li and colleagues (2018) recognise that how this lane change behaviour could be captured would be a worthy subject of further research.

3.4.3 Comparable Research Streams

It is questionable how well EV driver behaviour is currently understood, it is however clear that it is a complex issue. Yet, from previous reviews it is apparent that they have differing behaviour to ICEVs. In that there is a tendency for EV drivers to drive more economically (Rolim, et al., 2012) (Kolbenstvedt, 2015), have differing acceleration/deceleration profiles (Helmbrecht, et al., 2014) (Labeye, et al., 2016) and will typically have different route choice considering the need for recharging (Jing, et al., 2016). Whilst little research has concentrated on the driver behavioural element of the WPT charging process, similar work can be used to explore the kind of behaviours that may be present, and the ways in which they may influence traffic flow conditions.

A good analogy of a driver’s behaviour, especially choice of transit speed, is fuel consumption. A faster vehicle will consume a higher rate of fuel per unit of time, yet it will consume it for a shorter amount of time overall when compared to a slower vehicle undertaking the same trip. Therefore, much like fossil fuel vehicles, there is an optimum speed a vehicle can travel at to optimise fuel, or energy, consumption. Yet, is dependent upon the particular route, vehicle design, energy consumption, trip distance, as well as driver choice.

At first, it is unlikely that dynamic WPT systems will be deployed over multiple lanes of the carriageway, instead there will be predominately single lane charging. Therefore, it becomes necessary for the driver to stay within the charging lane to utilise the charging system. Whilst this behaviour cannot be accurately determined, a comparative measure would be to explore the consequential impact on traffic flow (and charging) for lane changes. Laval and Daganzo (2006) demonstrate that lane changes conducted by slower than average vehicles have a negative effect on traffic flow, in effect acting as a moving bottleneck until they are able to accelerate to the prevailing destination lane speed. The impact of a HGV completing an overtake manoeuvre is significantly longer than a car or other LGV, this has been shown to have a detrimental effect to surrounding traffic flow (TRL, 2010). Whether such overtake operations will be undertaken if the vehicle has to leave the charging zone is a further question. Further, lane restrictions, where vehicles cannot carry out lane changes, have been shown to improve flow characteristics and improve safety (Davis, 2012) (Sarvi, et al., 2003).

Speed variation is a further aspect that should be considered, minimising the variation across vehicle speeds on the same roadway will reduce the likelihood of unsafe stop/go traffic conditions being experienced (Marchesini & Weijermars, 2010). Choudhary and colleagues (2018) have demonstrated the safety aspects in speed variation, it is far safer to have traffic flow with a smaller range in upper and lower speed bounds, when compared to a flow with a significant range in vehicle speeds. Variable speed limit enforcements have been shown to reduce the crash potential during risky traffic conditions (Lee, et al., 2006), primarily through reducing the speed variation between vehicles (Allaby, et al., 2007). Comparable research also includes cruise control systems, and their effect on traffic flow characteristics. Adaptive Cruise Control (ACC) systems have been shown to improve traffic flow conditions and supress motorway traffic jams when a 20% concentration of ACC vehicles exist (Davis, 2004). In addition, transportation is moving further towards a more connected network. Cooperative Adaptive Cruise Control (CACC) is a system which adds V2V communication. Such a system has been shown to have positive effects on traffic flow, largely by increasing vehicle throughput (Arem, et al., 2006) and by increasing road capacity (Shladover, et al., 2012). It could be argued that a WPT charging system could be a segregated form of CACC, where vehicle speeds in the charging lane are controlled based upon input from surrounding vehicles. Alternatively, existing vehicle lane keeping technology should be assessed to understand its abilities to track the lane accurately. Whether this is within ideal WPT lateral alignment must be first understood before methods in which alignment can be improved investigated.

Eco-driving is another similar source of information, EV drivers have been shown to drive more economically, and as such, some behaviour traits can be similar to eco-drivers. McIlroy and Stanton (2015) describe some distinct driving behaviours that eco-drivers tend to follow. This includes smoother and earlier vehicle deceleration, when considering a change to a lower speed, for a road curvature, or when a vehicle stop is possible. Smoother and less harsh acceleration, either from a standstill or when increasing from a lower to higher speed. As well as maintaining a larger vehicle headway to aide in early responses for upcoming events.

It seems prudent to assume vehicles within the charging lane should be constrained in vehicle speed, most likely maximum speed, and follow a similar form of CACC systems in which V2V communication is implemented to see the same benefits of CACC traffic flow conditions. This assumption appears likely considering the ever-developing connected transportation network and implementation of autonomous systems. Thus, fixing charging lane speeds to a series of constant values appears a worthy subject of investigation within the traffic model.

3.4.4 Expected Behaviour Changes

Within the traffic model, driver behaviour is represented by underlying mathematical algorithms, this section outlines the expected behaviour changes when considering the dynamic WPT charging situation. It is important to note, whilst the behavioural implications have been discussed and reviewed at great length, this thesis has not been able to quantify such aspects. They are in themselves a significant body of work, of which would require extensive behavioural studies to at the least begin to understand such aspects. For example, a combination of experimental studies, on road testing and surveys could be used. However, such topics cannot be captured by a stated preference survey, current EV owners are considered early adopters and the behaviour will vary between this sample and the overall population. Further, asking individuals how people think they will use or act with a technology that is not available, and most will not have heard of, will be significantly unreliable. Whereas, driving studies will require extensive analysis of driving data and hypothesis' surrounding such behaviour to attempt to infer driver behaviour traits. The extent of the problem begins to be revealed.

Therefore, this behaviour discussion concludes by summarising the expected changes in driver behaviour when considering the dynamic WPT charging scenario. Thus, expected changes in driver behaviour, when considering a WPT, can be summarised as:

- Lane choice (desired lane)
- Lane positioning (alignment within the lane)
- Lane changing (suppression of lane changing)
- Vehicle headway (vehicle following gap)
- Vehicle speed (desired and variability)
- Situation awareness
- Route choice

The car following model determines vehicle headways, this can be influenced by reducing the driver reaction time or sensitivity factor, thus reducing the following headways; or vice versa, such headways can be increased by increasing the time it takes for the driver to react. The homogenisation of vehicle speed within the charging lane is a likely scenario, this will improve the systems operation and ensure that vehicles do not travel at a speed that exceeds the technologies capabilities. Headways will be more consistent ensuring the power electronics are able to maintain their switching capabilities. Whilst there will be a technical minimum vehicle headway that the WPT power electronics will be capable of switching coils at, this may not correlate to actual driver headways. A slower moving vehicle will receive more power than a faster vehicle given the same power transfer rates per unit of time, thus it could be argued that a charging lane may have a maximum speed limit imposed to ensure sufficient energy transfer. Dependent upon the technologies capabilities this may be below the speed limit of the carriageway. Furthermore, it is not realistic to assume that if given such a charging speed limit, that all vehicles will travel at 60 mph when charging, instead a charging speed bound of between 50 and 60 mph may be more realistic. Thus, drivers within the charging lane will fluctuate within this range of vehicle speed, as they do for normal driving with a carriageway speed limit. Hence, speed choice consists of a driver's desired speed and the variability of that speed. Alternatively, an automated system may see all vehicles travelling at the exact speed the system desires; such explicit control of vehicle speeds may be detrimental to traffic flow dynamics. Ultimately, a number of different charging speeds will be modelled to assess the sensitivity of the charging lane speed limit. Such values were fixed by adjusting the drivers desired speed values. Whilst in free flow traffic they will be able to reach such a speed, congestion of the network or charging lane will ultimately reduce such speeds witnessed.

Whilst there are a large array of parameters that can be manipulated to adapt lane change behaviour, the focus of this work centres on three expected changes in behaviour; lane choice, lane positioning and lane changing. When considering lane choice, in order to use the charging lane the driver must be driving in the lane with the charging infrastructure. This creates further questions over which lane should be equipped, if multiple lanes are needed, and what the lane choice behaviour of the non-equipped vehicles will be. Yet, lane choice can simply be a global rule that if the vehicle is to use the charging system then they will move to the necessary charging lane. A variety of charging lane locations will be modelled; lane specific as well as segregated and integrated. Lane positioning, notably the lateral lane positioning, will greatly affect the energy transfer efficiency. Yet, it is not a traffic behaviour element, instead an energy consideration that must be compensated for within the latter energy model. However, there are some behavioural impacts that could be considered surrounding lateral lane positioning; impact to situation awareness, driver workload, or indeed road surface degradation of vehicles attempting to track to the centre of a carriageway lane. Alternatively, the charging system may just terminate the charging process when the efficiency reduces beyond a lower bound, thus the driver is unaware (and not required) to specifically control lateral lane alignment. Finally, lane changing, WPT users may have a suppression in their lane change behaviour due to the choice to utilise the charging system in the charging lane they are travelling in. If the technology was deployed, or expanded in the future, to multiple lanes then lane changing may revert back to more normal driving conditions.

It is questionable as to the extent that additional driver requirements of lane control, speed keeping and general driver behaviour will have on situation awareness. Whilst some will become more aware of the surrounding environment in a WPT charging situation, many may become less aware due to the need to undertake additional driving tasks. Either way, it is expected that the driving task will be more demanding when considering a WPT charging situation; unless automation of the driving task, or sub-parts, is possible. Driver distraction, demand or situation awareness within a WPT charging scenario is in itself a separate body of work.

Typically, a driver's discretionary lane change decision is an attempt to improve their perceived driving condition, a higher transit speed is just one attribute that will increase the perceived utility of a neighbouring lane. However, the introduction of WPT charging lanes blurs the initial lane change decision and thus lane change models. An economic social forces model would be required to estimate the drivers perceived utility of remaining within the charging lane or changing lanes to overtake a slow vehicle. Such a model would require an extensive amount of input data; for example, vehicle speeds, road conditions, vehicles in the neighbouring lane, the time taken to execute the lane change, the route choice, the destination centroid, the rate of energy transfer, the vehicles SOC, the vehicles average energy consumption, the remaining trip distance. These are just some of the key parameters, thus highlighting the extent of the problem. In addition to this, the driver's willingness to stay in the lane is dependent upon the rate that they are paying to use the WPT system, thus economic elasticities. The development of such a model is unrealistic due to inevitable inaccuracies in the input parameters, thus a simplified method of constraining lane choice and change behaviour is considered sufficient for this study.

To summarise, there was a need to further understand the behavioural aspects of the WPT charging situation, it cannot be inferred that driver behaviour will remain constant given this new technology. Whilst literature generally acknowledges that there are behaviour differences between EV drivers and ICEV drivers, little work has been carried out to quantify such aspects. Definitive definition of EV or WPT driver behaviour is not attainable. Significant work is required in this field to begin to understand, and eventually quantify, such behavioural aspects. Without such advances in driver behaviour modelling, the underlying behavioural models must be deemed sufficiently accurate for the purposes of this research. It was however essential to discuss the behavioural aspects of the WPT situation.

3.5 Modelling of EV Charging Systems

This section reviews the existing work undertaken concerning the modelling of charging systems for EVs; specifically, static and WPT based systems.

3.5.1 Static Based Charging Systems

For EV’s, charging stations are a necessity, therefore they are either integrated into the users existing route or are new destinations; hence these stations are typically represented within models in the form of additional nodes. A review undertaken by Shareef, Islam and Mohamed (2016) identified that charging station locations can be optimised in one of three ways; through economic benefit analysis, based upon power grid impact or through EV route choice. Negating all other financial and physicality based constraints, the distance between charging nodes must be less than the EV range or preferably 80% of the range; Kolbenstvedt (2015) states that 85% of users are comfortable using 80% of battery capacity before recharging. A further study assessing the distribution and demand for interurban charging systems found that investment into such infrastructure is necessary to alleviate range anxiety (Xie, et al., 2018). He, Kockelman and Perrine (2019) proposed that a minimum EV range of 100 miles was necessary for the majority of US households to avoid range issues when completing long distance interurban trips.

An alternative approach to the distribution of charging systems was proposed by He, Yang, Tang and Huang (2018); their method used a bi-level mathematical model. The upper level focused on optimising the charging station location and flow rates, while the lower level covered users route choice and vehicle driving range equilibrium. This approach had good merit when applied on a test network, and emphasised that EV range had a significant influence on optimal charger location. The optimisation of static based charging systems is complicated by the large array of vehicle types, battery capacities and driving range. The system can only be optimised to a specific vehicle range, anything beyond or below such a range will inevitably see inefficiencies of system design at best, or at worst result in an unusable system for a proportion of EV users due to an unbalance between EV range and the distance between charging stations.

This dependency on vehicle design is further reinforced by a recent study assessing the current and future requirement of fast charging infrastructure (Gnann, et al., 2018). The authors developed a model to estimate the number of public fast charging stations required per thousand EVs. It was identified that charging infrastructure is highly dependent upon battery capacity and charging power rates; both of which may increase in the future. If such factors do continue to increase, the ratio of vehicle to charging points could be similar to the ratio seen for ICEVs and refuelling stations in the future. This would be a single 150 kW public charging station per one thousand EVs.

Other approaches to optimisation include the study conducted by Ge, Feng and Liu (2011), which was one of many to use a Genetic algorithm aimed to minimise transportation costs on the way to the charging station, whilst considering traffic density and charging station capacity constraints.

Yet, it did not consider cost functions to the model. The study conducted by Huang, et al (2016) optimises the network distribution of both slow and fast chargers, ensuring even coverage of both types of chargers and eliminating inefficient overlap of services. A further study (Lam, et al., 2014) focused on human factors rather than technological aspects for charging station placement, so distribution was based more upon driver convenience. In order to minimise travel time, EV drivers will prioritise route choice based upon the use of faster chargers closer to the origin of the route trip and being in the relative direction of desired travel (Yang, et al., 2015).

While future proportions of home charging (Mode 1 and 2) users are unknown, and should not be scaled from current levels at a high EV penetration scenario, it is expected to be a key component providing both a convenient and low cost method of charging. Most modelling studies assess the network distribution of fast charging systems (Mode 3 and 4), assuming that slow charging will be undertaken at home.

3.5.2 WPT Based Charging Systems

The majority of modelling and simulation work previously undertaken focuses upon the technological aspects of WPT charging systems; such as the way in which electrical energy is transferred, the methods in which efficiency can be improved and the safety considerations of such technology. This section summarises some of the notable work carried out in modelling of WPT charging systems within the traffic domain.

Abedin and Waraich (2014) successfully modelled different WPT scenarios within MATSim. Rather than focus on location, their aim was to identify the capabilities of the technology. Generally, they found that across these scenarios battery capacities could be reduced by up to 40% when WPT systems are installed into 20% of the road infrastructure. Further, Musavi and Eberle (2014) found that battery capacities could be reduced to just 20% when optimising both vehicle and WPT infrastructure design in parallel.

The study conducted by Deflorio and colleagues (2015), modelled the fitment of WPT charging system within the slow lane of the motorway. The authors used a mesoscopic approach to model single vehicle trajectories that were used to calculate energy information based upon their underlying technology and efficiency consumptions. A further approach by Deflorio and Castello (2015) focused on the use of WPT systems for freight vehicles travelling between urban distribution centres. Interestingly, the model set transit speeds based upon the vehicles SOC and hence route choice based upon required energy. One further mesoscopic study by Deflorio and Castello (2017) continues on their prior work and developed a basic kinematic energy consumption model. Yet, it only considered a limited range of WPT factors and applied only basic numerical traffic modelling, with a limited number of vehicles and specific routing.

Rather than simulation based efforts, Chen, He and Yin (2016) demonstrated a strictly numerical approach to the optimal deployment of dynamic WPT systems. A number of their assumptions are particular relevant; firstly, they separate links between regular and charging links with charging lanes being represented as additional links for clarity of the model. Secondly, the cost of electricity is insignificant against the travel time cost to the user; hence drivers are expected to minimise travel time whilst ensuring sufficient EV charge. Finally, they envision that a minimum and maximum charging speed limit will be imposed, leaving the decision with the driver to choose the exact vehicle speed. This should be optimised against WPT technology in order to maximise efficiency but a slower vehicle will receive more energy due to the extended period it spends within the charging zone as energy transfer is proportional to the transfer time period. However, a feasible minimum vehicle speed, given the type of road, is unknown and something that should be investigated.

The study by Xie and Huang (2016) proposed a WPT charging system along a 72 mile corridor, the authors developed models for optimum deployment locations as well as energy consumption and transfer. Yet, simplified the models, used fixed vehicle speeds, did not consider actual traffic flows, or include existing vehicles in the network.

A further mathematical modelling approach was used to determine a network configuration that ensures all EV drivers achieve the destination origin with a battery SOC above a certain threshold (Ushijima-Mwesigwa, et al., 2017). The approach was expanded to model using a fixed budget and attempted to minimise the number of infeasible routes. This methodology was applied with good success to both test networks as well as the Manhattan network in theory.

Liu and Song (2018) focused on developing a user equilibrium model for electric freight vehicles, the study aimed to determine optimal charging lane locations for vehicles travelling between distribution hubs. However, emphasis was placed upon the user minimising travel costs through route choice and fuel costs, with all energy consumption rate values being considered constant throughout the model.

He, Yang, Huang and Tang (2018) developed a modified energy model to investigate the effects of WPT charging lanes on travel time and energy consumption. The authors note that unlike ICEVs, where fuel consumption of such vehicles has been modelled to great extent, the modelling of EV energy consumption has received little analysis. However, they modified an energy model so that the output value was calibrated to the EPA’s value of Miles Per Gallon Equivalent (MPGe) for the given vehicle. This unit is not scientifically accurate as it is based upon an overly simplified conversion factor of heat energy from petrol, and then aggregated to electricity requirements to produce the same amount of heat energy. Further expansion of this issue is discussed within the next section. In addition, the study was very limited in its application using an arbitrary three kilometre straight road with almost singular traffic dynamics.

A further macroscopic modelling approach was proposed by Emre and colleagues (2018), the development of a kinematic energy model was the focus of the paper and demonstrated its use on an arbitrary 330km route. Yet, the study only focused on a single EV, over a single route, and at several fixed vehicle speeds.

Continuing on their prior work, He, Yang, Tang and Huang (2020) developed a WPT charging lane location model, the authors proposed a linearization modelling approach to optimise WPT locations. Yet, such a model is strictly numerical, considered only limited influential factors, used a very simplified energy consumption rate, and generally focused more on the higher macroscopic issues. Using inputs such as cost and vehicle charge per km to the model, rather than investigating such factors. However, they also introduced the idea that EV drivers utilising the WPT charging lane may drive slower than expected to get sufficient charge time. They suggest that WPT charging lanes may have an adverse effect on route choice behaviour and travel time.

A further modelling aspect is the effect the charging process has upon the electricity grid; depending on the power transfer capabilities of the charging station, this has varying effects. Karakitsios, Karfopoulos and Hatziargyriouet (2016) identify such issues and how the application of charging technology is expected to be within urban environments, further increasing network capacity issues. Whilst minimal work has been undertaken to simulate peak and cumulative electricity demand, Karakitsios, Karfopoulos and Hatziargyriouet (2016) model to some extent both static and dynamic fast charging scenarios. The resultant data can be extrapolated further to inspect the strength of the electricity grid given the optimised distribution of charging stations and specified WPT technology. The study conducted by Debnath, Foote and Onar (2018) was purely an assessment of the electricity grid, considering the requirements and impact of supporting dynamic WPT charging systems. They concluded that a combination of smart control and energy storage, or a parallel DC distribution grid is necessary to maintain grid stability.

Generally, studies either focused on the higher macroscopic level, the modelling of electrical energy, or did not consider real traffic flows, ICEVs, existing traffic, or were simplified in one area of their approach. The realistic modelling of WPT charging lanes with respect to how the systems are utilised, the network deployment strategies and the resulting impact to existing traffic conditions has yet received little analysis.

3.6 The Problems with Modelling Energy

When considering the energy criterion of WPT modelling, energy transfer can be derived from the length of the charging zone, rate of power transfer and the speed of the vehicle (see Figure 7). Yet, this is not representative of a real world dynamic WPT scenario. The cumulative power transfer over the charging zone is mathematically derived as a straight line, as $time = \mathrm{distance/speed}$ and both power and vehicle speed are constants. The influential factors documented within Section 2.3.1 – Dynamic Charging Infrastructure will ultimately affect possible energy transfer. The curves shown in could be considered upper limits, energy transfer cannot go above such technical limits and every influential factor (i.e. lane alignment, speed variation) will further reduce such energy transfer.

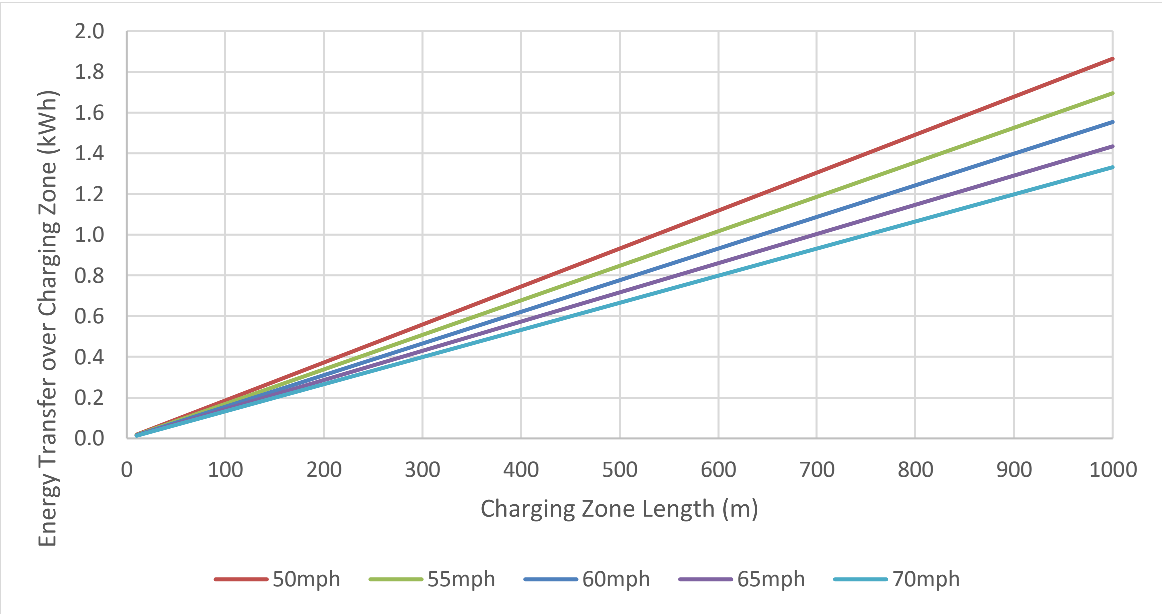


Figure 7 – Energy Transfer over Charging Zone (Power 150kW, Speed Varying)

Thus, energy transfer, and in turn energy consumption and emission generation, must be calculated using instantaneous vehicle information in order for realistic values to be obtained. Alongside transit speed, the vehicles rate of acceleration and road gradient are significant factors that influence energy consumption. Whereas, WPT specifications in culmination with traffic model factors will determine actual energy transfer. This demonstrates the need for a model which will use instantaneous vehicle information from the traffic simulation to calculate realistic energy consumption, WPT energy supply, and emission values.

It is important to consider that there are fundamental differences between the calculation of energy consumption and emission values between electric and ICE vehicles. A conversion factor cannot simply be applied, the issue is far too complex for that. Whilst there are many notable fuel consumption and emission production models for ICEVs (Zhou, et al., 2016), only a limited number of studies have been undertaken for modelling EV energy consumption (He, et al., 2018). Further, there is not a model that considers both electric and fossil fuel consumption in combination. Whilst AIMSUN is capable of outputting both fuel consumption and emission values over a particular road link, the accuracy of such models within commercial traffic simulation packages is somewhat questionable as such models are based around rates of fuel consumption at specific vehicle speeds. Therefore, there is a need to develop a more realistic energy/fuel consumption model for both EV and ICEVs.

Several methodologies exist, some research (Howey, et al., 2011) (Lorf, et al., 2013) has directly compared fossil fuelled vehicles to AFVs in terms of energy consumption and pollution aspects. These studies use data obtained from the RAC London to Brighton Future Car 2010/11 events, where the energy consumption of fuel efficient vehicles were measured as they drove over a 57 mile route. The 2010 event saw average energy consumption values of EVs 0.62MJ/km, HEVs 1.14 MJ/km, ICEVs 1.68MJ/km and HFEV 1.2 MJ/km (Howey, et al., 2011). Yet this is real world data, a very small sample of vehicles over a single route, has a degree of error considering it has been normalised to MJ/km, and was undertaken some time ago; newer technologies now exist so such data is not representative of current, or potentially future, vehicle capabilities.

As previously stated, a conversion factor cannot simply be applied, albeit one actually existing. The Environmental Protection Agency (EPA) initiated the Miles Per Gallon Equivalent (MPGe) unit to demonstrate the equivalent fuel consumption of electric and hybrid vehicles when compared to fossil fuelled vehicles. Its purpose is to demonstrate the fuel economy of an EV in a unit that is familiar to most people. However, to obtain an MPGe value, an overly simplified calculation is used. In terms of heat energy, 1 gallon of petrol is equivalent to 115,000 BTU, to get the same amount of heat from electricity, 33.7 kWh is required. Thus, 1 gallon of petrol is equivalent to 33.7 kWh of electricity. So, if an EV could travel 100 miles on 33.7 kWh, then it would have an equivalent fuel economy rating of 100 MPGe. Whilst such a unit is good for broadly comparing the fuel economy between EVs, it is not scientifically accurate for comparing fuel economy between EV and ICEVs due to its oversimplified conversion.

Rather than attempting to convert EV energy consumption to a fossil fuel consumption, or vice versa, something that is clearly not simple nor accurate, an alternative methodology would be to calculate consumption independently. The approach taken by the G-Active project (Fleming, 2018) (Yan, 2018) was to fit engine data, collected from a vehicle data logger, to a series of curves based on engine force and vehicle speed in order to calculate fuel consumption. Yet, this method is reliant upon the accuracy of fitting the data and, as it is real world data, is dependent upon the particular drive cycle, road conditions and vehicle; thus, is not considered transferrable. A more theoretical approach is needed to ensure that future vehicle technologies and capabilities can be considered, rather than relying on data obtained through real world driving conditions.

Fuel consumption can be calculated using kinematic equations, in the form of standalone fuel consumption models. An extensive review undertaken by Zhou, Jin and Wang (2016) classifies such models into white, grey and black box categories in terms of their transparency. White box models use an engines physical and chemical processes to calculate fuel consumption, thus require a detailed understanding of the system. While black box models consider either the entire vehicle, its engine, or a hybrid of the two, as a black box and as such lack any physics in their calculation, instead relying upon the input and output of data to the system. Typically, fuel consumption rates at given vehicle speeds are used to calculate total consumption, AIMSUN's built in fuel consumption model operates as such (Akcelic, 1982). Alternatively, models like VeTESS developed by Pelkman and colleagues (2004) are considered grey box models, they require a partial understanding of the internal system, and as such lie between white and grey models. Whilst the depth of a black box model is not necessary, the lack of detail in the white box models creates a too general model. Further, very few models consider the fuel consumption of an EV; the key component of this study. Therefore, a grey box model is required that is capable of considering both electric and ICE vehicles.

3.7 Chapter Conclusions

The chapter began by justifying the modelling approach used, it was clear that a tool was needed that enabled theoretical testing of WPT systems from a predominantly traffic viewpoint. This was identified as the current gap in knowledge, how such charging systems would be implemented and utilised within the road network. Through the review of WPT technology, a large array of influential factors and modelling inputs related to the dynamic charging situation were summarised in Table 4 – Model Requirement Specification. Relevant traffic modelling packages were assessed for their suitability on the basis of this specification, and ultimately, AIMSUN was identified as the most suitable package.

It was identified that the behavioural aspects related to the dynamic WPT charging situation were an important modelling consideration and required further investigation. It was however clear that definitive definition of such behaviour was a significant body of work in itself and beyond the scope of this study. Yet, a clear discussion of the expected behavioural differences given the WPT situation were presented. It was an important aspect to consider, yet given no other alternative, for the purposes of this research the underlying driver behaviour models were deemed sufficient.

Finally, literature was reviewed to assess different techniques and approaches undertaken in modelling EV charging and EV/ICEV energy consumption. It was identified that a grey box model seems most appropriate, and at the very basic level a series of kinematic equations forming the base vehicle energy consumption rates. Before which, a series of electrical and fossil fuel equations used to determine actual EV and ICEV energy consumption respectively.

Now that a comprehensive understanding of both WPT and traffic modelling aspects has been gained, the subsequent Research Methodology chapter will outline the various approaches taken with regards to the aim of this project; to investigate the issues related with transitioning Dynamic Wireless Power Transfer systems for Electric Vehicles from technical demonstrators to full scale deployments.

Chapter 4 Research Methodology

4.1 Introduction

This chapter serves to explain and justify the methods applied to this research project. As identified within the prior review chapters, the gap in knowledge exists within the traffic domain. Specifically, how such WPT charging systems will be deployed, utilised and function within the road network. Therefore, without commitment to physical infrastructure, a purely theoretical approach is needed. A methodology flowchart with a clear indication of steps is presented below, followed by the discussion and justification of the methods selected.

4.2 Research Framework

There is first a need to justify the adoption of a modelling approach. Given the application of such a study, WPT systems are profoundly within the research and development stage with little real world applications as yet. Thus, an appropriate approach would be a theoretical based study. It would not be feasible to implement such systems to the real world without prior optimisation of deployment scenarios within the theoretical domain. Hence, the development and simulation of a traffic model is necessary to facilitate the testing of various scenarios, technologies and behavioural elements; beyond commitment to physical infrastructure. Such a study can investigate the detailed interaction of users within the traffic network, as well as quantify the optimisation of deployment scenarios, environmental and user benefits.

The research methodology flow chart is presented in . The key stages of work are contained within boxes: Review, Theoretical Models, Microscopic Simulation and Macroscopic Simulation. Within these stages, key components of research are shown alongside associated sub tasks or investigation areas. Finally, output results and findings of such tasks are shown as moving between boxes where appropriate.

The methodology begins at the initial WPT review; where factors such as EV fundamentals, charging methods, WPT infrastructure requirements and current WPT capabilities are considered. This was a widespread review not limited to just standard literature but also included a lot of technical elements from system manufacturers and developers. From this review, the research gap was identified as a traffic related issue, thus a secondary review of traffic related elements was undertaken. The traffic review considered aspects related to driver behaviour, EV modelling, energy modelling, as well as presenting a model requirements specification and a review of suitable

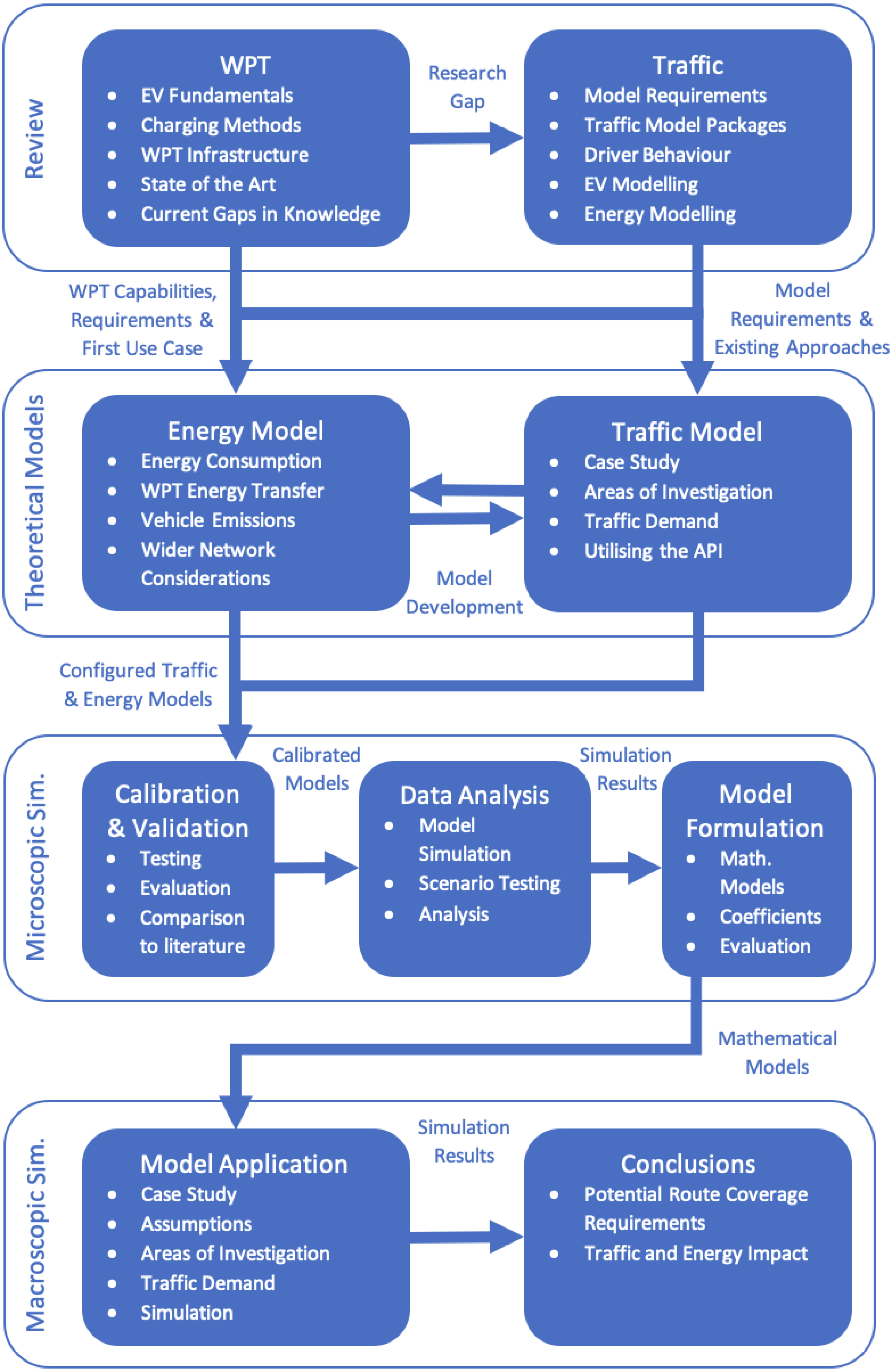


Figure 8 - Research Methodology Flow Chart

modelling packages. Several key bits of information are taken from the reviews. Firstly, the current WPT capabilities, requirements and first use cases are taken from the WPT review. While, the model requirements specification and literature of existing modelling approaches are taken from the traffic review. This information is used within the next stage of work, the theoretical models.

Both a traffic and energy model are proposed and developed in conjunction with one another. The traffic model specifies and justifies the selected case study, areas of investigation, traffic demand and configuration. Whilst the energy model focuses on four main aspects, energy consumption, WPT energy transfer, vehicle emissions and wider network considerations. The purpose of these models is to capture the detailed micro interactions of users, system technicalities, as well as energy and environmental aspects related to the WPT charging situation. Thus, the modelling work commences at the microscopic level.

Whilst a traffic model can be developed purely mathematically or analytically, commercially available traffic simulations packages are highly capable tools that enable the development of a model within a graphical user interface. Whilst no existing package considers WPT systems, many offer an API that can be used to integrate such additional functionality. Therefore, allowing a separate energy model to be developed and integrated with the traffic model.

A review of existing modelling work identified the common approach of using a base level of kinematic equations to calculate vehicle energy usage. From which a series of ICE and electrical equations are proposed to understand and calculate the energy conversions, consumption rates and emission factors. In addition to this, WPT charging functionality will be added to the energy model in order to investigate the impacts of such a dynamic charging situation. Thus, existing modelling approaches will be further developed and expanded from such kinematic equations to result in an energy model that considers a wider range of aspects at a greater level of accuracy.

At a more general level, the development of a realistic modelling environment is dependent upon the input variables to the model. The models must be able to consider a mix of vehicles with varying proportions, from an initially small EV population to expected levels of growth. They must consider the behavioural aspects of the drivers; both on a dynamic WPT user level, as well as existing road users encountering vehicles charging dynamically. The underlying system parameters, coil types, dimensions and headways, as well as the power electronics infrastructure must be considered. All of which are key components in developing the realism of the model, in which further scenarios and variables can be adjusted to analyse the effects of WPT charging systems.

Moving to the microscopic simulation section of work, it is important the models are first calibrated and validated to ensure they produce both realistic and accurate results. The energy consumption rates, emission values as well as WPT transfer capabilities from the models will be compared to literature to understand if they are producing realistic results. Such literature will include prior kinematic based modelling studies, real world vehicle use data, and WPT charging system data. Once the models have been established as producing realistic and accurate results, the various scenarios will be simulated and initial exploratory data analysis undertaken. This initial analysis will aim to understand any themes or things that are occurring within the data, again ensuring any expected patterns or behaviours are occurring where appropriate. For example, when limiting charging lane speeds, does the average speeds of EV's reduce accordingly.

With respect to further analysing the simulation results. When attempting to identify methods which quantify the impact of explanatory variables on an end result variable, it is considered that these variables may well act with a main effect and also with interactive effects within a cause and effect relationship. Therefore, there are only two approaches. Firstly, to make assumptions to predefine the form of the equation and then attempt to calibrate the parameters within that equation. Secondly, to have no prior assumption of functional form (i.e. a neural network/black box approach) to apply the data and see what comes out. The prior defining of functional form is by far the best way if it works. As these are fundamentally a predictable relationship of kinematic equations with no human psychology it is expected that the functional form be formulated to allow flexibility. Then an Analysis of Variance (ANOVA) approach with variable selection will allow that functional form to be refined down to its parsimonious nature using as few bits as possible. It is expected that because an understanding of the basic kinematic and functional aspects of the model is known (i.e. they are all linear equations) it is anticipated that the end result will also form, albeit a somewhat more complicated but fundamentally, linear relationship. Therefore, this will be the first approach. However, if this does not produce a reasonable level of fit then more freeform approaches such as neural networks will be considered allowing for wider range of functional forms.

The final results of this thesis are expected to form a series of mathematical models defining energy consumption, energy transfer and vehicle emissions. Such models will allow a user to apply their own WPT scenario factors and determine resultant energy and emission factors without commitment to extensive microscopic modelling work. However, to go one step further it is hoped that these models will be applied at a higher macroscopic level assessing WPT charging at the SRN level. In order to do so a number of limitations and assumptions will be present, yet such a study will form a first look into the required infrastructure route coverage to fulfil certain end of route scenarios.

With respect to the limitations of this methodology, as with any model, it is heavily reliant upon the underlying assumptions and input data. Due to the nature of this unestablished, unproven and untested technology (beyond prototype systems), a large number of behavioural and simplifying assumptions are necessary. Further, the accuracy of the calibration and validation process is essential given that this will result in a model that is firstly, realistic of existing traffic conditions and secondly, realistic of future unknown conditions. The rate of technological development of WPT systems is significant, thus specific WPT specifications are very much uncertain, and subject to likely future advancement. Yet, the development of the tools described within this framework will enable testing of a variety of WPT specifications, as well as latter testing if further data becomes available beyond this thesis.

4.3 Chapter Conclusions

The research methodology, alongside justification and limitations of such methods, has been presented within this chapter. The flow chart presented in clearly shows the various components of work, the different steps required, as well as the flow of data and information between such tasks. The next step of the research framework is to begin to develop the traffic model, which is documented within the subsequent chapter.

Chapter 5 Traffic Modelling

5.1 Introduction

The purpose of this chapter is to document the development of a microscopic traffic model that will enable further investigation into various charging scenarios, test cases and general scaling of WPT systems within a realistic modelling environment. A case study for the microscopic modelling work is outlined and justified, as well as the various areas of investigation, data requirements, and traffic demand documented. Finally, the base model is configurated and a discussion undertaken as to how the models capabilities can be extended through external programs. This chapter documents the development of a microscopic traffic model, the energy modelling aspects of the WPT situation are to be contained in a later chapter and will be developed on the basis of the traffic model documented here.

5.2 Microscopic Case Study

The following sections outline the microscopic case study scenario; including the areas of investigation, the various traffic and vehicle data requirements, the estimation of travel demand and route choice data, and finally the base model configuration.

5.2.1 Scenario Outline

From Chapter 2, it was identified that the most likely scenario for WPT deployment are interurban freight corridors where repeatable trips are expected. While freight users appear the first use case, systems should be developed to ensure that smaller vehicles can also access such charging infrastructure. As such, the microscopic case study focuses on the road link between Southampton and Winchester, within the South of England. This case study was selected because it aligns well to the likely first use case, features a number of the influential factors previously highlighted allowing for a good level of investigation, doesn't include anything that could potentially complicate or skew the results, and will generally result in a situation that is realistic.

The route begins at the A27 and M27 junctions, before progressing northbound on the M3, finishing just North of Winchester on the A34/M3 junction; Figure 9 details this route. The Avenue road link is considered the arterial light freight route into and out of Southampton; the M271 being the main heavy freight trunk road accessed via the M27. Generally, this southern section of the M3 has a high proportion of freight transport, providing a link from Southampton to both the A34 (towards

Oxford) and continuation of the M3 (towards London); emphasising the importance of this part of the SRN.

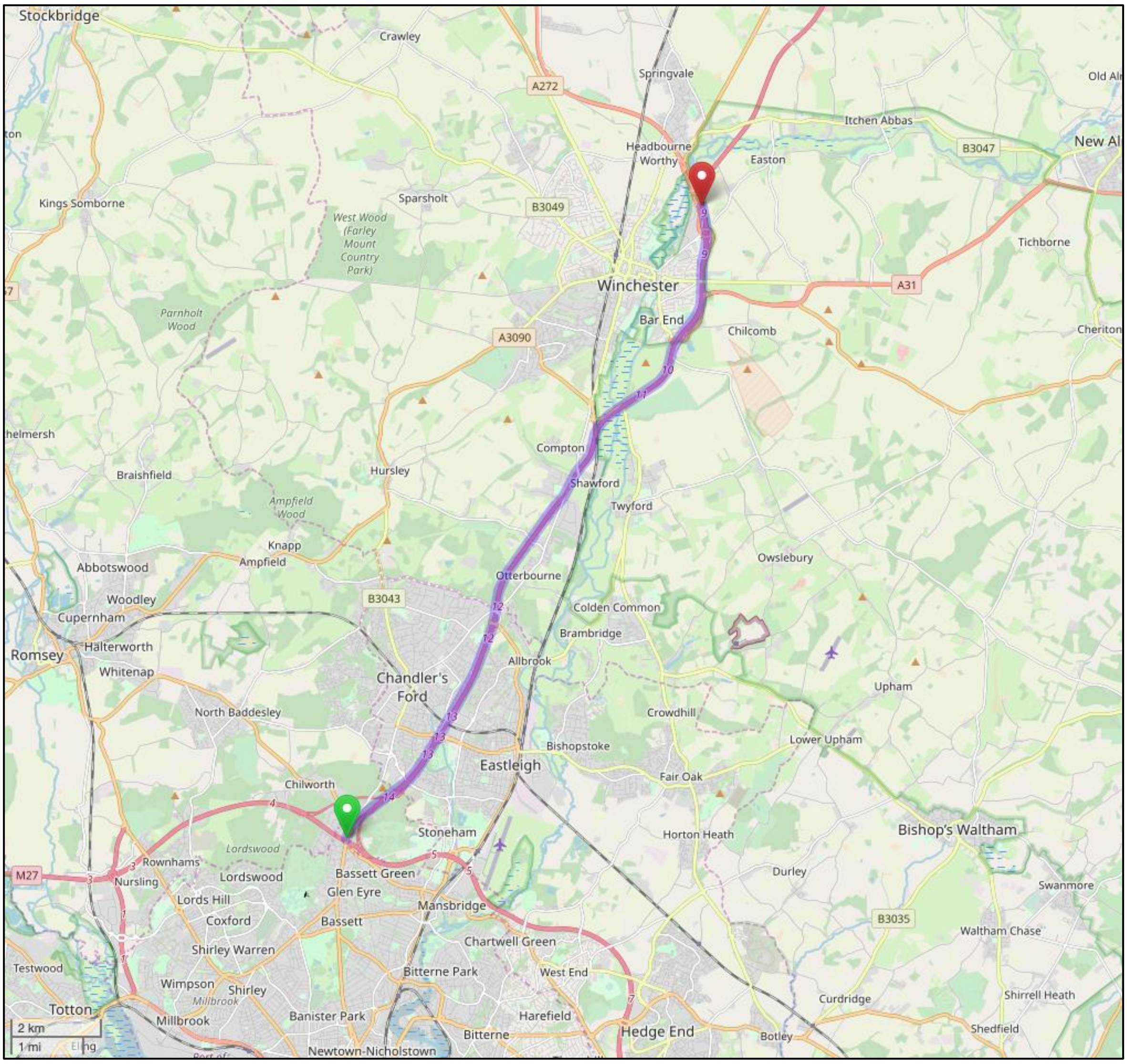


Figure 9 - Microscopic Case Study Location

5.2.2 Areas of Investigation

Two distinct areas of investigation exist; the detailed traffic element, and the energy component, of WPT charging. Whilst some layouts may be optimised for high levels of WPT efficiency, and to minimise demand placed upon the electricity grid, they may have certain undesirable effects on traffic flow dynamics. In contrast, some scenarios may have very little impact to traffic, but result in an inefficient charging situation. Whilst each can be modelled and tested as individual entities, it is the culmination of both aspects that must be understood to optimise the deployment of WPT systems.

Typical traffic modelling criteria includes aspects such as average journey time, vehicle speeds, flows and queue lengths. Whereas, the energy criteria includes charging time, coil length, coil location, power transfer, transfer efficiency, energy consumption, battery size, vehicle SOC, and potential emission factors. This produces the following list of investigation areas:

Charging location: Lane specific, segregated or integrated

Charging criteria: Fixed speed intervals, i.e. 55-70mph, as well as average link speeds

Equipped vehicles: Different user groups/classes, i.e. private, freight, varying proportions

Power transfer: Varying power levels, i.e. 25-250kW, power transfer efficiency

Energy criteria: Energy consumption, vehicle SOC, minimum battery size

Environmental: Potential point of use emission reduction

This modelling work concerns itself with the investigation of WPT systems and the various methods of deployment. Therefore, the modelling work gathers evidence on various deployment scenarios, areas of investigation, identifying and distinguishing desirable and not so desirable effects. Key results will be related to the following points, encapsulating three main areas; traffic conditions, energy criteria and environmental aspects:

Journey time: The headline travel time figure over the route

Reliability of journey time: The variation of travel time around the average, i.e. the disruption to traffic flow

Safety (Speed): The detailed variation in vehicle speed, signalling potentially unsafe traffic flow conditions, i.e. not steady state flow, stop/go traffic

Energy: Individual vehicle energy consumption, power transfer

Environmental: Individual vehicle point of use emissions

Whilst the headline travel figure will give an immediate indication towards the impact on traffic flow a particular scenario may have, the reliability of that journey time will further indicate potential disruptive effects on that traffic flow. The detailed variation in vehicle speed will indicate if potential unsafe traffic flow conditions (i.e. stop/go) are being experienced (Marchesini & Weijermars, 2010), it is safer to have a steady constant link speed of 60 mph, than a variation between 50 mph and 70 mph. Furthermore, a more consistent travel speed is better for both energy consumption and vehicle emissions. Comparing scenarios against the amount of energy consumption and emission production are as important as the prior traffic criteria. Until this point, TRL have stated WPT costs associated per km (TRL, 2015), yet the quantity of km's required are unknown. The results from modelling the energy component should being begin to identify such criteria.

5.2.3 Traffic Demand

Typically, a transport model uses a four stage model (Ortúzar & Willumsen, 2011a) to determine traffic demand data; consisting of trip generation, trip distribution, mode choice and assignment. The first stage, trip generation, concerns itself with where the production of trips to and from zones are within the network. The second stage, trip distribution, is the process in which trips are linked to and from attraction and production zones. The third stage, mode choice, determines how users will travel considering the perceived cost of doing so. Finally, the fourth stage, assignment, determines route choice for each individual trip. Within this iterative process, shown in Figure 10, the results from each stage can be used to re-evaluate prior stages to iteratively refine the demand data.

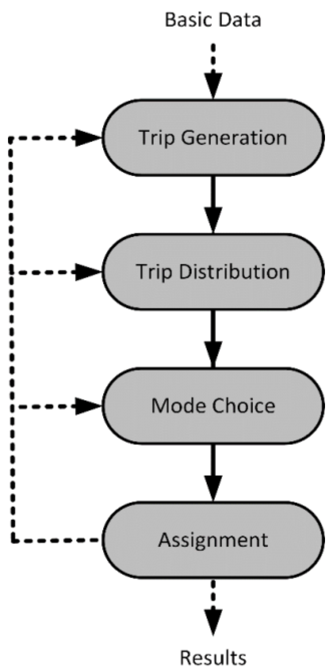


Figure 10 – Four Stage Model

In order to develop a realistic simulation model, the predicted or actual traffic conditions should be present, in order to achieve these conditions the traffic demand data must be representative of such conditions. Traffic demand data can be derived from traffic flow or count data through the estimation of Origin-Destination (OD) matrices or traffic states. The model will then be able to simulate representative traffic conditions, resulting in a model in which further scenarios and parameter changes can be simulated and tested. Within AIMSUN, traffic demand can be inputted to the model through either OD matrices or traffic states. The former consists of a matrix containing each trip between origin and destination centroids for a given time, vehicle type, and trip purpose. While traffic states contain the input flows at the origin centroids and the turning proportions at each node within the network for a given time and vehicle type. Whilst traffic states are faster to implement, OD matrices provide a higher level of accuracy to the base input data; if such data is of sufficient quality.

Highways England use the Motorway Incident Detection and Automatic Signalling (MIDAS) to log traffic count data from mostly inductive loops, and some radar sensors, positioned within the motorway network. These historic filtered datasets, to within 15 minute demand aggregates, are available within the public domain, whilst the raw datasets are available through Highways England and Mott MacDonald. The MIDAS dataset was used for the case study, Figure 11 shows the capture locations of the relevant MIDAS loop/radar detectors within the modelling area. While there are additional MIDAS detector locations, the ones highlighted within the figure provide sufficient data for the study. Most detectors were active within the case study area, some inactive detector flows were calculated from active detectors.

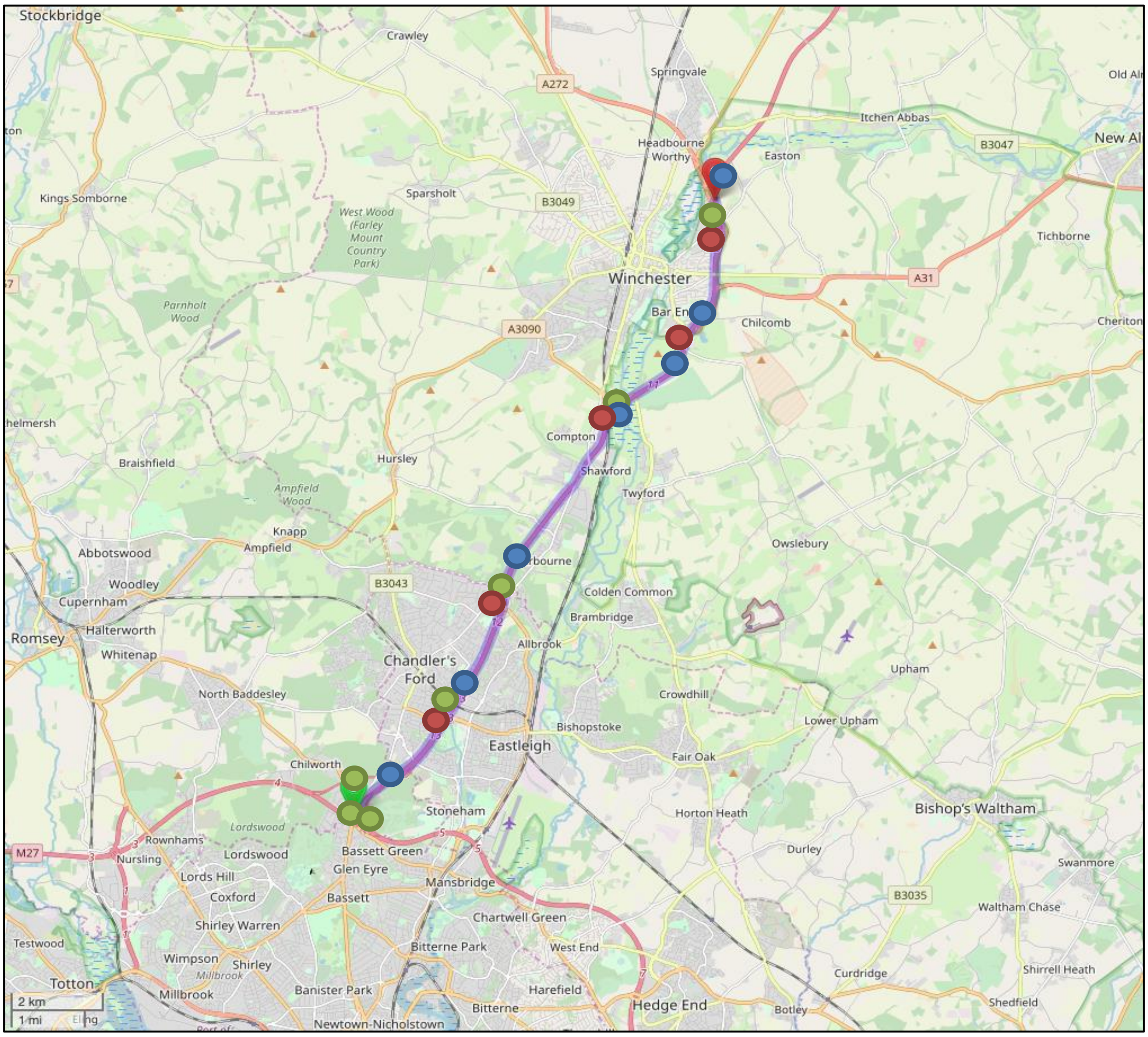


Figure 11 – Case Study Detector Locations (Entering, Exiting, Continuing Traffic Flow)

Taking a single days' worth of data is not representative of a typical day over the period of a year; the day of the week, the time of year, weather and road conditions are just some of the factors that influence traffic flow. In order to achieve a dataset of a 'typical' day, the data was filtered to remove inactive loop/radar data before averaging a year's worth of weekday data to provide the final traffic flow dataset. Figure 12 presents this average traffic flow for cars on a particular MIDAS detector located within the network.

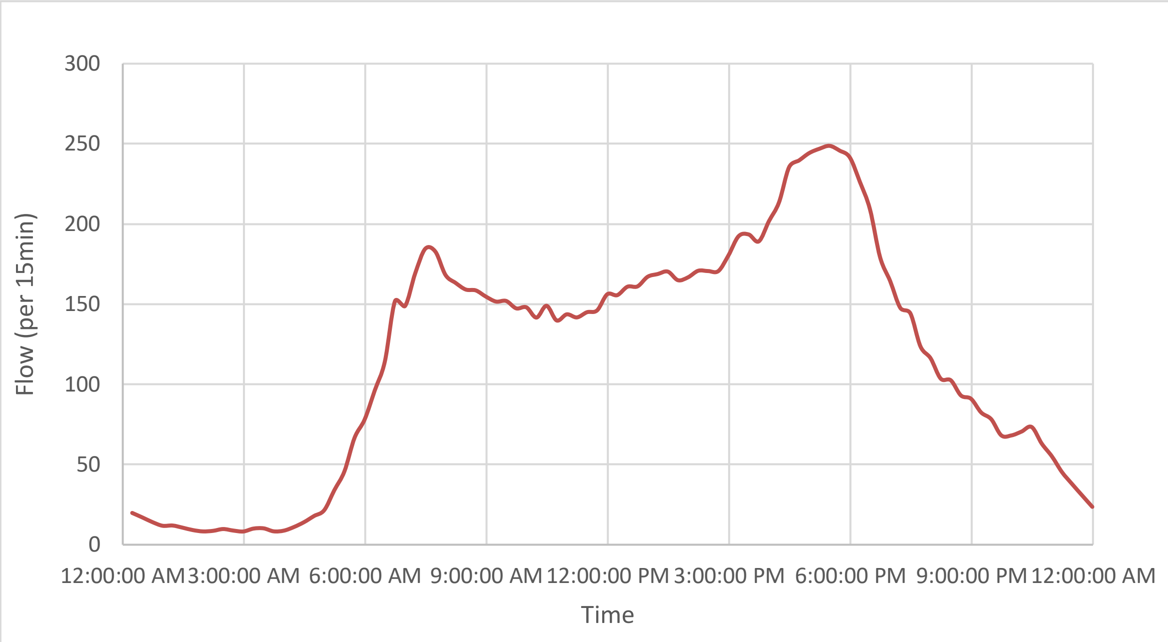


Figure 12 – Traffic Flow Data for Cars on a Single Loop Detector (M3/2178B)

The MIDAS dataset provides traffic flow data for the network, yet this is redundant of turning proportions or OD pairs. In order to model the traffic flows within the model, traffic demand files must be estimated from the measured flows. Estimating OD matrices from traffic count data is discussed by Ortúar and Willumsen (2011b), and numerous techniques have been proposed over prior decades to make use of the low cost, readily available traffic count data (Bera & Rao, 2011). An alternative methodology would have been to use traffic states. However, OD matrices allow further manipulation when simulating a variety of dynamic scenarios, as opposed to traffic states that determine traffic flows and turning proportions at each node.

With respect to the resolution used, the MIDAS dataset is contained within 15 minute aggregates, this was transposed to appropriate 15 minute OD matrices. The dataset provided the traffic flows at the entry and exits (or origins and destinations), some error was present given the marginal error of inductive loops (Highways England, 2019). This was removed, by eliminating data from incomplete days, then the remaining flows were used to determine the final flows for applying the growth factor method, specifically the Furness method. Such a matrix balancing method scales the base trip matrix to the new total end flows, yet is reliant upon the accuracy of the base matrix. The base matrix is not easily obtainable through estimation of traffic flows. The nature of the network being a single corridor between a major origin (Southampton) and destination (Winchester) or vice versa, results in a major OD link with additional origins and destinations along the route, as opposed to a city wide spread of origins and destinations across zonal areas. Thus, an assumption was made to determine that as each user enters the network, they are equally likely to exit at any of the destinations ahead of them, discounting their own entry junction or junctions south of their heading. Hence, initially all upstream exits appeared equally probable from the same origin. Application of the Furness Method applied at a maximum of 25 iterations with an epsilon of 0.01 iteratively scaled such values based upon the final flows. Thus, if an exit has a higher final flow (such as the major end point of the network), whilst each origin has an equally probable chance of exiting at each destination along their route, the higher final flow pulls the values within those respective matrix cells upwards resulting in a realistic matrix.

Rather than determining mode choice through travel surveys and road user demographics, it can be determined exclusively by the real-world datasets used within the study. The MIDAS dataset is classified by vehicle length; 0-520cm, 521-660cm, 661-1160cm and 1160+cm, these were reclassified as Cars, Light Goods Vehicle (LGV), HGV Rigid and HGV Articulated respectively. Such vehicle specifications are documented later in the thesis to ensure that factors relating to both traffic and energy models are identified. Yet, within each classification potentially a petrol, diesel and electric vehicle exist. Hence, the demand data consists of: 4 vehicle classifications, up to 3 fuel types, 96 OD matrices in a 24 hr period (each 15 minutes), with each OD matrix consisting of 30 cells; equating to nearly 35,000 cells that need data input for every single scenario modelled. Thus, it was necessary to write a program to automate the generation and scaling of a master set of OD matrices for each scenario change or manipulation. Table 5 is a blank example of an OD matrix; the green boxes highlight the viable OD pairs of the matrix.

With respect to route choice, the shortest path routine within AIMSUN is based on a variation of Dijkstra’s (1959) label setting algorithm, and returns the shortest path tree for each destination centroid within the network.

Emphasis is placed upon realism, over absolute accuracy at a particular point in time, the model must be representative of typical conditions. The focus of this research is to develop a tool to simulate a variety of WPT systems within a traffic network, thus the methodology used satisfies this component without delving excessively into creating a model that is overly accurate to a single particular point in time.

Table 5 – Blank OD Matrix containing Viable OD Pairs (with Reference Numbers)

Origin-Destination	M3 J13 Exit (28)	M3 J12 Exit (32)	M3 J11 Exit (36)	M3 J10 Exit (40)	M3 North (42)
A27 (22)					
M27 West (24)					
M27 East (26)					
M3 J13 Entrance (30)					
M3 J12 Entrance (34)					
M3 J11 Entrance (38)					

5.2.4 Base Model Configuration

The following process outlines the configuration and simulation of the model within the AIMSUN traffic modelling package:

1. Import map: Import Open Street Map (OSM) map of case study area
2. Working area: Define the case study working area
3. Network: Create road network
4. Mode choice: Define vehicle classes and user classes
5. Demand data: Import traffic demand data, OD matrices
6. Import API: AIMSUN API scripts are imported to the network (inc. traffic and energy)
7. Scenario: Define scenario settings, time step, outputs
8. Simulation: Run simulation
9. Post process: Resulting simulation data is post processed through an energy model
10. Results: AIMSUN generated results and energy model results

The base model configurations are as follows:

Vehicle Classes: Electric Class, Combustion Class, Private Class, Freight Class

Vehicles: Car Petrol (CP), Car Diesel (CD), Car Electric (CE), LGV Diesel (LD), LGV Electric (LE), HGV Rigid Diesel (HRD), HGV Rigid Electric (HRE), HGV Articulated Diesel (HAD), HGV Articulated Electric (HAE)

Centroids: A27, M27 West, M27 East, M3 J13 Exit, M3 J13 Entrance, M3 J12 Exit, M3 J12 Entrance, M3 J11 Exit, M3 J11 Entrance, M3 J10 Exit, M3 North

OD Matrices: 15 minute aggregates, 96 per 24 hour period, for every vehicle type

Lane Types: Reserved optional/compulsory depending upon scenario and vehicle

Traffic Demand: Base (No Electric), Electric Mix (varying proportions)

Technically, each simulation consists of 10 replications with 10 random seeds, the same 10 replications and seeds will be used for each scenario or adjustment made; enabling the comparison between simulation results and adjustments to the model.

5.3 Extending the Models Capabilities

The inherent lack of understanding concerning how such WPT systems will be deployed and utilised creates the need for further investigation of both behavioural and energy components for inclusion within the model. Yet, a method in which such aspects can be considered and adjusted within the model is therefore necessary.

Microscopic modelling work is undertaken within the AIMSUN traffic simulation package, whilst a comprehensive program at installation, the AIMSUN API (AAPI) further extends the capabilities of the software. The AAPI module provides a communication link between the vehicle-based simulator and external applications, see Figure 13. The AAPI functions allow passage of simulated data to a separate application for external processing, dependent upon the simulated situation, an appropriate response will be made to change dynamic properties within the simulation; this iterative process continues for each simulation time step.

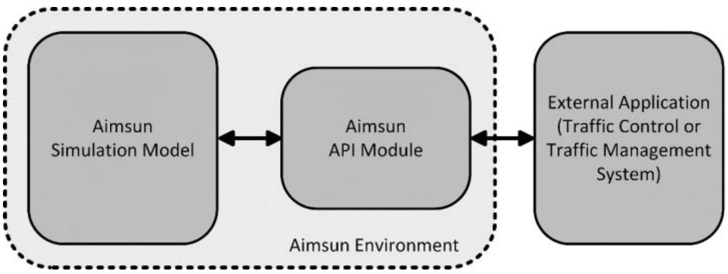


Figure 13 – Schema of AIMSUN API Module (AIMSUN, 2020)

As with most API's, AIMSUN provide documentation of the possible building blocks that can be used to develop the required program. The microscopic AAPI has six high level functions that communicate between the simulation model and AAPI module; AAPILoad, AAPIInit, AAPIManage, AAPIPostManage, AAPIFinish, AAPIUnload. As well as seven functions that are called when a certain simulation event occurs; AAPIEnterVehicle, AAPIExitVehicle, AAPIEnterVehicleSection, AAPIExitVehicleSection, AAPIEnterPedestrian, AAPIExitPedestrian and AAPIPreRouteChoiceCalc. For functionality, all 13 AAPI functions must be called within the programming script. The interaction process between the AAPI module and simulation model is shown in Figure 14.

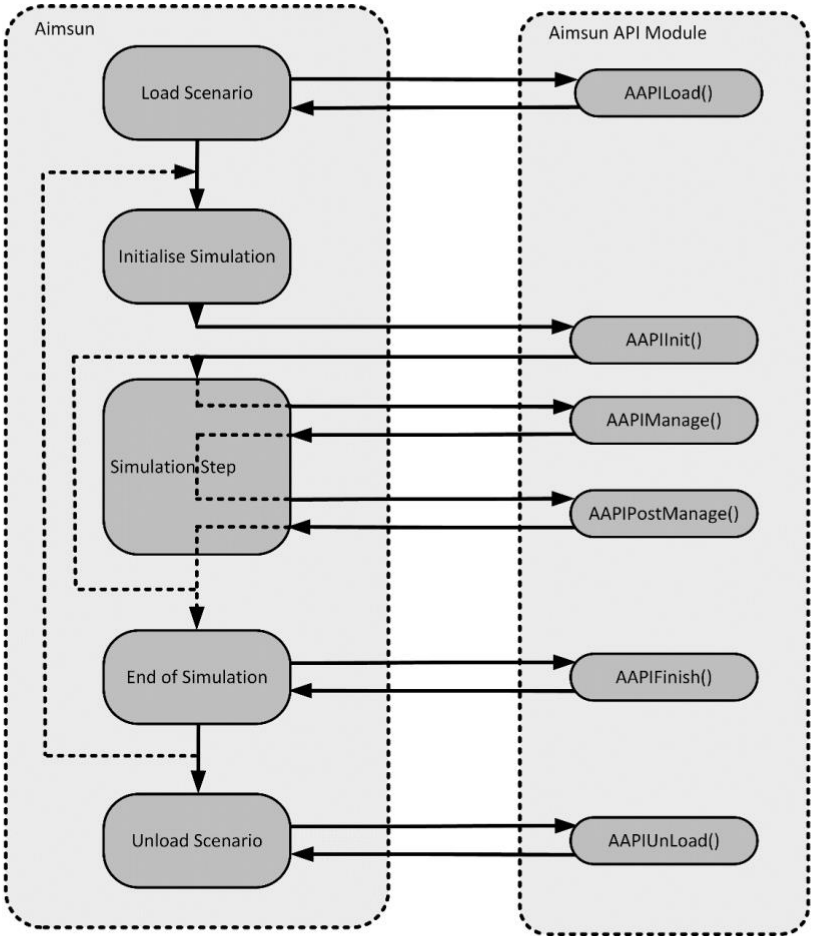


Figure 14 – Schema of AIMSUN and AIMSUN API Module Interaction (AIMSUN, 2020)

Additional programs had to be developed that used the AAPI to gather individual vehicle movements at each time step throughout the simulation. The following simulation variables were gathered for each vehicle, at each timestep, such data was outputted to an external dataset for latter processing with an energy model:

- Simulation Time
- Vehicle ID
- Vehicle Type
- Section ID
- Lane Number
- Origin Centroid
- Destination Centroid
- Elevation
- Distance Travelled
- Vehicle Speed
- Charging/Motoring
- Tracked/Untracked

Current microscopic traffic simulation packages do not lend themselves to the modelling of WPT systems, thus API features were utilised to enhance the software's capability to WPT specific elements. It was decided that the energy modelling of the WPT situation should be developed as an external program and implemented using the AAPI.

5.4 Chapter Conclusions

It was identified in Chapter 2 that the most likely scenarios for WPT deployment are interurban freight corridors where repeatable trips are expected. Therefore, a microscopic case study was outlined that focused on the SRN route between two cities; Southampton and Winchester. Traffic demand was estimated from MIDAS traffic count data, this was inputted into the model in the form of OD matrices. A framework for construction of the base model was provided, detailing the base configurations used as well as methods of extending the models capabilities using the API.

Expectedly with such a new, evolving, and enabling technology, a number of behavioural, energy and road network uncertainties exist within the study. Whilst the base traffic side of the model is complete, in order to understand the dynamic WPT situation in its entirety, the energy aspect must be further explored and defined. There is a need for a separate energy model that can calculate instantaneous energy consumption and power transfer from individual vehicle movements; as opposed to simply using rates of energy consumption or WPT transfer. The traffic model developed within this chapter will provide such vehicle movement data. It was clear from the review chapters that the detailed energy elements of the WPT situation are important questions and are unanswered comprehensively in previous research. It is also clear that to answer these questions will require a significant advance in modelling capability. These aspects are further analysed and defined in the subsequent Energy Modelling chapter, further adding to the development of the microscopic traffic model.

Chapter 6 Energy Modelling

6.1 Introduction

It was identified within the review chapters that further investigation into the potential of WPT charging within the energy and traffic domains appears necessary; something that was lacking from prior research. While a traffic model was developed in Chapter 5, the energy component must now be investigated. The purpose of this chapter is therefore to continue the development of the modelling tool to investigate the detailed energy aspects of the dynamic charging situation. In particular, the energy consumption and environmental impact of both electric and ICE vehicles, as well as the supply of energy to the vehicle from dynamic WPT charging infrastructure.

To achieve this, a number of additional energy modelling features must be incorporated within the modelling process; such entities will be included within the AIMSUN traffic model using the AIMSUN API. With respect to energy consumption, TRL have developed a basic energy model that uses kinematic equations to model electrical energy consumption. This model will form the initial basis of the eventual energy consumption model. In addition, likely WPT system specifications are documented and discussed; a range of probable specifications must be incorporated within the model, to account for the inherent uncertainty surrounding such a developing technology. Research was also undertaken to outline several vehicle specifications which best represent the vehicle categories modelled.

When considering the energy component of WPT modelling, four aspects must be considered:

i. Vehicle Energy Consumption (Section 6.2)
ii. Vehicle Energy Transfer (Section 6.3)
iii. Vehicle Emission Production (Section 6.4)
iv. Wider Network Energy System (Section 6.5)

These aspects cover; (i) how much energy is consumed (liquid or electric fuel) by the vehicle over the network, (ii) how much energy is transferred to the vehicle over the various charging zones, (iii) the emission production of the vehicle, both point of use or through electricity generation, (iv) the sum of all energy consumption and WPT, ultimately looking at transport as an energy system. All four aspects will be assessed throughout this chapter for inclusion within the model; progressively building up the dependency of the entire energy model.

6.2 Vehicle Energy Consumption

When considering vehicle energy consumption, two scales exist; liquid fuel and electrical fuel. With each agent (vehicle) travelling throughout the road network, they consume energy. The inherent difference in design of electrical motors makes EVs more efficient than liquid fuelled ICE vehicles. However, oil derived fuels have far higher energy densities when compared to electric batteries. Typical energy densities of diesel are 46MJ/kg, and petrol 45MJ/kg (Hore-Lacy, 2011), with Li-ion batteries featuring energy densities of up to around 1MJ/kg (Nair, 2016) (Hawkins, 2019). A single kWh of electrical energy equates to 3.6MJ, thus a Tesla Model S P100D has a 100kWh, or 360MJ, battery pack. The equivalent oil fuelled vehicle would require just over 10 litres of diesel or petrol, demonstrating the significant gap between energy densities of fossil fuels and current battery capabilities. However, the poor thermal efficiency of ICEs compared to electric motors, increases such fossil fuel requirements.

As demonstrated, energy densities vary significantly between fossil fuels and current electric battery capabilities, thus the mass and volume of electric batteries are significantly larger than the equivalent liquid fuel alternative. When comparing electrical power and liquid fuel power, the most significant issue is the medium that is used in storing the energy within the vehicle. Removing, or significantly reducing, the on-board storage of such energy (potentially through dynamic charging), negates all related issues. EVs are significantly more efficient even with the increased vehicle mass; removing the on-board storage of fuel, electrical or liquid, will further increase the efficiency of the vehicle.

Consideration was given to route elevation, Liu and colleagues (2017) observed that EVs are actually more energy efficient, when compared to ICEVs, in mountainous areas because of their energy regeneration capabilities. Within the case study, the route has a considerable change in elevation over its duration, see Figure 15. Both energy consumption and emissions will be influenced by such undulations in road elevation. Elevation points were incorporated within the traffic model in order for the energy model to factor gradient changes into energy consumption calculations.

When considering the exact energy consumption of a vehicle, a given vehicles energy efficiency is derived from a near infinite array of factors, it is not possible to determine exact energy efficiency of a given vehicle under said speed, road, weather and travel conditions. In order to simplify the model, four vehicle classifications were defined with a finite set of vehicle specifications; these were: Car, Light Goods Vehicle (LGV), Heavy Goods Vehicle (HGV) Rigid and HGV Articulated. Where possible, every effort is made to develop a model that is representative of the real world.

Figure 15 – Case Study Elevation by Distance

Over the subsequent sections a model is developed to estimate energy consumption for both electric and conventional ICE vehicles. The energy model is developed to estimate the required battery discharge for an EV, alongside liquid fuel consumption of an ICE vehicle.

6.2.1 Base Energy Model

Energy consumption can be derived from vehicle speed and energy consumption at that given speed, for EVs this equates that battery discharge is directly relatable to vehicle speed and energy consumption, equally fossil fuel consumption also follows such a relationship. The TRL energy model (Emre & Naberezhnykh, 2014) (Emre, et al., 2018) calculates energy consumption for an electric vehicle, given a number of route and vehicle configuration inputs:

- Route length
- Slope of the route
- Vehicle speed
- Acceleration/deceleration
- Vehicle specification (i.e. mass, surface area, drag coefficient, drivetrain efficiencies)
- Route conditions (i.e. air pressure)

The TRL energy model, like other kinematic models reviewed previously, reverse calculates energy consumption through first calculating energy and power requirements at the wheel; before mechanical losses, electrical inefficiencies and potential regenerative braking energy savings are accumulated to estimate the total required discharge of the vehicle battery. While the TRL energy model considers battery electric, series hybrid, parallel hybrid and series-parallel hybrid vehicles, it does not consider fossil fuel consumption of ICE vehicles. As noted by TRL, energy values are estimated using a 'reverse' calculated approach, thus real-world operating conditions will likely result in higher power and energy demand. Yet such a tool provides a good indication of energy consumption and has been found to produce comparable results with other literature and studies (Emre & Naberezhnykh, 2014), with discrepancies potentially due to the model parameters, specifically the type of drive cycle used.

The pre-existing format of the energy model was contained within a Microsoft Excel workbook, individual vehicle GPS routes were manually cleaned and entered to the model to obtain the resultant energy data. This does not lend itself well to automation of large quantities of simulation data, thus the requirement to recode the model to a specific program was essential to automate the model for potentially tens of thousands of vehicles per single iteration of an experiment. In addition, a number of alterations were required to the model to process the traffic simulation data; as well as considering ICE vehicles, and dynamic WPT charging.

Rather than process energy consumption instantaneously within each simulation time step, which would be computationally intensive to run within the traffic simulation, post processing the simulation data would enable the model to be run separately to the traffic simulation. The energy results calculated from the energy model will not influence the traffic simulation, hence it was not necessary to undertake such calculations at real time within the traffic simulation.

The base energy model (consumption component) can be expressed as the following kinematic equations. The **total energy consumption** (Wh) of the model can be calculated as:

$$E_{total} = \sum \Delta \mathrm{E}_{traction} \qquad [1]$$

where, E_{total} is the total energy consumption of the vehicle; this is calculated through summing all time step data for $\mathrm{E}_{traction}$ the total energy consumption at the wheel. The **traction demand energy** (Wh) can be calculated as:

$$\Delta E_{traction} = \Delta \mathrm{E}_{kinetic} + \Delta \mathrm{E}_{gravitational\ potential} + \Delta \mathrm{E}_{drag} + \Delta \mathrm{E}_{rolling\ resistance} + \Delta \mathrm{E}_{auxillary} \qquad [2]$$

where, $\mathrm{E}_{kinetic}$ is the kinetic energy, $\mathrm{E}_{gravitational\ potential}$ the gravitational potential energy, E_{drag} the energy requirement to overcome drag, and $\mathrm{E}_{rolling\ resistance}$ the energy requirement to overcome rolling resistance, and $\mathrm{E}_{auxillary}$ the auxiliary energy demand. The **kinetic energy** (Wh) requirement can be calculated as:

$$\Delta\mathrm{E}_{kinetic} = \frac{m \times (v^2 - u^2)}{2} \qquad [3]$$

where, m is the total vehicle mass, v the final speed, and u the initial speed. The **gravitational potential energy** (Wh) requirement can be calculated as:

$$\Delta\mathrm{E}_{gravitational\ potential} = m \times g \times (\Delta\mathrm{h}) \qquad [4]$$

where, g is gravity, and $\Delta\mathrm{h}$ the change in elevation. The **drag energy** (Wh) requirement can be calculated as:

$$\Delta\mathrm{E}_{drag} = 0.5 \times \rho \times C_x \times A \times v^2 \times \Delta\mathrm{d} \qquad [5]$$

where, ρ is air density, C_d the drag coefficient, A the vehicles surface area, and $\Delta\mathrm{d}$ the change in distance. The **rolling resistance energy** (Wh) requirement can be calculated as:

$$\Delta\mathrm{E}_{rolling\ resistance} = m \times g \times C_{rr} \times \Delta\mathrm{d} \qquad [6]$$

where, C_{rr} is the rolling resistance coefficient.

These equations form the base of the model functionality as well as numerous other kinematic based fuel consumption models (Zhou, et al., 2016). The same kinematic equations calculate the traction energy required to move the vehicle given aerodynamic drag and rolling resistance. Thus, such equations are not segregated to electric or fossil fuel propulsion; the subsequent sections will assess the individual aspects related to electric and ICE vehicles respectively.

To summarise, the main issue of the base TRL model was its inability to be automated, there were also some inaccuracies in its calculations, it was excessively complicated in some areas (different vehicle classes), and essentially it did not consider ICE vehicles. Therefore, the kinematic equations were used as a basis of the energy consumption model developed over the subsequent sections. This also meant that where necessary, calculations were improved, values corrected, unnecessary hybrid considerations were removed, and generally simplification of the model. Overall, a program was developed that enabled the automation of the model. The AAPI was used to output simulation data on an individual vehicle basis for every simulation time step, Table 6 demonstrates the type of data the model outputs.

Table 6 – Example Simulation Data Output from AIMSUN through the API

Time	Veh ID	Veh Type	Type Name	Sect ID	Lane No.	Cent. Orig.	Dest. Orig.	Charge	Elev.	Dist.	Speed
0	1	1	Car	98	2	26	42	0	48	8.3	54.2
0.8	1	1	Car	98	2	26	42	0	48	8.3	54.2
2.4	1	1	Car	63	4	26	42	0	47.8	32.4	54.2
3.2	1	1	Car	63	4	26	42	0	47.4	44.4	54.2
4	1	1	Car	63	4	26	42	0	47.1	56.5	54.2

Initially the program was created with the intention to read the entire simulation dataset to memory before processing each row of data and outputting the calculated dataset. This was found to be ok for datasets below the size of the computers memory, above this Pandas data frame structures were incorporated. Again, this was found to work ok for relatively small data sets, below, up to, and just beyond the computers memory. Yet a far quicker method computationally was to read the CSV file in to the program line by line, the program would then calculate the results based on the simulation data and then output the desired results back to the same CSV file by appending new data columns. Issues with this method included the sorting of the CSV data file; the simulation data was structured by time step, thus individual vehicle IDs were mixed up in the data. The last row of data was always kept in memory because some calculations required the prior time step data. Therefore, reading the simulation data in line by line meant that the prior row of data often corresponded to a different vehicle. Rather than sorting and filtering the datasets (that often were in the region of tens of gigabytes in size) before processing them, the energy model was developed to automatically undertake this operation as it processed the data. The resulting dataset was then sorted by vehicle ID, and then time step of each vehicle ID.

Several scripts form the final model program, these include:

- Main: for running the program, selecting the CSV file and outputting the results
- Analysis: contains the order of calculations, this script calls functions from…
- Functions: contains the individual function calculations
- Constants: contains the constants used in the calculations
- Vehicle Config: contains the vehicle, WPT system and scenario configuration

A number of vehicle, passenger and (where appropriate) engine, battery, supercapacitor and charger configurations can be inputted to the model through the vehicle configuration script.

Where, classes are used to store and call the appropriate values for the energy function calculations.

6.2.2 Electric Vehicle Considerations

Unlike the ICE side of the fuel consumption model, which can be summarised in just a few main equations, the electrical component is far more complex. It cannot be documented in its entirety due to the large number of equations and variations of those equations based upon a series of logic operations. This section will outline the main equations, as well as the basic operation and considerations of the EV fuel consumption model component. It is important to note, the model has been simplified in order to express these equations in this manner.

The vehicles **SOC** (%) can be calculated as:

$$\mathrm{E}_{SOC} = \frac{E_{battery}}{E_{battery\ capacity}} \quad [7]$$

where, $E_{battery}$ is the current battery energy and $E_{battery\ capacity}$ the total battery capacity. The **battery energy** (J) can be calculated as:

$$\mathrm{E}_{battery} = E_{battery\ Pr} + \mathrm{E}_{charger} + E_{regen\ battery} - E_{battery\ discharge} \quad [8]$$

where, $E_{battery\ Pr}$ represents the battery energy in the prior time step, $\mathrm{E}_{charger}$ the energy of the charging system, $E_{regen\ battery}$ the regenerative energy provided to the battery, and $E_{battery\ discharge}$ the discharge energy of the battery. Whilst this section focuses on the energy consumption model, the WPT charging element of the model is further developed in the subsequent section, 6.3 – Vehicle Energy Transfer. When the vehicle is harvesting energy through decelerating, the **regenerative charge to the battery** (Wh) can be calculated as:

$$E_{regen\ battery} = E_{regen\ battery\ charge\ rate} \times \eta_{battery\ charge} \times \eta_{battery\ to\ wheel} \quad [9]$$

where, $E_{regen\ battery\ charge\ rate}$ is the regenerative battery charge rate, $\eta_{battery\ charge}$ the charge efficiency of the battery, and $\eta_{battery\ to\ wheel}$ the battery to wheel electrical efficiency. The **battery discharge** (J) can be calculated as:

$$\mathrm{E}_{battery\ discharge} = \frac{\mathrm{E}_{traction}}{\eta_{battery\ discharge} \times \eta_{battery\ to\ wheel}} \quad [10]$$

where, $\eta_{battery\ discharge}$ represents the battery discharge efficiency. The required **energy the battery can provide** (Wh) can be calculated as:

$$\mathrm{E}_{battery\ can\ provide} = \frac{\mathrm{E}_{traction}}{\eta_{battery\ to\ wheel}} - \mathrm{E}_{battery\ discharge\ rate} \qquad [11]$$

If the vehicle has a supercapacitor fitted, then the following equations become necessary. The energy of the **supercapacitor energy** (J) can be calculated as:

$$\mathrm{E}_{supercap} = \mathrm{E}_{supercap\ Pr} + \left(\mathrm{E}_{supercap\ charge} \times \eta_{supercap\ charge}\right) - \left(\frac{\mathrm{E}_{supercap\ discharge}}{\eta_{supercap\ discharge}}\right) \qquad [12]$$

where, $\mathrm{E}_{supercap\ Pr}$ is the supercapacitor energy in the prior time step, $\mathrm{E}_{supercap\ charge}$ the supercapacitor charge energy, $\eta_{supercap\ charge}$ the charge efficiency of the supercapacitor, $\mathrm{E}_{supercap\ discharge}$ the supercapacitor discharge energy, and $\eta_{supercap\ discharge}$ the discharge efficiency of the supercapacitor. When charging, the **supercapacitor charge energy** (J) can be calculated as:

$$\mathrm{E}_{supercap\ charge} = \left(\mathrm{E}_{total} - E_{regen\ battery}\right) \times \eta_{supercap\ charge} \times \eta_{battery\ to\ wheel} \qquad [13]$$

When discharging, the **supercapacitor discharge energy** (J) can be calculated as:

$$\mathrm{E}_{supercap\ discharge} = \frac{\mathrm{E}_{total}}{\eta_{supercap\ discharge} \times \eta_{battery\ to\ wheel}} \qquad [14]$$

6.2.3 Internal Combustion Engine Vehicle Considerations

The following equations summarise the calculation of fuel consumption based upon the energy consumption obtained through the initial vehicle kinematic equations. The required **engine horsepower** (HP) can be calculated as:

$$\mathrm{E}_{engine} = \frac{E_{traction}}{745.699} \qquad [15]$$

where, 745.699 represents the conversion factor used in converting between HP and kW. The **traction demand energy** (Wh) can be calculated as:

$$\mathrm{E}_{traction\ demand} = \frac{E_{traction}}{\eta_{engine\ thermal} \times \eta_{drivetrain}} \qquad [16]$$

where, $\eta_{engine\ thermal}$ is the thermal efficiency of the engine, and $\eta_{drivetrain}$ represents the efficiency losses of the vehicles mechanical drive system. The vehicles **fuel use** (litres) can be calculated as:

$$\mathrm{E}_{fuel\ use} = \frac{E_{traction\ demand}}{\mathrm{E}_{fuel} \times 3600} \qquad [17]$$

where, E_{fuel} is the energy density of the fuel.

This completes the energy consumption models for both electric and ICE vehicles.

6.3 Vehicle Energy Transfer

Unlike the prior energy consumption component, energy transfer is only related to EVs, not ICEVs. Yet, this could be expanded to any vehicle featuring an electrical drive system, such as PHEVs or FCEVs, as electrical energy could be transferred and directed towards the vehicles motors or small on-board energy storage if fitted.

As indicated by the Model Requirement Specification, a large number of factors influence energy transfer; such as the air gap, frequency and coil design. As such, not all aspects can be investigated and incorporated within this study. Therefore, a simplifying assumption is made that uses a generic transfer rate and transfer efficiency; in turn encapsulating all of the influential factors. Such WPT values are documented and justified within the next section.

In order for the energy transfer to be included within the model two aspects must be incorporated, the vehicle and road coil interaction, as well as the actual transfer of energy. The first criterion involves the assessment of when a vehicle is within the charging zone/s in the network, while the latter is the achievable energy transfer given the vehicles speed, rate of power transfer and elapsed charging time. Both aspects are investigated and incorporated within the model, and documented in subsequent sections.

Consideration is also given to other forms of dynamic charging; specifically conductive systems. The model is developed to allow the rate of power transfer and transfer efficiency to be manipulated based upon the charging system specification; thus, is not specific to WPT systems.

6.3.1 WPT System Specification

Energy transfer capabilities of WPT technology are very much uncertain, given that no real world applications have been implemented for long distance travel. The closest example to real world applications is the KAIST system (Suh & Cho, 2017), yet is limited in its approach and primarily uses static WPT based charging rather than dynamic. It is evident from literature that much work has been undertaken in the development of prototype systems and establishing realistic power capabilities of such systems.

Current dynamic WPT systems start at 20kW and range to power levels of several hundred kW's. For steady state motorway scenarios, an EV would need approximately 20-25 kW of power at an average transit speeds (70 mph), increasing to 120-150 kW of power for an electric HGV (60 mph) (Emre & Naberezhnykh, 2014). Hence, a 25 kW system, or even a 50 kW system, would be sufficient for an EV; the remaining power would be used to charge the battery, through a DC link. The DC link being a physical electrical connection between the battery and motor, electricity follows the path of least resistance, thus WPT energy will feed the motor first with any spare capacity fed to the battery. However, a larger 100 kW WPT system would result in 75 kW of power having to be provided to the EV battery. Typically, EVs are equipped with 20-30 kWh batteries, charging at 75 kW may have a negative effect on the battery life. Increasing power levels further to 200 or 300 kW could further reduce the longevity of the EVs battery.

Yet a system optimised for an EV, 25-50 kW, would not provide sufficient power to an electric HGV, which could potentially charge at 200 kW or above if equipped with a suitable traction battery and power electronics. It is clear that dynamic WPT systems must be designed to operate at different power levels. One such solution would be a system that uses multiple 25 kW coils, if a vehicle is fitted with two coils, they will pick up energy from two road based transmitters, equating to a 50 kW system. An electric HGV could be equipped with a higher number of receiver coils, such as four or six, resulting in a 100-150 kW system. The road based transmitter coils would be switched on at different sequences depending upon the vehicle and coil configuration. A further consideration is the available space and the mass of such equipment. Even if an EV is capable of charging at 100 kW (i.e. Tesla Model S), the vehicle may not have sufficient space for installation of four 25 kW coils, or such a system may be too heavy. It is important to consider, as technology advances coil sizes are likely to get smaller and lighter, but at present this is something that should be considered.

Therefore, a series of WPT power configurations will be modelled, this will range from 25-250 kW and be dependent upon vehicle type. The particular WPT specifications (i.e. voltage, air gap, coil misalignment) are not considered, instead a global WPT efficiency of 90% is assumed to account for each of these aspects within a single efficiency value. Thus, a 100 kW system with an efficiency of 90% will achieve a transfer of 90 kW of usable power to the vehicle. Power electronic and battery charging efficiencies within the vehicle will then further reduce this value; such specific vehicle efficiencies are detailed within Section 6.6 – Vehicle Specifications. The WPT values detailed within

Table 7 are used throughout the modelling process; a low, medium, and high scenario will be used with varying power levels.

Table 7 – Wireless Power Transfer Model Specifications

Parameter	Specification
WPT Power Level (Car and LGV)	Low: 25 kW, Medium: 50 kW, High: 75 kW
WPT Power Level (HGVs)	Low: 50 kW, Medium: 150 kW, High: 250 kW
WPT efficiency	90%

Whilst such values are discrete and assumed, they appear most suitable at present according to literature and given the current state of technological development. The exact specification of the WPT system will have a significant influence upon the efficiency and feasibility of such systems. Through modelling a variety of power levels it is expected that questions can be answered over the minimum technological power levels to achieve sufficient operation, as well as compensating for both current and possible future WPT power levels.

When considering system efficiency, a large number of factors make up the eventual efficiency of the WPT system. This comprises of the WPT charging system efficiency (i.e. coil design, coil alignment, material selection), vehicle based efficiencies (vehicle power electronics, battery design, charger specification), electricity grid aspects (grid power electronics, power factor) as well as real world factors discussed within Section 2.3.1 – Dynamic Charging Infrastructure, such as coil misalignment, manufacturing aspects and weather conditions. To provide context, a simple example of a 25 kW WPT system can be assessed as shown in Table 8; beginning in the middle at a WPT charger rate of 25 kW, it can be calculated out towards both the generation, and kinetic use of such energy. Some aspects are out of scope for the project (power station and fuel efficiency), or are dependent upon instantaneous kinematic values (vehicle traction demand, current SOC); therefore, have been left blank and calculations haven't carried beyond such values.

Thus, whilst the WPT system is rated at 25 kW, usable energy at the vehicle is substantially less than this depending upon how the energy is used, and requires generation of electricity above such values. Table 9 documents the usable energy and respective generation requirements of such WPT specifications previously documented. Adjusting the particulars of the vehicle specifications and charging system will inevitably tailor the power levels to ones given scenario.

Table 8 – Energy Transfer of a 25 kW WPT System; from Fuel to Vehicle

Quantity of fuel required	**X kg**
Efficiency of fuel	X %
Efficiency of power station	X %
Grid generation requirement	**27.13 kW**
Grid power electronic efficiency	95%
Grid power factor	97%
WPT charger rate	**25 kW**
WPT efficiency (includes misalignment, design, real world use)	90%
Energy transferred to vehicle	**22.5 kW**
Vehicle power electronic efficiency	95%
Vehicle battery charge efficiency	95%
Usable energy delivered to the battery	**20.31 kW**
Vehicle SOC	Y %
Vehicle traction demand	Y kW
Vehicle battery discharge efficiency	95%
Vehicle power electronic efficiency	95%
Vehicle electric motor efficiency	95%
Vehicle drivetrain efficiency	95%
Vehicle battery energy	**Y kW**

Table 9 – Energy Delivery and Generation Requirements of WPT Charging System

Scenario	**Parameter**	**WPT Specification**	**Energy delivered to battery**	**Electrical energy generation required**
Low Power	Car/LGV	25 kW	20.31 kW	27.13 kW
	HGV Rigid/Articulated	50 kW	40.61 kW	54.26 kW
Medium Power	Car/LGV	50 kW	40.61 kW	54.26 kW
	HGV Rigid/Articulated	150 kW	121.84 kW	162.78 kW
High Power	Car/LGV	75 kW	60.92 kW	81.39 kW
	HGV Rigid/Articulated	250 kW	203.06 kW	271.30 kW

6.3.2 Vehicle and Coil Interaction

Energy transfer is dependent upon the quantity of time the vehicle and WPT charger remain in a state of power transfer, thus it becomes necessary to track the vehicle as it enters, travels within, and exits the charging zone. This was established through the integration of detectors within the AIMSUN model and a corresponding AAPI script that identifies a WPT equipped vehicle, tracks and monitors its movements, and converts its state (motoring or charging) as it travels along the road. Output of vehicle data (static and dynamic), as well as statistical data to an external document is also undertaken. This process can be expressed as:

1. Identify vehicle type
2. Read vehicle information
3. Locate vehicle within model
4. IF vehicle is within charging zone:
    - Set vehicle as tracked
    - Modify vehicle information
5. Output data to external document

Figure 16 shows the car pseudocode description of the AAPI functionality during each simulation time step; specifically, the AAPIManage function.

```
begin simulation step
    for sectionID do
        for vehicleID do
            DO: read vehicleInformation
            if vehicleType = electricCar then
                if vehicleLocation = detectorLocation
                and vehicleLane = detectorLane then
                    DO: read currentSimulationTime
                    vehicleTracked ← TRUE
                    vehicleType ← electricCarCharging
            if vehicleType = electricCarCharging then
                if vehicleLocation ≠ detectorLocation
                or vehicleLane ≠ detectorLane then
                    DO: read currentSimulationTime
                    vehicleTracked ← FALSE
                    vehicleType ← electricCar
            DO: compile simulation data
            DO: export data to .csv file
```

Figure 16 – Vehicle and Coil Interaction AAPI Pseudocode (Car)

For each simulation time step, section, and vehicle, the program reads the vehicles static information. If it determines the vehicle is an electric car equipped with WPT capability, it will then assess the vehicles location. If the vehicle is within the predetermined charging zone boundary, in both distance along the carriageway and equipped charging lane, then it will action three functions; read the simulation time step, set the vehicle as tracked, and change the vehicle type from motoring to charging. The program was written to enable charging zones (detectors) to be positioned within the AIMSUN GUI, rather than hard coding the detector locations in the script with coordinates and ultimately having to change them for each experiment. This also reduced the need for processing coordinate data, which proved computationally intensive. When the program finds that the vehicle exits the charging zone, it again reads the simulation time step, sets the vehicle as untracked, and returns the vehicle type to motoring. The program compiles and writes the simulation data for every vehicle within the network at every time step to an external file. This includes both static and dynamic vehicle information, such as the vehicle ID, tracked status, desired speed, current speed, location or lane number. Such information was exported to a Comma-Separated Values (.csv) file format, external to the AIMSUN package; thus, facilitating post processing and analysis of the simulation data. Additional 'for' loops are included within the program to monitor and track other electric vehicle classifications; LGV, HGV Rigid and HGV Articulated.

The creation of a view mode within AIMSUN (Figure 17) enables the graphical display of a vehicle transitioning between the motoring and charging phase when within the charging zone, indicated as red and green respectively.

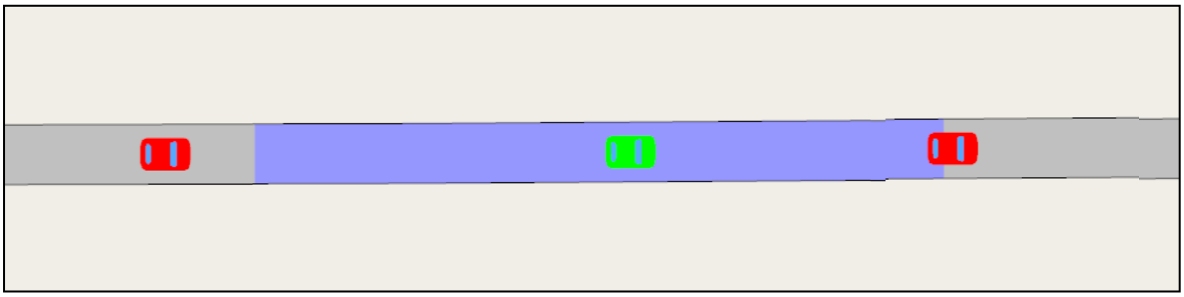


Figure 17 – Vehicle Transition between Motoring (Red) and Charging (Green) Phase

Setting the vehicle to 'tracked' status when within the detector boundaries enables further control and manipulation of the vehicles static and dynamic attributes, such examples include assigning rules that all tracked vehicles will travel at '*x*' speed, or maintain '*x*' headway.

Rather than modelling individual coils, of given length, the model will incorporate charging zones with an array of coils, as the vehicle reaches a charging zone, equivalent energy transfer can be calculated through elapsed charging time and energy transfer rate of that charging zone. This also enables different forms of dynamic charging systems to be considered through implementing different power transfer specifications; albeit varying such technology will influence other areas of the study beyond energy transfer.

It is important to consider, the resolution of the simulation time step will greatly affect the traffic models ability to output accurate timings of when a vehicle is within the specified charging zones. At a vehicle speed of 70mph the vehicle will travel 31.2m in a 1 second time interval, reducing the time step to 0.1 seconds consequently improves the models ability to position vehicles by a whole magnitude, yet at the expense of simulation time and data size. At either time interval, it is likely that the model will not be capable of detecting vehicles over single coils, a further reason why charging zones that contain an array of coils were utilised. Depending upon the length of the charging zone, the margin of error produced from varying time step increments will have more or less of an impact. The margin of error between a 0.1s and a 0.8s time step for a vehicle travelling at 70 mph is negligible for a 1 mile charging lane, yet is crucial for a single 5m coil. This is further shown in Table 10. A compromise must be made between model accuracy and the cost, in both computational time and data size.

Table 10 – Time Spent (seconds) by a Vehicle on a Charging Coil/Loop at various Charging Speeds (Emre & Naberezhnykh, 2014)

Coil/Loop length	**Charging Speed**					
	50 mph	**53 mph**	**57 mph**	**60 mph**	**65 mph**	**70 mph**
0.5 m	0.02	0.02	0.01	0.01	0.01	0.01
1 m	0.04	0.04	0.03	0.03	0.03	0.03
5 m	0.22	0.21	0.19	0.18	0.17	0.15
10 m	0.44	0.42	0.39	0.37	0.34	0.31
20 m	0.89	0.84	0.78	0.74	0.68	0.63
30 m	1.34	1.26	1.17	1.11	1.03	0.95
50 m	2.23	2.11	1.96	1.86	1.72	1.59
100 m	4.47	4.22	3.92	3.73	3.44	3.19

A further consideration is the DSRC protocol between the vehicle and charging infrastructure. Whilst initiating this process will take a discrete quantity of time, it is assumed that communication infrastructure will be positioned ahead of the charging zones, thus transfer can be initiated as soon as the vehicle reaches the charging zone. Therefore, any time it takes to commence this electronic handshake is insignificant, and it is globally assumed that the DSRC protocol will be able to maintain vehicle and grid communication sufficiently throughout the charging process.

Whilst the ability to model charging lanes within Aimsun was developed, the latter microscopic simulation work assumes that the entire route is equipped; with single, multiple, and differing lanes dependent upon the particular scenario modelled. All simulation work will be undertaken at four power levels, the base scenario (zero WPT) will be used to estimate vehicle energy consumption as it would be expected when there is no charging zone. Therefore, through 100% route equipment, it removes the very specific variable of where exactly to place the charging zone within the network; charging lane location is still present (inside or inside and middle). Hence, the exact coordinate position of the charging zone/s is not assessed within this research.

6.3.3 Vehicle Energy Transfer

The energy model uses the estimated discharge of the vehicle battery to calculate the vehicles SOC over the route distance, as well as considering the recovery of energy through regenerative braking and the use of WPT charging systems. Whilst the energy consumption model has been developed in the previous section, the complimentary charging component of the energy model can be expressed as the following electrical equations. The **vehicle charge rate** (W) can be calculated as:

$$\mathrm{P}_{charge\ rate} = P_{charger\ rate} \times \eta_{charger} \tag{18}$$

where, $P_{charger\ rate}$ represents the particular charge rate of the charging system, and $\eta_{charger}$ the efficiency of that charger. When in a charging situation the **charger energy** (J), specifically the energy the charger provides to the vehicle battery or motor, can be calculated as:

$$\mathrm{E}_{charger} = P_{charge\ rate} \times \eta_{vehicle\ power\ electronics} \times \eta_{battery\ charge} \times \Delta\mathrm{t} \tag{19}$$

where, $\eta_{power\ electronics}$ is the efficiency of the vehicles power electronics, and Δt the time step. The **energy from the grid** (VA) can be calculated as:

$$\mathrm{E}_{grid} = \frac{P_{charger\ rate}}{\eta_{charger} \times \eta_{grid\ power\ electronics} \times \eta_{power\ factor}} \tag{20}$$

where, $\eta_{power\ factor}$ is the power factor.

This completes the energy transfer model for the WPT charging system.

6.4 Vehicle Emission Production

A further modelling aspect that should be considered is the environmental impact of each vehicle as it passes through the network. This exists in several forms: CO_2, NOx, Volatile Organic Compounds (VOC) and PM. Whilst ICEVs produce these GHG emissions and PM, electric vehicles have zero point of use emissions, instead emissions are produced at the point of electrical generation. This model could be extended to include each and every emission aspect related to fossil fuels; from extraction of crude oil, to refining to liquid petroleum or diesel fuels, and then distribution of those fuels to filling stations. Equally, EV emissions include the generation method of the electricity supply, as well as the transmission and distribution of that supply to the end user. Each stage of either fossil or electrical fuel supply involves energy conversion, energy losses, input energy, and in turn emission production; thus, such an area grows in complexity exponentially given the required depth of the investigation.

For the purpose of this study, emission figures are generated to give the reader an indication to what is happening to the emissions given the particular scenario modelled. Thus, a simplified model is produced that focuses on GHG emission production for both ICEVs and EVs. To further simplify the model, emphasis is placed upon the CO_2e unit to consider all GHG emissions, rather than specifying each individual pollutant.

The **emissions of an ICEV** can be calculated from fuel use as:

$$N_{ICEV\ emissions} = \mathrm{E}_{fuel\ use} \times N_{pollutant\ per\ litre} \quad [21]$$

where, $N_{pollutant\ per\ litre}$ the quantity of pollution produced per litre of fossil fuel.

The **emissions of an EV** can be calculated from battery discharge as:

$$N_{EV\ emissions} = \mathrm{E}_{battery\ discharge} \times N_{pollutant\ per\ kWh} \quad [22]$$

where, $N_{pollutant\ per\ kWh}$ is the quantity of pollution produced per kWh of electrical energy.

6.4.1 Electric Vehicle Considerations

A significant advantage of EVs is the fact that they generate zero emissions at the point of use, resulting in localised air pollution benefits. However, the electrical energy stored within a vehicles battery is generated from primary energy, this generation process is typically a kinetic energy conversion process. Dependent upon the generation process and particular primary energy used, the efficiency of this process varies, as does the environmental impact. A high level analysis of this issue is undertaken; neither the particular generation method or primary energy source are considered, instead the current average UK grid mix is used.

The Department for Business, Energy and Industrial Strategy (BEIS) (2019) produces conversion factors for calculating emissions for EVs from UK electricity. This is based upon the size and efficiency of the vehicle, then specified as the particular pollutant (CO_2, CH_4, N_2O) production in grams per mile. Whilst this provides an indication to the emissions of EVs based on average vehicle sizes, the traffic and energy models estimate actual electrical energy consumption in kWh, thus this can be used to provide a more realistic figure. The BEIS produces the emissions per kWh of electricity, this data is shown for 2019 in Table 11.

Table 11 - Carbon Dioxide Equivalent Emissions from UK Electricity (kg CO_2e/kWh) (Department for Business, Energy & Industrial Strategy, 2019)

Process	Emissions (kg CO_2e/kWh)
Generation	0.28307
Transmission and Distribution	0.02413
Total	**0.30720**

Therefore, for 2019 the UK had an average emissions factor of 0.307 kg CO_2e/kWh including generation, distribution and transmission emissions.

6.4.2 Internal Combustion Engine Vehicle Considerations

Similarly, to the EV emission model, BEIS alongside the National Atmospheric Emissions Inventory (2018) produce average emission production values of differing size vehicles based upon distance. Therefore, pollutants such as CO_2, NOx or VOCs could be calculated from simulation data. Yet, such data would be based upon vehicle distances, this does not take advantage of the rich dataset produced from the traffic simulation. Thus, there is a case for an emission model that utilises specific vehicle data, not total trip distances. Such a model would be based upon individual vehicles speed and acceleration to determine pollution production.

Two emission models exist within AIMSUN; the QUARTET (1992) pollution emission model and the Panis, et al. (2006) pollution emission model. Typically, instantaneous vehicle data as well as emission parameters or factors are used in either model, with the simulation generating outputs in the form of emission quantities for each kind of pollutant over the entire network. The Panis et al model derives emission factors with non-linear multiple regression, using vehicle instantaneous speed and acceleration as parameters. The model considers CO_2, NOx, VOCs and PM. Yet, the Panis model was developed using predicted data for the 2010 UK traffic fleet (forecasted in 2006); thus newer data is now available and the original emission factors calculated by Panis, et al. (2006) may not be representative of the current and future fleet. Alternatively, the QUARTET model uses pollutant look up tables generated from pollution values at differing vehicle states; idling, cruising, accelerating and decelerating. Whilst, the base model considers Carbon Monoxide (CO), NOx and unburned Hydrocarbons (HC), further pollutants can be modelled if suitable data is available. Yet, a rich dataset is required to use such a model; each vehicles rate of emission production (grams per second) in every state is necessary.

Neither pollution model is ideal in this case, instead a simpler model is used that still retains the specific vehicle dynamics data input. The Department for Transport publish average vehicle CO_2 emissions per litre of fuel burnt or kWh used. Thus, the prior energy consumption model can be used to estimate fuel consumption, and in turn this value can be used to calculate CO_2e emissions for each vehicle trip. Therefore, emissions are based upon a particular vehicles speed and acceleration (as fuel use will vary dependent upon these attributes), rather than simply based upon trip distance (that does not consider differing vehicle dynamics). The CO_2e emissions per fuel source are contained within Table 12.

Table 12 – Carbon Dioxide Equivalent Emissions of different Vehicle Fuel Sources (Department for Transport, 2019)

Fuel	Emissions
Petrol	2.100 kg CO_2e/litre
Diesel	2.465 kg CO_2e/litre
Electricity	0.307 kg CO_2e/kWh

Therefore, for 2019 the UK had average emission values of 2.100 and 2.465 kg CO_2e/litre, and 0.307 kg CO_2e/kWh for petrol, diesel and electricity respectively. The electricity emissions value from the Department for Transport (2019) correlates with the prior BEIS (2019) value (Table 11). It is important to note, these ICEV values are merely hot emission values, they do not include cold start, brake, tyre and evaporative emission factors. Furthermore, the values provided for petrol and diesel do not consider the emissions of extracting, transporting and distribution of such fuels.

Vehicle pollution is not considered a crucial component of this research, instead aims to supplement the energy research. Thus, estimating emissions based upon vehicle fuel use provided sufficient depth of research and accuracy into this field. The values stated within Table 12 were implemented to the model using the prior emission equations for ICEV and EVs, this completes the emission element of the model.

6.5 Wider Network Energy System

One final aspect of the model is to assess the WPT charging network in its entirety; it is necessary to investigate the energy in and out of the complete network. Each agent consumes and receives energy as it travels throughout the network, with equipped agents receiving additional energy through WPT where appropriate. The summation of these values will begin to explore the transport network as an energy system. The process can be expressed as:

1. Simulation ends
2. Sum energy consumption for each agent and total across network (electric and fossil fuel)
3. Sum emissions for each agent and total across network (electric and fossil fuel)
4. Sum WPT energy transfer per charging zone
5. Sum WPT energy transfer for each agent and total across network (electric and fossil fuel)
6. Output data to external document

The following equations are used estimate the above values. The **total electrical energy consumption** of an EV as it travelled through the network can be estimated through summing the vehicles battery discharge at each time delta:

$$E_{battery\ demand} = \sum \Delta E_{battery\ discharge} \quad [23]$$

The **total fossil fuel consumption** of an ICEV as it travelled through the network can be estimated through summing the vehicles fuel use at each time delta:

$$\mathrm{E}_{fuel} = \sum \Delta\, \mathrm{E}_{fuel\ use} \quad [24]$$

The **total emission production** of a vehicle as it travelled through the network can be estimated through summing the vehicles emissions at each time delta:

$$N_{emissions} = \sum \Delta N_{emissions} \quad [25]$$

The **total energy demand on the WPT system** can be estimated through summing the charger energy at each time delta:

$$E_{WPT\ system} = \sum \Delta E_{charger} \quad [26]$$

Further, this can be used to estimate the energy required at each charging zone, for each individual vehicle, for each road link, or across the entire network as shown.

This completes the entire energy model, as developed and documented throughout this chapter.

6.6 Vehicle Specifications

Through the development of the energy model, it is clear that a number of vehicle variables and values must be outlined for use with the model; this section serves to define such values.

The vehicle specifications have been segregated into several categories that are required as inputs to the model, consisting of: vehicle, motor, battery, supercapacitor, charger, and passenger specification. This section outlines the base data, as well as the assumptions made in determining the vehicle specifications used within the simulation work. All variables used within the modelling work have been highlighted in **bold** for reference. Within the real world, the traffic composition will be made up from a far greater number of vehicles, with an infinite number of parameter settings. In order to constrain the model, a finite number of vehicles and classifications must be used.

Vehicle:

Four **vehicle types** will be modelled; car, LGV, HGV Rigid, HGV Articulated. Where appropriate, up to three vehicle configurations will be used for each vehicle type; petrol, diesel, and electric. The values documented throughout this section are average values based upon the vehicles in their classification, not precise replications of exact vehicles. Yet, typical vehicles in each category include:

Car: Tesla Model S (75D), BMW 3 series (2.0i/2.0d), Skoda Octavia (1.5TSI/2.0TDI)

LGV (3.5T): Mercedes Sprinter Luton, Citroen Relay Luton, Ford Transit Luton

HGV Rigid (7.5T): IVECO Eurocargo, DAF LF, MAN TGL

HGV Articulated (44T): IVECO Stralis, DAF XF, MAN TGS

In terms of **fuel type** proportions, the base scenario will consist of solely petrol and diesel type vehicles with no EVs present. Whilst the market is now moving away from diesel fuel, towards cleaner petrol or low emission vehicles, the same petrol to diesel proportion will be used throughout the modelling work, with an increasing EV proportion over time as EVs gain market penetration. This fossil fuel proportion was 45% petrol/55% diesel for cars, and with diesel LGVs dominating the current freight market within the UK at a <98% market share, it was assumed that all freight vehicles would use diesel; these values are in line with WebTAG and other sources of data (Department for Transport, 2019) (Department for Transport, 2017). Elsewhere around the world, and if the current trend in switching to petrol from diesel continues, the fossil fuel proportions will inevitably vary, yet are considered accurate enough for this modelling work. Both fossil fuel proportions will be scaled down linearly as the EV proportion increases.

For goods vehicles where the payload will vary depending upon, and potentially throughout, the trip it becomes necessary to use an average vehicle mass based upon the expected **payload utilisation rate** of the vehicles load carrying capacity. It was assumed that freight vehicles will have a utilisation rate of 50%, this value is in line with previous research (Larsson, 2009) (Knight, et al., 2008). The base **vehicle mass** has been assumed to be 1.75T for cars, 2.5T for LGVs (1T payload), 5.3T for rigid HGVs (2.2T payload), and 18T for articulated HGVs (26T payload) (Quadrant Vehicles, 2020) (Delivered, 2020). Typically, electric versions of the same vehicle will likely weigh more than their ICE counterpart, this difference is accounted for later within the battery mass configuration.

Rolling resistance coefficients consider the energy losses of the vehicles tyres; primarily due to cyclic deformation of the tyre. Such coefficients vary between vehicle classifications, individual vehicles within each classification, as well as the different axles of such vehicles, dependent upon the loading on each axle. Therefore, rolling coefficients have been assumed as 0.012 for cars and LGVs, and 0.008 for both HGV classifications, both are consistent with literature (Arteaga, 2011) (Wong, 2008) (Michelin, 2003). The higher loads, and thus tyre pressures, of HGVs result in a lower rolling resistance coefficient due to less tyre deformation. It is acknowledged that the use of energy saving tyres, those with a lower rolling resistance, differing tyre pressures, tyre constructions, and vehicle dynamics will all influence the rolling resistance coefficients listed above, thus average realistic values are used.

The aerodynamic design of a vehicle will greatly influence the speed performance and fuel efficiency of said vehicle, a vehicles **drag coefficient** is a measure of its aerodynamic drag to airflow. In addition to the shape of the vehicle, its **frontal surface area** also contributes to the vehicles resistance to pass through the air; reducing either the drag coefficient or frontal surface area will improve the vehicles ability to pass through the airflow. Average drag coefficients were 0.29 for cars, 0.34 for LGVs, and 0.75 for HGVs, while frontal surface areas were 2.24m^2 for cars, 4.06m^2 for LGVs, and 9.7m^2 for HGVs (Kühlwein, 2016) (Stenvall, 2010). Vehicle mass, in culmination with vehicle power and frontal surface area, will influence the vehicles performance with respect to gradients within the traffic model. Arguably, EVs have a lower drag coefficient due to the desire to improve efficiency in their design, yet there is a generic trend in the development of more aerodynamic energy efficient vehicles so the same values stated above will be used irrespective of the vehicles fuel source.

Motor:

The **specific energy density** of both petrol and diesel automotive fuels is open to variation depending upon the refining process and additives used. As diesel fuel has a slightly higher density than petrol (at 833kg/m^3 compared to 740kg/m^3), the energy density of diesel is marginally higher per litre. The specific energy densities used are 38.6 MJ/l for diesel, and 34.2 MJ/l for petrol (IOR Energy, 1999). This equates to 10,700 Wh/l for Diesel and 9,500 Wh/l for petrol.

Equally, the **thermal efficiency** of an ICE is heavily dependent upon the technical design of the engine and particular engine cycle (Otto or Diesel); thus for the purposes of the simulation work a thermal efficiency of 28% for petrol engines and 32% for diesel engines is assumed (Nuclear Power, 2020). The modern ICE is very inefficient when compared to an electrical motor; on average only a third of input energy is turned into useful work, the rest is waste heat.

The electric motors within an EV enable 100% torque delivery at initial movement, with torque dropping off linearly as speed increases. They are a good match to a vehicles torque requirements; where acceleration that requires the most amount of torque is done at lower speeds, and less acceleration, and thus less torque, is required at higher speeds. As such, EVs do not require a multi-ratio gearbox and therefore do not encounter the efficiency losses of a mechanical gearbox when compared to ICEVs, albeit a reduction gearing system often being used in an EV. Equally, with EVs typically having front and/or rear mounted electric motors, an EVs drivetrain is simplified and thus does not encounter the same level of energy losses when considering a Real Wheel Drive (RWD) ICEVs gearbox, propshaft, differential and driveshafts. It is important to consider, as speed increases the efficiency of either vehicles drivetrain reduces. In order to simplify such calculations, it was assumed that an ICEV would have a **drivetrain efficiency** of 85%, while an EV would be assumed to have a drivetrain efficiency of 95%; these values correlate with other studies (Damiani, et al., 2014).

The **electrical motor efficiency** of an EV was considered to be 95%, and the **power electronics efficiency** was also assumed to be 95%, such values are coherent to existing studies (Campanari, et al., 2009). In order to recover energy, an EV will use the motor to slow the vehicle (in conjunction with the traditional braking system) and thus recover some kinetic energy. The efficiency of this regeneration process is the culmination of the generator (or motor) efficiency, which was previously documented as 95%, and the efficiency of the wheel to battery regeneration process. This wheel to battery process includes the generator efficiency but also accounts for the drivetrain efficiency and battery efficiency of putting the electrical energy into the traction battery. Thus, this

regeneration (wheel to battery) efficiency was assumed to be 60% (Toll, 2018), in that 60% of the recovered energy is put back into the battery, and 40% is lost to energy transformations and mechanical losses. These inefficiencies for EVs: motor (95%), power electronics (95%), drivetrain (95%), and for ICEVs: motor (30/35%), drivetrain (85%), result in total efficiencies of 86% for EVs and 26/30% for ICEVs.

The **vehicle emissions**, were defined as 2.1 kgCO_2e/l of burnt petrol, 2.465 kgCO_2e/l of burnt diesel, and 0.307 kg CO_2e per kWh of electricity used (Department for Transport, 2019); Section 6.4 further describes the specific values used.

Battery:

When considering vehicle packaging and technical constraints, several smaller batteries may be used in the future, especially for freight applications. In terms of **battery quantity**, for simplicity it was assumed that all vehicles had a single battery fitted whereas masses and capacities may in fact be spread across multiple smaller batteries. The **initial battery energy** of all vehicles has been set to 100% of their capacity, whilst this doesn't technically leave room for energy recovery or immediate WPT charging, within this theoretical simulation such values can go beyond 100%, and thus starting from such a value can make it easier to identify how the particular scenario is performing. The **battery mass** will vary dependent upon the capacity, a larger capacity battery pack requires a higher number of cells. The Tesla Model S 75D has a battery mass of 530kg, according to Wright (2017), with a specific energy density of 141 Wh/kg, equating to a total battery capacity of 75 kWh. The Model S 75D uses a **battery voltage** of 350V, with the larger models using 400V (Tesla Tap, 2020). When converting Wh to Ah, assuming a 350V battery voltage with a 75kWh capacity this equates to a 214Ah **battery capacity**. It was assumed that LGVs would use the same battery specification as cars, while batteries for HGVs will use the same specification, but scaled based upon battery capacity due to the limitations of available electric HGVs. In other words, it was assumed there would be a linear correlation between energy density and battery mass using the base specification of the Tesla Model S 75D.

For the rigid HGV category, a battery capacity of 300kWh was selected; this is in line with slightly larger trucks currently produced such as the Volvo FL Electric or the Daimler Freightliner eM2 (Volvo, 2018) (Daimler, 2018). Assuming a battery voltage of 800V, which appears likely for truck applications (Jung, 2017), this equates to a 375Ah battery capacity. Again, assuming the prior linear correlation of energy density to mass, then a 300kWh battery would weigh 2,120kg. Whilst articulated HGVs are typically used for long distance trips between freight distribution depots, smaller rigid HGVs as well as LGVs are used for a much wider range of applications. This variability in use can include short urban trips, longer interurban journeys, or rural delivery services. Thus, manufacturers will likely offer different sized battery packs to suit the desired application of the vehicle, and provide different price points accordingly.

For the articulated HGV category, a battery capacity of 600kWh was selected; this is currently an unknown due to the limited knowledge around electric HGVs of this size. Tesla state that their new electric truck will be capable of travelling up to 500 miles with an energy consumption of less than 2kWh per mile (Tesla, 2020); indicating towards a battery capacity of up to 1000kWh. Further, Tesla state that their truck will have a drag coefficient of 0.36, significantly lower than any truck of that size. Thus, 600kWh is double that of the Volvo and Daimler vehicles, but still conservatively less than the Tesla Semi which has not yet been produced, and significantly more than the 170kWh DAF CF Electric Innovation Truck (DAF, 2020). Again, assuming a battery voltage of 800V and the same energy density to mass ratio, this equates to a 750Ah battery capacity at a mass of 4,240kg.

With regard to the battery mass, electric vehicles tend to be heavier than comparable ICEVs due to the addition of this battery mass. Yet, when considering the mass of a full tank of fossil fuel, and the fact that the actual EV chassis is typically lighter than an ICEV chassis through design and material selection, the difference becomes more marginal. Another factor not accounted for is the additional weight of the WPT coils and power electronics. An assumption was made that EVs will be heavier but only by 75% that of the stated battery mass. For example, within the car class vehicle mass was 1750kg, adding three quarters of the battery mass of that class, 397.5kg, results in a total mass of 2147.5kg; a mass not too dissimilar from a Tesla Model S at 2163kg (Tesla, 2020). Whilst additional vehicle mass will affect freight payload capacity, with utilisation rates of 50% the fact that maximum gross vehicle weight exceeds legal limits is not considered, as all vehicle masses will be below this limit within the model.

The **charge and discharge rates** are a key component of the model, they determine the maximum amount of power the battery can provide or the total amount of energy that can be recovered during regenerative braking. The ideal charge and discharge rates for the model are the motor rate. A Tesla Model S 75D has two 193 kW motors, totalling 386 kW of motor power (Wright, 2017), when considering the motor voltage of 350V, this puts maximum current at 1103A. Thus, charge and discharge rates cannot exceed these values. Generally, such maximum discharge conditions will only ever be experienced for a very short amount of time – just a few seconds during maximum acceleration. Tesla use Lithium Nickel Cobalt Aluminium Oxide (NCA) batteries. Whilst such batteries have a high specific energy density, good power density and long lifespan (Buchmann, 2020), they are not the best in group for charge and discharge rates. For continuous charge and discharge rates, NCA batteries should not exceed 1C to achieve maximum cycle life. In comparison, some batteries are capable of discharging at a higher C-rate, such as Lithium Nickel Manganese

Cobalt Oxide (NCM) batteries, beyond this, Lithium Iron Phosphate (LFP) batteries are capable of even greater discharge rates (Buchmann, 2020). Importantly, the exact Tesla battery specification and chemistry are unknown, and thus may allow for greater charge and discharge rates than the standard battery chemistries stated. It is therefore assumed that the Tesla Model S 75D is capable of charging and discharging at 368 kW (or 1103A); with the 75 kWh (or 214Ah) battery pack this equates to a rate of 5.15C, albeit for only a few seconds. Therefore, within the model the motor rating is used for maximum charge and discharge rates; 368 kW for cars and LGVs. For HGV applications, it is assumed that motor capacity would be 500 kW, as such the maximum charge and discharge rates for HGVs is 500 kW. To provide some context to this assumption, 500 kW is greater than the Volvo FL Electric that uses a single 185 kW motor (Volvo, 2018), and the Daimler Freightliner eM2 that uses two 125 kW motors (Daimler, 2018), whilst conservatively less than the Tesla Semi that is expected to use four 211 kW motors from a Tesla Model 3 (Alvarez, 2018). Finally, across all classifications, **charge and discharge efficiency** of the batteries were assumed to each be 95%; thus equating to a near 90% average efficiency when transferring energy into and out of an EV battery pack (Valøen & Shoesmith, 2007) (Forward, et al., 2013).

Supercapacitor:

At present, no EVs utilise a supercapacitor. Yet, such devices are able to quickly store and discharge a large amount of energy, making them ideal for an EV where large amounts of regenerative braking energy can be quickly recovered and reused. The main difference between supercapacitors and batteries are the way in which they store energy. A battery will hold its energy in electrochemical form, while a supercapacitor stores energy in electrostatic form. Thus, supercapacitors can charge and discharge significantly quicker than batteries, yet cannot store such energy for large amounts of time. Development of supercapacitors is still underway and could compliment EV batteries, or in fact replace them entirely in the future as once predicted by Elon Musk (Yvkoff, 2019). Future scenarios will likely see supercapacitors fitted to buses and heavy freight vehicles. Whilst the latter energy model was developed to include supercapacitors in its calculation, at this stage it was assumed that vehicles did not have a supercapacitor fitted as they are not common place.

Charger:

The WPT **charge rate** has been assumed to be between 25-75 kW for car and LGV applications, while for HGVs between 50kW-250kW; the **charge efficiency** of the WPT process is considered to be 90%. These power levels and efficiencies are comparable to current and future WPT systems reviewed previously. The WPT charger **power factor** was assumed to be 97% (Liu, et al., 2018), while the **grid power electronics efficiency** was assumed to be 95% (Ramos, et al., 2008). Section 6.3.1 further explains the WPT system specification and justifies the use of such values.

Passenger:

In terms of **vehicle occupancy**, Department for Transport (2019) state that average car and van occupancy for all trip purposes is 1.55, it is assumed for HGVs that vehicle occupancy will be 1.0. Whilst the study conducted by Wapole and colleagues (2012) identifies that the average **human body mass** globally is 62kg, thus will be compensated for within the model.

This section has outlined the required parameters and specific values used within the modelling work, the numerous assumptions have been justified to appropriate literature and it is considered that these values realistically represent the typical vehicles in each of the four vehicle classifications. As further research and literature becomes available, the model can be rerun to account for such new data. But at present, the values documented within this section and further presented within Table 13 are considered sufficiently realistic and, having not previously been compiled before, are a key contribution of this research.

Table 13 – Vehicle Specifications

Category	Factor	Units	Car			LGV		HGV Rigid		HGV Artic	
Vehicle	Fuel Type	-	Petrol	Diesel	Electric	Diesel	Electric	Diesel	Electric	Diesel	Electric
	Mass	(kg)	1750	1750	1750	2500	2500	5300	5300	18000	18000
	Payload	(kg)	-	-	-	1000	1000	2200	2200	26000	26000
	Payload Utilisation	(%)	-	-	-	0.5	0.5	0.5	0.5	0.5	0.5
	Rolling Resistance Coefficient	(#)	0.012	0.012	0.012	0.012	0.012	0.008	0.008	0.008	0.008
	Drag Coefficient	(#)	0.29	0.29	0.29	0.34	0.34	0.75	0.75	0.75	0.75
	Surface Area	(#)	2.24	2.24	2.24	4.06	4.06	9.7	9.7	9.7	9.7
Engine	Fuel Density	(Wh/l)	9500	10700	-	10700	-	10700	-	10700	-
	Regenerative Efficiency	(%)	-	-	0.6	-	0.6	-	0.6	-	0.6
	Engine Thermal Efficiency	(%)	0.28	0.32	-	0.32	-	0.32	-	0.32	-
	Drivetrain Efficiency	(%)	0.85	0.85	0.95	0.85	0.95	0.85	0.95	0.85	0.95
	Generator Efficiency	(%)	-	-	0.95	-	0.95	-	0.95	-	0.95
	Electric Motor Efficiency	(%)	-	-	0.95	-	0.95	-	0.95	-	0.95
	Power Electronics Efficiency	(%)	-	-	0.95	-	0.95	-	0.95	-	0.95
Battery	Voltage	(V)	-	-	350	-	350	-	800	-	800
	Capacity	(Ah)	-	-	214	-	214	-	375	-	750
	Mass	(kg)	-	-	530	-	530	-	2120	-	4240
	Quantity	(#)	-	-	1	-	1	-	1	-	1
	Charge Rate	(kW)	-	-	368	-	368	-	500	-	500
	Discharge Rate	(kW)	-	-	368	-	368	-	500	-	500
	Charge Efficiency	(%)	-	-	0.95	-	0.95	-	0.95	-	0.95
	Discharge Efficiency	(%)	-	-	0.95	-	0.95	-	0.95	-	0.95
Charger	Charge Rate	(kW)	-	-	25-75	-	25-75	-	50-250	-	50-250
	Charge Efficiency	(%)	-	-	0.9	-	0.9	-	0.9	-	0.9
	Power Factor	(%)	-	-	0.97	-	0.97	-	0.97	-	0.97
	Power electronics in grid	(%)	-	-	0.95	-	0.95	-	0.95	-	0.95
Passenger	Quantity	(#)	1.55	1.55	1.55	1	1	1	1	1	1
	Mass	(kg)	62	62	62	62	62	62	62	62	62

6.7 Energy Model Configuration

The following process outlines the configuration and operation of the energy model, using the simulated traffic dataset generated from AIMSUN:

1. Sort dataset: Use the 'sort' program to sort the traffic datasets by vehicle ID and then by time step
2. Setup Energy Model: Define scenario settings within the vehicle configuration script
3. Run Energy Model: Run the 'energy model' program using the sorted traffic dataset, the energy model appends associated vehicle energy data to the traffic dataset using equations outlined within this chapter
4. Analyse energy data: Submit and run the 'analysis' program using IRIDIS (supercomputer) to analyse, condense, and summarise statistical data for each scenario
5. Compile datasets: Use the 'compile' program to amalgamate all traffic and energy datasets together
6. Data analysis: Analyse traffic and energy simulation data

Technically, a variety of scripts and programs were developed to automate the traffic and energy models as far as possible. The energy model was parallelised on the local PC to optimise resources and time. Each traffic simulation consisted of 10 replications, thus resulted in 10 datasets that required processing for each experiment; exact results for each experiment are then an average of the 10 replications once processed through the energy model. The University supercomputer was used because of the additional RAM needed to process the large datasets generated by the energy model.

Whilst the specific scenarios have been discussed throughout the prior model development chapters, the specific experiments modelled and their varying parameters are outlined in Table 14. The explanatory variables (vehicle type, WPT power level, charging lane location, charging lane speed, and EV proportion) are tested independently of one another, equating to approximately 160 varying experiments.

Table 14 – Microscopic Experiments and Explanatory Variables Tested

Variable	Values
Vehicle Type	CP, CD, CE, LD, LE, HRD, HRE, HAD, HAE
EV/WPT Enabled Proportions	0%, 5%, 10%, 15%, 20%
Charging Speed	55 mph, 60 mph, 65 mph, 70 mph, Typical/Average
Charging Lane Location	Integrated Inside, Integrated Inside and Middle
WPT Power Level	None, Low, Medium, High

6.8 Chapter Conclusions

Whilst traffic modelling element was assessed previously in Chapter 5, the consideration of the energy component was the final modelling aspect that required attention. While no microscopic traffic package reviewed was well suited to the application of WPT charging systems, several methods were developed to create an interface for implementing such required energy functionality. Four areas of investigation existed; vehicle energy consumption, vehicle energy transfer, vehicle emission production and the wider network energy system. This chapter has documented the development of appropriate models for including the four energy aspects to within the traffic model.

AIMSUN's API was used to monitor, track, and control individual vehicles; assessing the interaction environment between the vehicles and the WPT charging system. Such traffic simulation data is outputted to a dataset for post processing. In turn, an external program was extensively developed to calculate both energy consumption and energy transfer values for each vehicle within the simulation dataset. Such consumption values were reverse calculated using kinematic, electrical and combustion equations, where appropriate. Individual vehicle emissions were modelled through fossil fuel and electricity grid conversion factors for ICEVs and EVs respectively. It was identified that it was not possible to simply convert energy or emission values accurately between EVs and ICEVs. As such, models were developed to consider both vehicle fuel sources and, where appropriate, use differing calculations to estimate energy consumption and emission production.

Whilst this chapter has documented the main specifications and equations used within the model, a series of logic operators create a network of parallel and complimentary equations to culminate in the final model depending on specific scenarios, vehicle specifications, vehicle state, or other influential factors modelled. The energy model configuration process and varying simulation experiments were also documented. It is important to note, the models developed within this section are considered tools used to estimate the level of energy consumption, energy transfer and emission production; rather than calculate precise values, accurate to a finite day, driver, vehicle, network layout, traffic condition and charging system specification.

This chapter was the final component in developing a microscopic traffic model that is capable of understanding the WPT situation in its entirety; to do so both traffic and energy criteria were considered and included within the model. The next requirement is the calibration and validation of the models to ensure they are both realistic and representative of expected conditions, after which the microscopic model can be used to assess varying WPT charging scenarios.

Chapter 7 Microscopic Simulation

7.1 Introduction

It was identified that there was a need for a tool that could integrate WPT systems into a traditional traffic simulation model, so that energy, traffic and WPT technicalities could be investigated within the computational domain. The development of such a tool has been documented up until this point. This chapter serves to contain the results and analysis of the previously described microscopic case study.

It is essential that each component of the model is calibrated and validated before the models are used to generate results. This process sees the comparison between the model developed and real world data taken from standardised drive cycles. Energy consumption and emissions, for both fossil and electrically fuelled vehicles, are compared against manufacturer and research values obtained from literature for such given drive cycles. Initial exploratory analysis is undertaken to test the realism of the results obtained through the traffic and energy models. It is the purpose of this analysis to provide confidence in the results, and ensure they represent what would be expected if this theoretical model were implemented as physical tests.

Whilst the exact energy consumption of a given vehicle within a given scenario could be assessed, it provides little context to the wider system at this level. Such a value would be specific to this case study, as well as the charging scenario, vehicle specification and general model configuration. Thus, the main results are used to derive a series of equations with weighted coefficients in order to estimate: average speed, battery gain/loss, ICEV fuel consumption, and vehicle emissions. Such estimations are based upon a number of explanatory factors: vehicle type, vehicle speed, WPT power level, charging lane location, charging lane speed, and EV proportion. Such mathematical models allow various scenarios to be assessed depending upon the user's requirements, in terms of both the traffic impact and energy considerations, without requiring extensive traffic and energy modelling.

7.2 Calibration and Validation of Models

Assessing calibration and validation as two separate entities; calibration is the process of ensuring the model reflects the reality (getting the model to equal what you can observe), whilst validation is the process of ensuring the model reflects something you cannot observe (checking that the model is responding appropriately). Without either process, the model will be inaccurate and untrustworthy, thus the calibration and validation of both the traffic model and energy model is fundamental. This section documents this process, as well as identifying the limitations and issues in calibrating and validating such models.

7.2.1 Traffic Model

When dissecting the traffic model, three main components exist; the road network, the traffic demand, and the individual vehicle behaviour models. Calibration and validation efforts must consider each entity in conjunction with the other components of the model.

The development of the network within AIMSUN can be undertaken automatically through importing an Open Street Map (OSM) or manually through superimposing sections over an appropriate background map. Configuring the various road classifications, speed restrictions and traffic control systems within the network is the main intention of calibrating the road network component.

The four stage model (Ortúzar & Willumsen, 2011a) was used to determine traffic demand data. Calibration of the traffic demand data is the most important component when calibrating the model. Typically demand data is estimated from observed data, thus ensuring that demand data is representative of reality is somewhat complex. Demand data was estimated from traffic flow data, as detailed within Section 5.2.3 – Traffic Demand. While some assumptions were made in the estimation of OD matrices, the use of real world traffic data associated with the case study network results in a model that will be to some degree already representative of reality. Inputting the demand data into the model as 15 minute aggregates ensured that time varying scenarios such as morning and evening peaks, as well as school runs at an even shorter time interval, are represented through the high resolution of the OD matrix data.

Individual vehicle behaviour models, the base car following, lane change and gap acceptance algorithms, are assumed to be representative of existing vehicle behaviour. Much work has been undertaken concerning the development of realistic driver behaviour models as well as the calibration of such algorithms. Yet, such models are inherently difficult to calibrate, and in some cases are questionable as to how well they can represent a real driver's behaviour. Adding EV and WPT driver behaviour to the situation further complicates the issue; such behaviour differences are very much uncertain. The development and refinement of such models were deemed beyond the scope of this project and an assumption was made that, whilst differences are acknowledged, the underlying models are sufficiently realistic for this application. Through initial simulation of the model, and analysis of its preliminary results, the model appears representative of current traffic conditions, reinforcing the calibration measures undertaken.

The validation process is somewhat more complex, it is notoriously difficult to validate a traffic model due to the need to make the model emulate future scenarios that are currently unknown. For example, how well the model represents a WPT charging lane is unknown. The simulation results can only be trusted through prior validation of the model, ensuring that it acceptably reflects future scenarios representatively; underlining the importance of a validated traffic model. The ideal method in validating such a model is to compare simulation results to a real observed data for the same scenario, yet such data is not attainable. Instead, simplified example scenarios were constructed and the resultant data analysed to ascertain that the model was responding as would be expected. For example, when the number of vehicles in the network increased, flows and traffic congestion increased. When desired speeds increased, average speeds across the network increased. This was the extent of the possible validation process, yet such simple examples demonstrate that the model was behaving as would be expected.

The calibration and validation process has demonstrated the traffic models ability to realistically represent the current network, as well as its scope to emulate predictable results for future scenarios. It is important that exploratory data analysis is undertaken to ensure that initial results are both as would be expected and realistic; this process is undertaken at a later stage.

7.2.2 Energy Model

With respect to the energy model; the consumption, transfer and emission elements must be calibrated and validated to ensure that the results generated are realistic to real world conditions. Whilst energy transfer and emission production are mathematical calculations, it is the energy consumption model that requires more extensive validation.

Initially the traffic model was used to generate vehicle data over a 1 mile section of the network, the vehicle speed/time data over this section was processed through the energy model and the resultant energy consumption provided. The following graph (Figure 18) shows that energy consumption, be it electrical or fossil fuel, varies with vehicle speed as would be expected. Whilst EV energy consumption increases with vehicle speed, ICEV fuel consumption decreases as speeds increase; this is correlated with prior literature that demonstrates these trends.

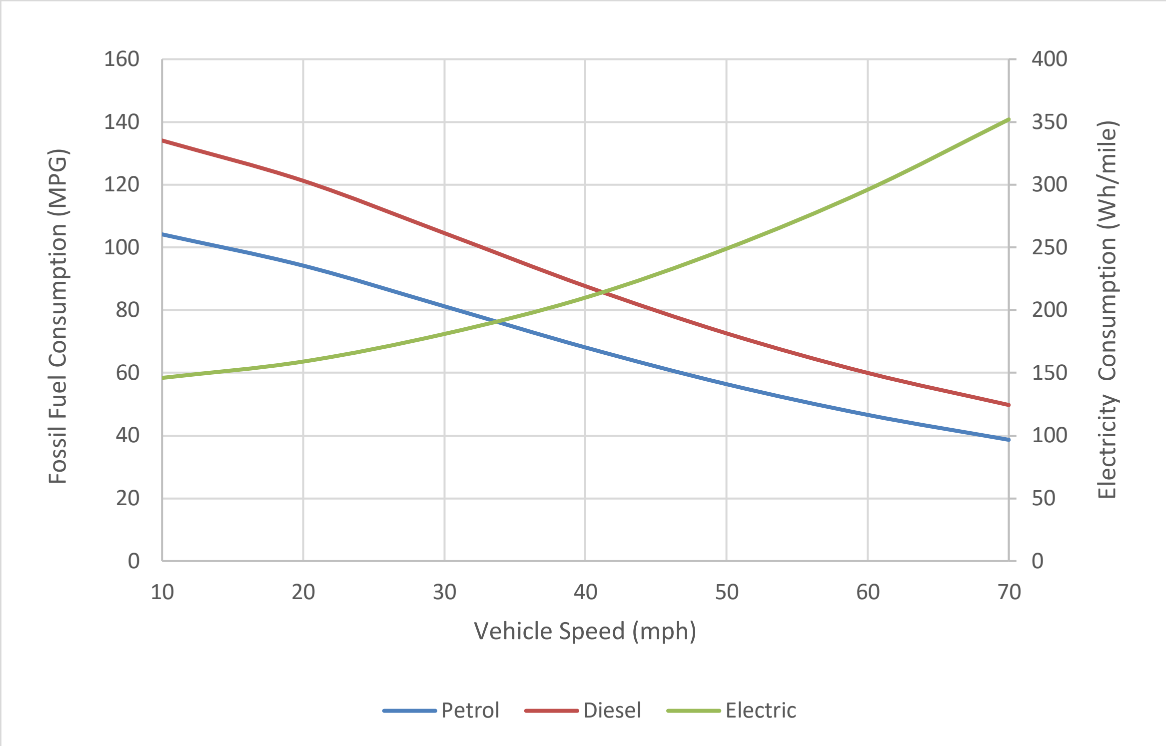


Figure 18 – Fossil Fuel and Electricity Consumption by Vehicle Speed

From literature, aerodynamic drag should become more dominant than rolling resistance at a particular vehicle speed (U.S. Department for Energy, 2000). The following graph (Figure 19) of an EV travelling at different fixed speeds identifies that for this particular vehicle specification aerodynamic drag overcomes rolling resistance energy at 57 mph. Energy consumption values are for a 1 second time step. Such curves follow the same trends as seen in literature.

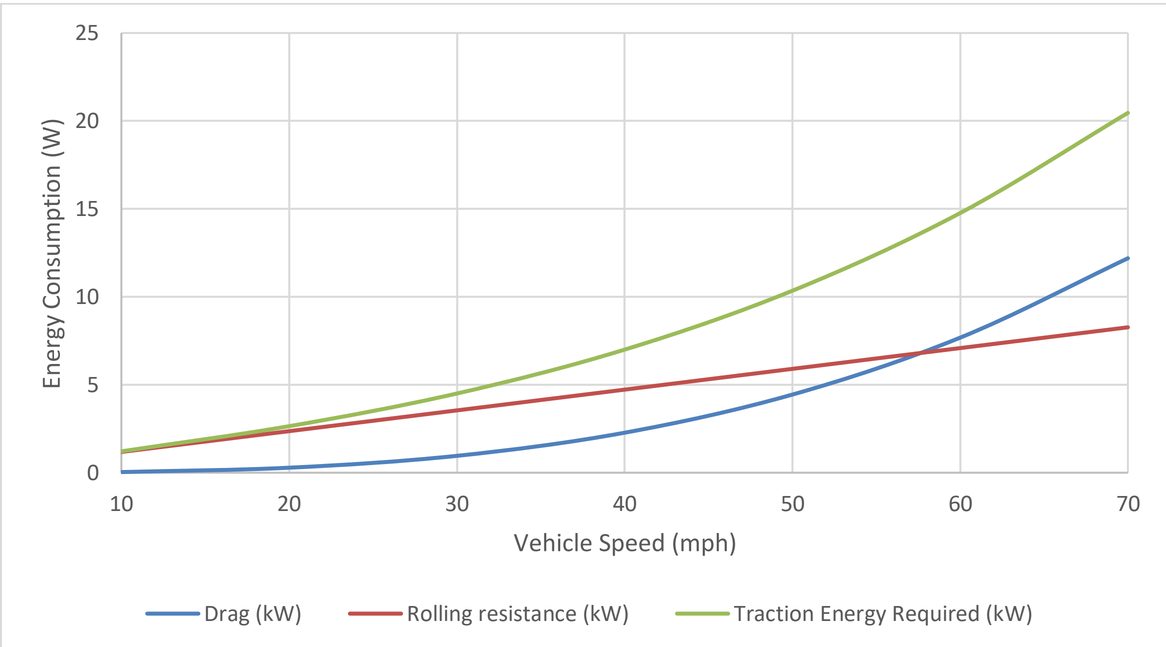


Figure 19 – Energy Consumption at differing Vehicle Speeds

In order to validate that the model is functioning realistically throughout a vehicles entire trip, accounting for differing acceleration and deceleration cycles, a driving cycle must be modelled. Within the UK, manufacturers use the Worldwide Harmonised Light Vehicle Test Procedure (WLTP) developed by the EU (Tutuianu, et al., 2013) to determine fuel consumption and emission production. The WLTP drive cycle (Figure 20) consists of four dynamic stages based on vehicle speeds (low, medium, high, and very high) over a 14.45 mile distance, taking 30 minutes to complete.

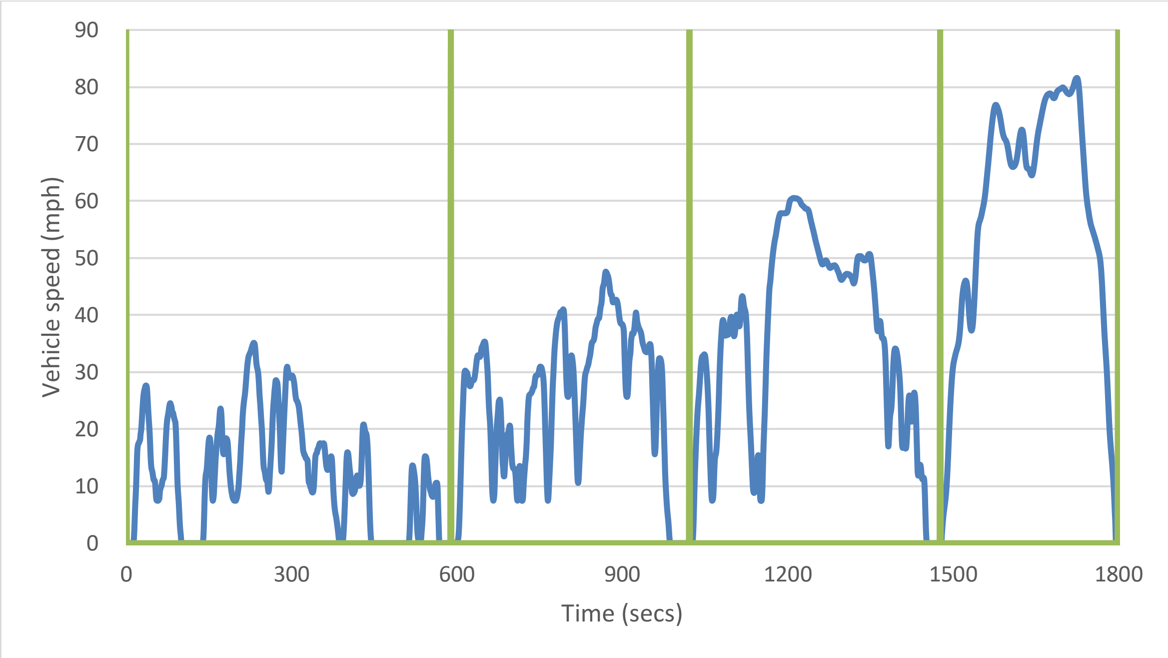


Figure 20 – WLTP Test Cycle

Table 15 shows the energy consumption over the WLTP test cycle of a petrol, diesel, and electric car using the prior vehicle configurations laid out in Section 6.6 – Vehicle Specifications. Vehicle data from other sources are added to the table as comparison between the results obtained from the energy model and those values specified by literature.

Table 15 – Energy Consumption Comparison between Energy Model and Literature (Car)

Car	Petrol	Diesel	Electric
Energy model (WLTP cycle)	44.3 MPG	57 MPG	310 Wh/mile 241 mile range
BMW 320i / 320d (WLTP)[1]	43.5 MPG	56.5 MPG	
Skoda Octavia 1.5 TSI / 2.0 TDI (WLTP)[2]	46.3 MPG	55.5 MPG	
DfT: Average new car fuel consumption in UK[3]	51.7 MPG	61.2 MPG	
Tesla Model S 75D (NEDC)[4]			235 Wh/mile 304 mile range
Tesla Model S 75D (Real Range)[4]			300 Wh/mile 240 mile range
Tesla Model S 75D (EPA)[5]			330 Wh/mile 259 mile range
Jaguar I-Pace (WLTP)[6]			350 Wh/mile 292 mile range

[1] (BMW, 2020) [2] (Skoda, 2020) [3] (Department for Transport, 2019) [4] (Electric Vehicle Database, 2020a) [5] (U.S. Department of Energy, 2020) [6] (Electric Vehicle Database, 2020b)

Table 15 indicates that the results generated from the model are comparable to manufacturer stated fuel economy using the same WLTP drive cycle where possible. The recent change from the New European Drive Cycle (NEDC) to the more accurate WLTP cycle has meant that Tesla did not release the WLTP drive cycle data for the Tesla Model S 75D. Yet, the WLTP data for a Jaguar I-Pace (a similar specification vehicle to a Tesla) has been included within the table for comparison. With respect to ICEVs, both the BMW 3 series and Skoda Octavia compare well to the MPG fuel consumption. The Department for Transport average new car fuel consumption is too vague as it includes all new vehicles registered, thus if there was a greater number of smaller more efficient vehicles then the dataset will be positively skewed, and vice versa for less fuel efficient vehicles.

It should be noted, EV consumption is susceptible to a greater number of influential factors and operating conditions when compared to traditional ICEVs; of which charging conditions, battery health and temperature are most significant. Thus, when comparing energy consumption per mile or vehicle range, there is a large variance in vehicle data. Vehicle range also generates further issues with respect to the inability to fully charge or discharge the vehicles battery completely; in order to maintain battery health. Therefore, whilst a manufacturer may state battery capacity, the usable capacity will in fact be less. For example, the Tesla Model S 75D has a battery capacity of 75 kWh, yet its usable capacity is actually 72.6 kWh (Electric Vehicle Database, 2020a).

Whilst generating vehicle data over a single mile of the road network and processing it through the energy model yields the correct expectations, with respect to energy and fuel consumption criteria. The model has been further validated using the WLTP drive cycle to ensure that the results generated are realistic to real world conditions. It is important to state, the model does not use a specific vehicle specification, instead uses generic parameter values based upon average vehicles in that category. Thus, for comparison outside of this study, the model provides results that are realistic to a vehicle that achieves 44 MPG if a petrol derivative, 57 MPG if a diesel derivative, and 310 Wh/mile if an electric derivative. Table 15 shows that these results are comparable to similar sized vehicles that the energy model vehicle specifications are based upon.

Whilst the car classification has been validated, three further vehicle categories exist and must be validated to ensure that they too provide realistic energy consumption results. Yet, the WLTP drive cycle was specifically developed for light vehicles (cars and LGVs), thus is inaccurate for heavy freight, not least because the high speed phase of the drive cycle reaches 80 MPH. When compared to light vehicle testing, there has been less development within the heavy vehicle field. Due to the higher number of engine, transmission, and body style combinations of freight vehicles, type approval for every combination is impractical. This is also apparent in the lack of fuel economy or emission production data available from manufacturers. Typically, engine dynamometer testing has been used for type approval emission testing. Yet, such testing is not capable of measuring fuel economy or accurate CO_2 emissions because the complete drive system and vehicle are not reflected within the engine dynamometer testing. However, as there was previously no official unified measurement or test, there has been a recent push to regulate the heavy freight domain. The use of vehicle simulation software and specific drive cycles are being used by the EU to determine fuel consumption and CO_2 emissions for the whole vehicle. The Vehicle Energy Consumption calculation Tool (VECTO) was first introduced in 2017, and then from 2019 it was mandatory that certain truck categories used the tool to make the resultant fuel consumption and emission values publicly available (European Commission, 2019). Therefore, whilst the WLTP was used for the LGV comparison, the VECTO Long Haul drive cycle was used for the heavy freight comparison. Table 16 shows the model results for each freight category (LGV, HGV Rigid, HGV Articulated) alongside similar specification vehicles, government data, and drive cycles.

Table 16 – Energy Consumption Comparison between Energy Model and Literature (Freight)

LGV	Diesel	Electric
Energy model (WLTP cycle)	32.4 MPG	531 Wh/mile
Mercedes Sprinter (WLTP)[1]	33.6 MPG	
Volkswagen Crafter (WLTP)[2]	32.1 MPG	
HGV Rigid	**Diesel**	**Electric**
Energy model (VECTO: Long Haul)	12.3 MPG	1525 Wh/mile
DfT: Average HGV fuel consumption (3.5T – 14T)[3]	13.7 MPG	
European Baseline study VECTO (Urban Delivery Cycle)[6]	13.2 MPG	
HGV Articulated	**Diesel**	**Electric**
Energy model (VECTO: Long Haul)	7.1 MPG	2644 Wh/mile
DfT: Average HGV fuel consumption (<33T)[3]	7.9 MPG	
Volvo FH[4]	7.4 MPG	
Individual study Euro VI[5]	7.6 MPG	
European baseline study (VECTO: Long Haul)[6]	8.5 MPG	
Tesla Semi (predicted consumption)[7]		<2000 Wh/mile
Future battery requirements for electric trucks study[8]		2200-2900 Wh/mile
Electric truck development study[9]		2600 Wh/mile

[1] (Mercedes-Benz, 2020) [2] (Volkswagen, 2020) [3] (Department for Transport, 2017) [4] (Griffin, 2014) [5] (Sharpe & Muncrief, 2015) [6] (Delgado, et al., 2017) [7] (Tesla, 2020) [8] (Sripad & Viswanathan, 2017) [9] (Burns, 2015)

Table 16 shows that the results from the energy model are again comparable to similar vehicles within each classification. Further reinforcing that the model is producing realistic results. The results obtained for the LGV within the model are similar to the WLTP cycle data stated by the both Mercedes and Volkswagen; albeit the values stated are for the largest panel vans not specifically the Luton body style so some discrepancy may be present. With respect to the VECTO Long Haul drive cycle, it was the most appropriate cycle to use as it was the most representative of the case study network. Further it was the most current tool introduced by the EU to begin to publish realistic fuel consumption and CO_2 emissions of heavy freight vehicle combinations. However, the VECTO drive cycles are velocity target plots, these were smoothed considering the vehicles acceleration and deceleration rates. Thus, some error was introduced as the VECTO software also considers far more factors; such as the engine map, transmission gearing, axle configuration, tyre characteristics, and road gradients. Yet, the smoothed VECTO cycle was considered appropriate for this validation purpose.

Where possible, every effort has been made to provide vehicle data for realistic comparison. Yet, due to the lack of available data for comparison, there are inevitably some errors in correlating the data between the model and available literature. No vehicle is the same, all will vary significantly between vehicle types, payloads, aerodynamics, engine performance and axle configuration; with vehicle mass being the most significant. Thus, it is difficult to ascertain accurate MPG, typically manufacturers do not state fuel economy for this reason. Further, the Department for Transport fuel consumption values include a wide range in gross vehicle weights, as well as both laden and unladen vehicle examples, hence there is some uncertainty in their fuel economy values.

However, the results obtained from the model are of the same magnitude, and the majority of which are within approximately 10% of other studies and data sources. This difference is not considered error as the model is not accurate to one particular vehicle, merely representative of the average vehicle specification in that category. It was found to be a complex issue to compare between the energy model and available data for heavy freight due to limitations in this area; yet the recently introduced VECTO simulation tool goes someway to try and bridge this gap.

There is further uncertainty concerning the energy consumption of electric freight; most significantly because of how new the field is, and the numerous technical challenges in achieving the electrification of heavy freight. The best available data has been provided for comparison, this consists of real world studies, as well as what Tesla indicate energy consumption will be for their future Semi truck. The model produces similar consumption rates to the available data, and again each data source is specific to the case study and vehicle specification used. Unfortunately, there was a lack of available data for both electric LGVs and HGV Rigids.

To summarise, the energy model has demonstrated that it is capable of providing realistic results for car and LGVs, and whilst there is a lack of data concerning HGVs energy consumption (both fossil and electrical), it is considered that the results obtained are realistic to those that would be expected. When considering the energy transfer and vehicle emission production elements of the model, the former is calculated based upon a predetermined transfer rate and the efficiency of that transfer (Table 7), whilst the latter is calculated based upon a set CO_2e rating for the fuel source used (Table 11 and Table 12). Thus, both are calculations based upon fixed values and contained within the energy model calculations. The real world power transfer rate and its efficiency will likely be less than the values calculated by the model due to the influential parameters; many of which are beyond the scope of this research. Yet, the energy model provides a realistic estimate of energy transfer, and is considerably more accurate than merely calculating transfer mathematically as explained previously. Further, the emission values will inevitably vary between the model and a specific vehicle as they do not consider the engine torque curve and specific vehicle specification;

yet are realistic enough to estimate the level of emission production. Also, the CO_2e unit is used to approximate all GHG emissions, rather than the specific pollutants and their quantities produced by the ICE process. Whilst there are limitations in the estimation of the energy transfer and emission production levels, they are realistic estimates and are based upon values from literature.

7.3 Exploratory Data Analysis

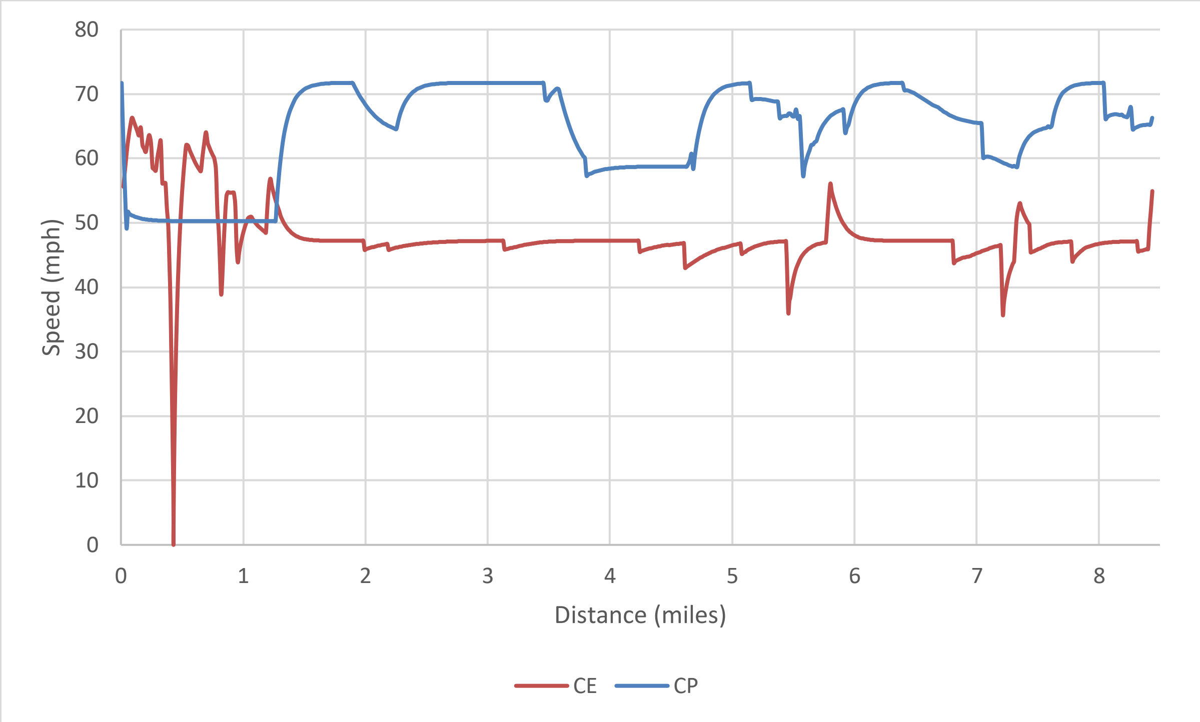
Whilst both the traffic and energy models have been calibrated and validated against existing literature, confidence must be gained to ensure the results from the scenario testing are realistic and follow the basic underlying trends that would be expected. For example, if charging lane speeds reduce, average EV speeds reduce. If EV proportion increases, congestion in the charging lane increases. If the WPT power level increases, EV SOC increases respectively. Therefore, an average experiment featuring a mixture of different explanatory factors was taken, the variables and values used are shown in Table 17.

Table 17 – Exploratory Analysis Experiment with Variables and Values

Variable	Value
EV Proportion	10%
Charging Lane	Integrated Inside Lane
Charging Speed	Typical/Average
WPT Power Level	Medium

Through application of the AIMSUN API, a program was used to output statistical traffic data to an external file for the purposes of post processing through the energy model; the essential simulation information documented previously within Section 1.1 – was captured with this program. The resultant dataset used simulation time as the global index, as it was captured vehicle data at each time step. The raw dataset was first sorted with an additional program that would sort the data by vehicle ID and then time, thus vehicle 1's trip data was listed, then vehicle 2's, and so forth. The cleaned datasets were then applied to the energy model, this calculated and appended the various energy consumption, charging and emission factors to the existing vehicle dataset.

Taking two vehicles from the experiment, specifically a petrol (ID: 27597) and electric vehicle (ID: 27670), some initial exploratory analysis can be undertaken. To provide context, the approximate time is 8:00AM, and both vehicles travel the entire route distance from the A27 continuing northbound on the M3 past Winchester.



CE (Car Electric), CP (Car Petrol)

Figure 21 – Vehicle Speed by Trip Distance (Single CP and CE)

Figure 21 shows that the petrol vehicle has a higher transit speed than the electric vehicle for the majority of the trip. Remembering that the specific scenario constrains EVs to charge within the inside lane on the motorway, the lower speeds witnessed are due to the freight vehicles slowing traffic within that lane; a disadvantage of constraining all EVs to charge, and to do so within the single inside charging lane. Further, as EVs must remain within the charging lane, they must slow to allow vehicles onto the motorway at the various junctions along the route. The extent of the early morning congestion is also shown as the EV comes to a complete standstill early on in its trip. Whilst vehicle speed by elevation could be shown, congestion has a far greater effect on vehicle speeds than elevation. On an uncongested free flowing route, elevation would influence vehicle acceleration more than vehicle speed, as drivers will accelerate or decelerate to maintain their desired transit speed.

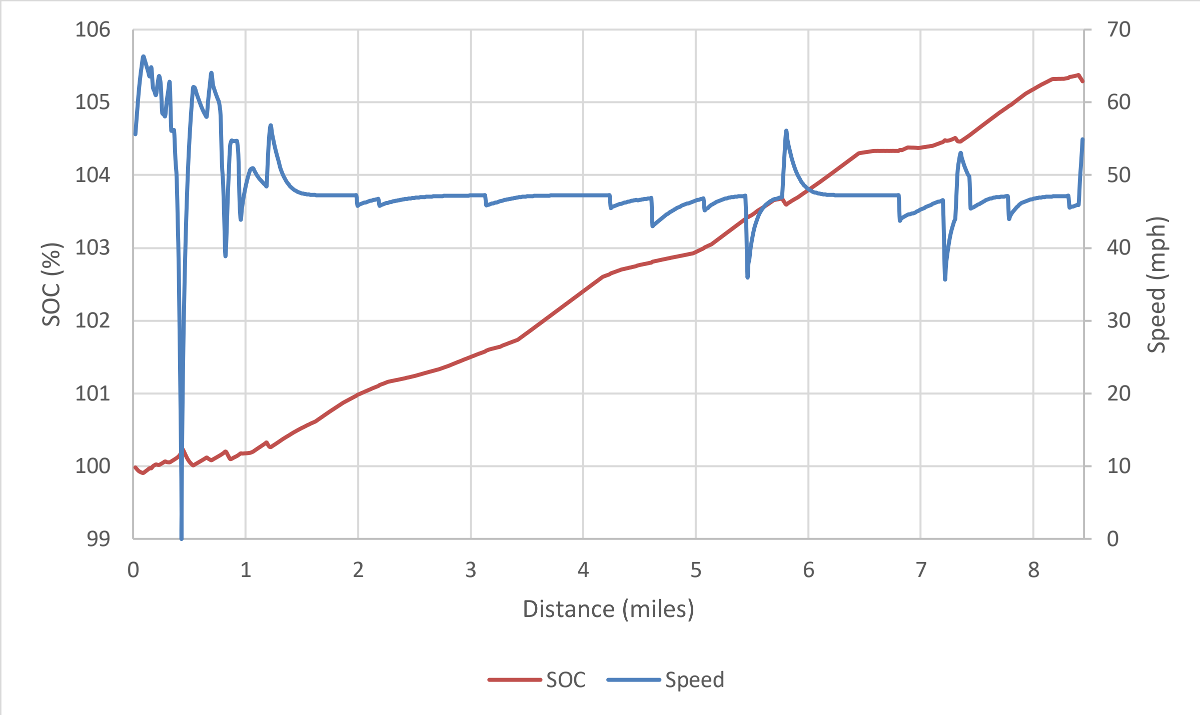


Figure 22 – Vehicle SOC and Speed by Trip Distance (Single CE, Medium WPT)

The EVs SOC over its trip distance is shown in Figure 22. It is important to note that SOC cannot technically go beyond 100%, but as previously discussed 100% was the baseline used to make scenario performance clearer, and to easily recognise whether the vehicle is charging or depleting the vehicle battery. Further, the entire route is equipped to remove the specific charging zone location variable from the modelling process. As shown in the graph, whilst the level of power transfer remains constant (50 kW WPT system, entire route equipped), the power received by the vehicle is dependent upon its speed, as well as the efficiency of the various WPT and vehicle systems. Thus, Figure 22 demonstrates the expected real world variability in energy transfer; attainable through the use of the microscopic simulation. As the vehicle slows, the energy transfer, and in turn, its SOC increases. The rate of energy transfer remains constant, but the slower vehicle speed results in a longer time for energy transfer to take place.

Whilst assessing the WPT power level, Table 18 further shows the differences in energy transfer when using different power levels. Given this specific vehicle, the low power (25 kW) system is sufficient to not only maintain, but marginally increase the vehicles SOC. Albeit a different vehicle, different time and an uncongested network will vary this result. Further, without a charging system (zero WPT) the vehicle consumes 2.82 kW of energy.

Table 18 – Battery Energy using different WPT Systems (Single CE)

WPT Scenario (kW)	Initial Battery Energy (kW)	Final Battery Energy (kW)	Battery Gain/Loss (kW)	Final Battery SOC (%)
ZERO (0)	75.00	72.18	- 2.82	96.36
LOW (25)	75.00	75.44	+ 0.44	100.72
MED (50)	75.00	78.86	+ 3.86	105.29
HIGH (75)	75.00	82.47	+ 7.47	110.11

Assessing the zero WPT scenario further, Figure 23 shows the SOC decline over the trip distance for the same EV and trip data shown in the prior graphs. As would be expected, increases in vehicle speed causes a depletion in vehicle SOC as energy is used to accelerate the vehicle. Equally, energy recovery through regenerative braking can be shown as SOC increases at points of deceleration.

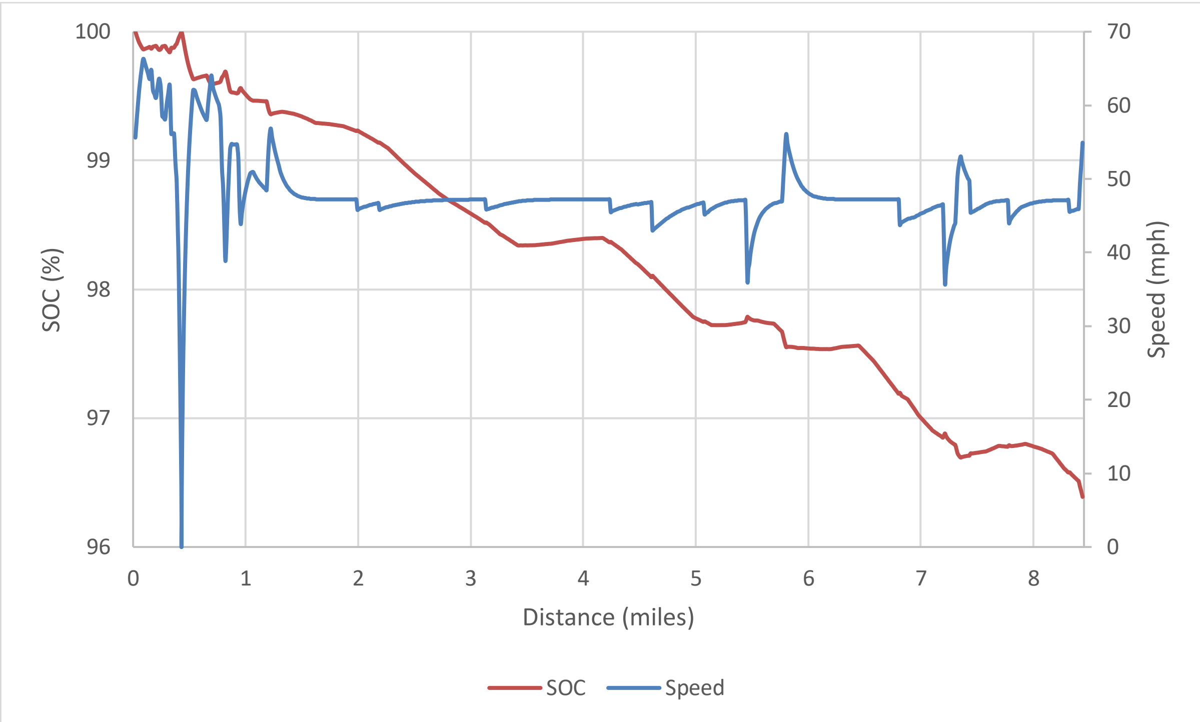


Figure 23 – Vehicle SOC and Speed by Trip Distance (Single CE, Zero WPT)

In comparison, Figure 24 shows the petrol vehicles fuel use over the route. Again, it follows the same realistic trend, as the vehicle accelerates, fuel use increases, and as the vehicle decelerates, fuel use decreases.

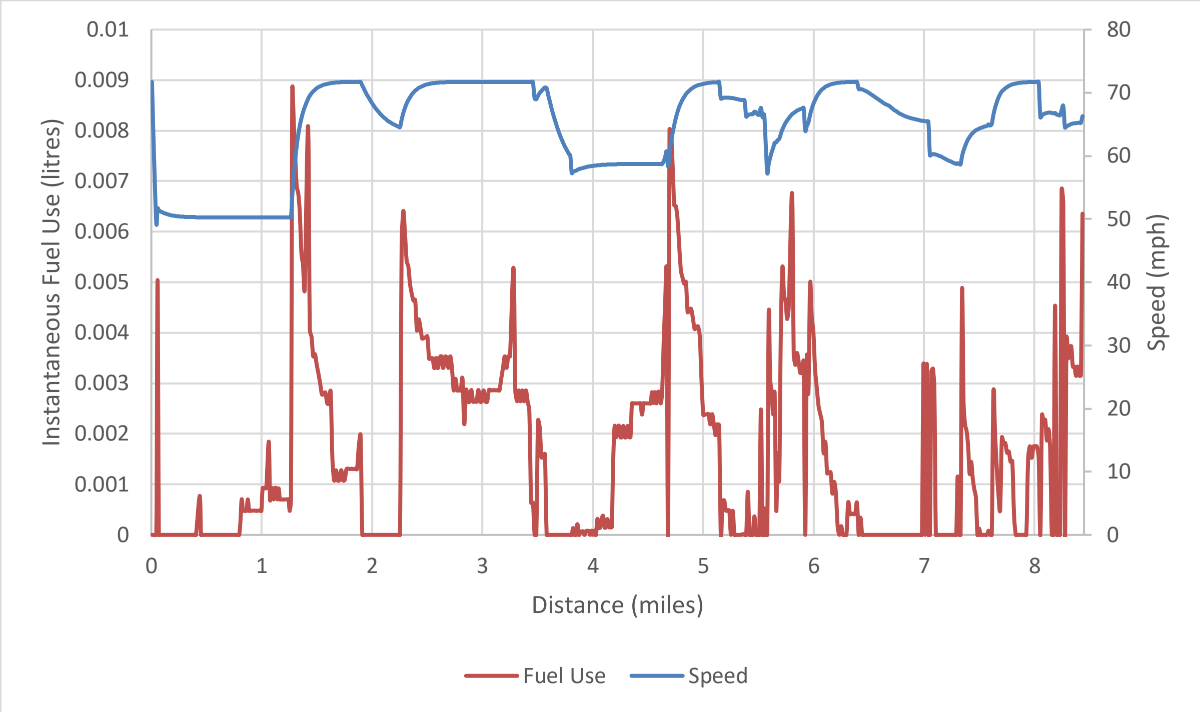


Figure 24 – Vehicle Fuel Use and Speed by Trip Distance (Single CP)

These graphs demonstrate the effects of the speed and time variable data obtained through the microscopic simulation of the network. Without such data, battery usage, WPT charging, and ICE fuel use would simply be linear scales calculated mathematically. Emphasising the ability of the microscopic simulation tool in providing realistic traffic movements throughout the network.

Initial exploration of single vehicle data has demonstrated some detailed microscopic results. However, the process of outputting the detailed energy model data for every single vehicle trip was found to be computationally intensive and required significant file storage capacity. Therefore, several changes were made before the traffic simulation data was processed by the energy model.

The individual trips can be aggregated to the initial and last vehicle state, in effect the first and last time step of a vehicles trip. This would give the initial start condition of the vehicle; this is necessary as the vehicle enters the network at speed and has spent a small amount of time and distance outside of the model. Whilst at the initialisation state, the majority of the energy model variables consists of zeros. Therefore, the initial state is necessary to calculate both the time and distance deltas, after which it can then be removed from the dataset; leaving each vehicles movements summarised to a single row of data. Furthermore, many of the energy model variables are live values based on that particular time step, thus final cumulative values can be calculated where possible, and data related to a specific time step (rather than the entire trip) removed. Through aggregation of the dataset, both file size and computational time can be reduced. Aggregation was both necessary to complete this work, and the very detailed individual vehicle movements of every single trip was unnecessarily data rich. In order to not skew the data, vehicles that remained within the network when the simulation ended were removed in their entirety from the dataset, as well as very few vehicles that had incomplete vehicle data. This rectified issues with faster than realistic origin destination trip times and excessively high energy/fuel economy.

Whilst an individual vehicles trip can provide some insight into detailed vehicle movements and intervehicular interaction within the network. It is the effect on all vehicles within such a network and scenario domain that is of note. Thus, the entire 24 hour period, c. 86,000 vehicles, are then aggregated through the energy model. This process was significantly faster and resulted in smaller file sizes by having only a single row of final data to output per vehicle, rather than every vehicles data, at every single time step.

Consideration is first given to experiment iterations. When determining the number of iterations, the variability of the results inevitably dictates the number of iterations required to provide realistic repeatable results. As previously explained, the simulation of many thousands of vehicles over a 24 hour period in itself introduces time varying effects and iterative results. As shown in Figure 25 and Figure 26, there was some small variation in travel time and travel distance between iterations. This demonstrates the variability introduced with random seeds in the microscopic simulation work, and represents what would be expected.

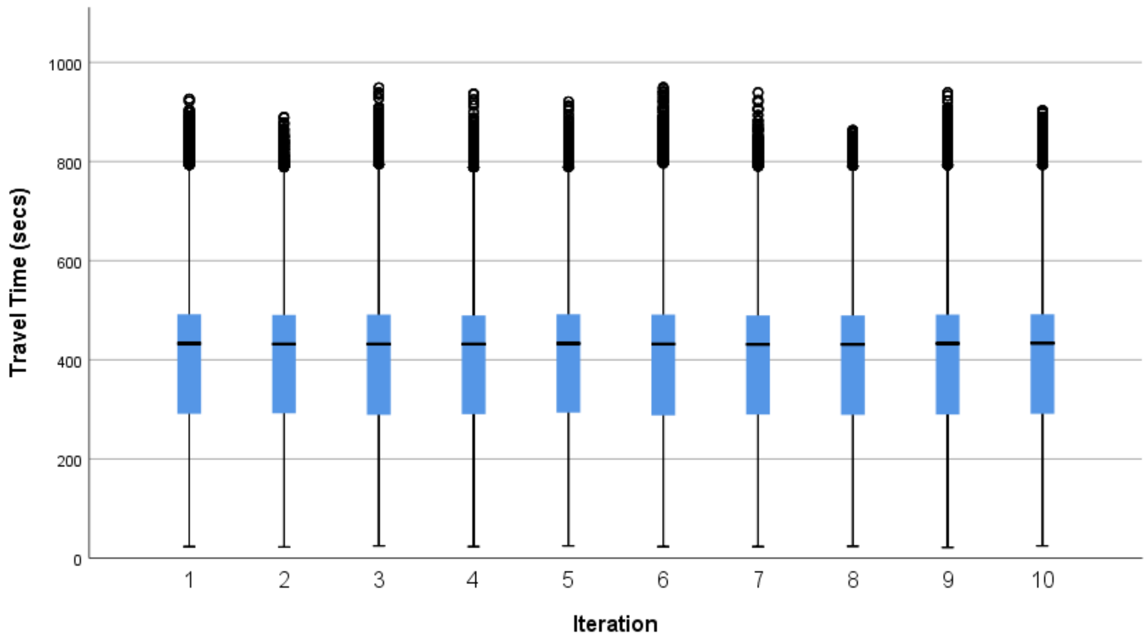


Figure 25 – Travel Time by Iteration

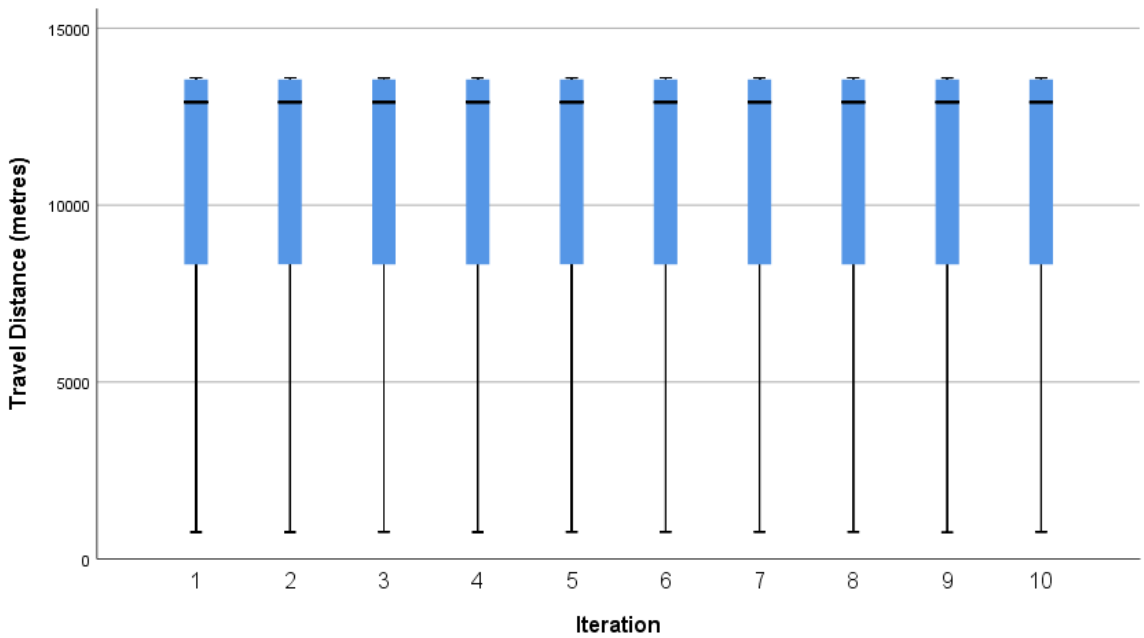
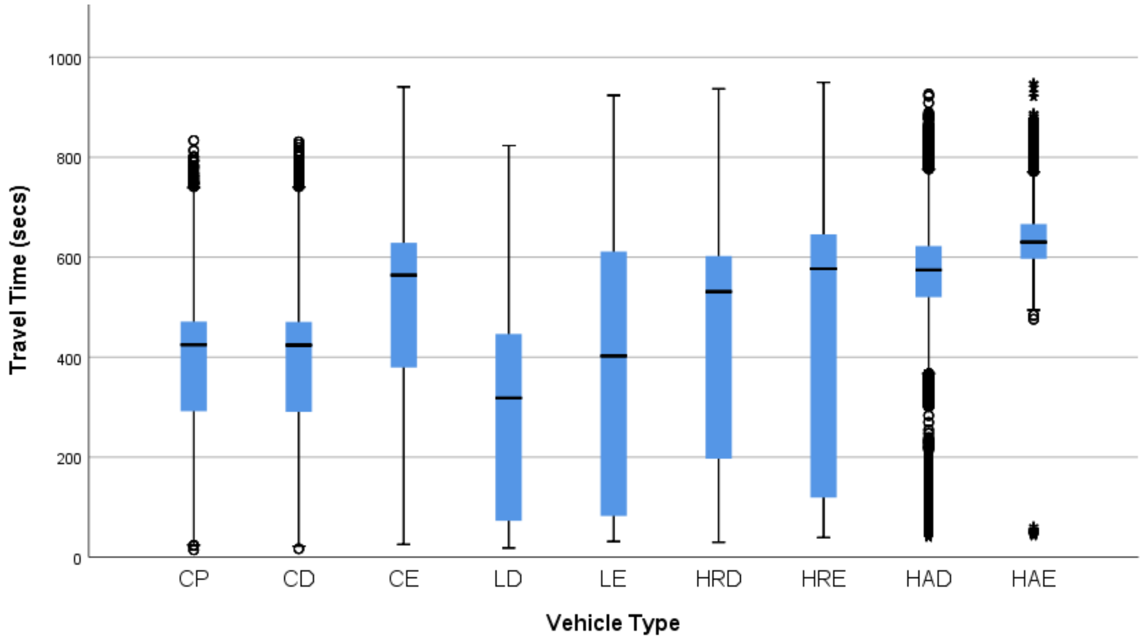


Figure 26 –Travel Distance by Iteration

As shown, whilst not strictly necessary, ten iterations were completed for each experiment scenario. Thus, moving forward all calculations, graphs and statistical data include all ten iterations for their respective experiment. Within this section, the particular experiment outlined in Table 17 is further examined. In order to have confidence in the aggregation of vehicle trips, the dataset must be assessed to ascertain if it is realistic of the expected results, it is the purpose of the following graphs and initial exploratory data analysis to demonstrate this.

Figure 27, shows the distribution of travel time by vehicle type. An array of outliers exist, this is generally seen across the entirety of this initial exploration analysis. Essentially, the outliers that should be removed because of incomplete data have been removed. Inevitably when assessing a large number of vehicles with different trip distances some will have excessively short or long travel times. Some trip distances are a single junction, whilst a large number of trips are from the bottom of the M3 and continue Northbound; thus, some variation is expected and as such are not considered incorrect or unrealistic outliers. Excluding such outliers would remove a proportion of realistic results. Due to the large number of vehicles now in the experiment over ten iterations (totalling c. 860,000), the number of outliers will inevitably increase and it is realistic to expect a large number to be outside of the normal Inter Quartile Range (IQR). Therefore, at first sight such outliers seem incorrect, but to put it into context a small number of unlikely vehicle trips/statistics, paired with a high number of vehicles will inevitably cause a greater than average number of outliers.



CP (Car Petrol), CD (Car Diesel), CE (Car Electric), LD (LGV Diesel), LE (LGV Electric), HRD (HGV Rigid Diesel)
HRE (HGV Rigid Electric), HAD (HGV Articulated Diesel), HAE (HGV Articulated Electric)

Figure 27 – Travel Time by Vehicle Type

When assessing travel time by vehicle type; as expected, both petrol and diesel cars have a similar travel time distribution as the only difference between the two is fuel type. Whereas, larger goods vehicles have a greater travel time than the smaller, faster vehicles. Further, as EVs are constrained to the charging lane their travel time is respectively higher than their fossil fuelled counterparts as they are effectively being held up by other slower traffic within that lane.

Due to the large number of cars within the model undertaking longer trips (M27 – M3), this positively skews the distribution of travel time for cars. This can be demonstrated when assessing the travel time for different ODs. Figure 28 shows the travel time by OD for petrol vehicles; each vehicle class follows the same distribution of OD travel times as OD trip distance remains constant (refer to for full list of OD reference numbers). As shown, travel time varies significantly between OD pairs; and generally the majority of outliers exist at a greater than average time, as would be expectant at times of traffic congestion. Similarly, the greater the trip distance, the larger the range of travel times; as there would be more variance in drivers desired speed and time in which other network conditions could affect the vehicles trip.

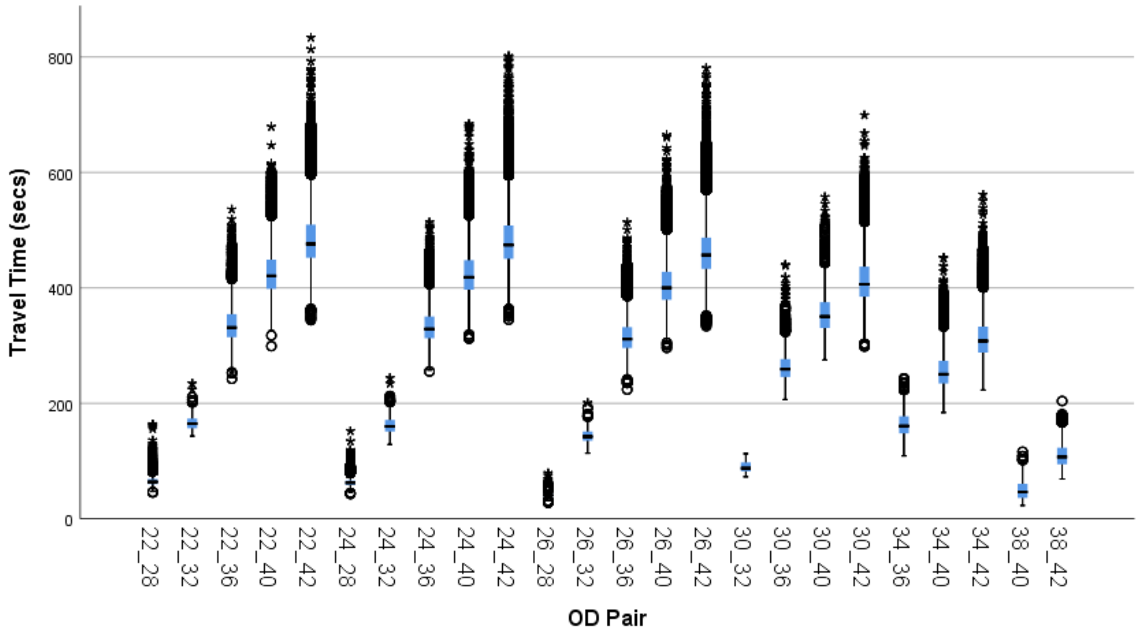
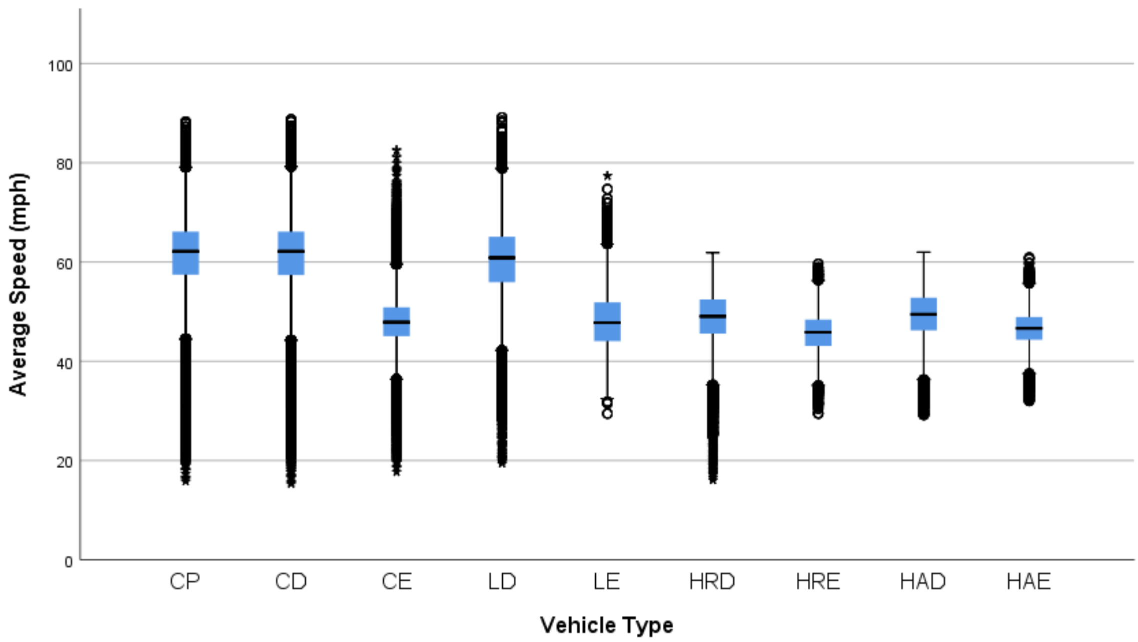


Figure 28 – Travel Time by OD Pair (CP)

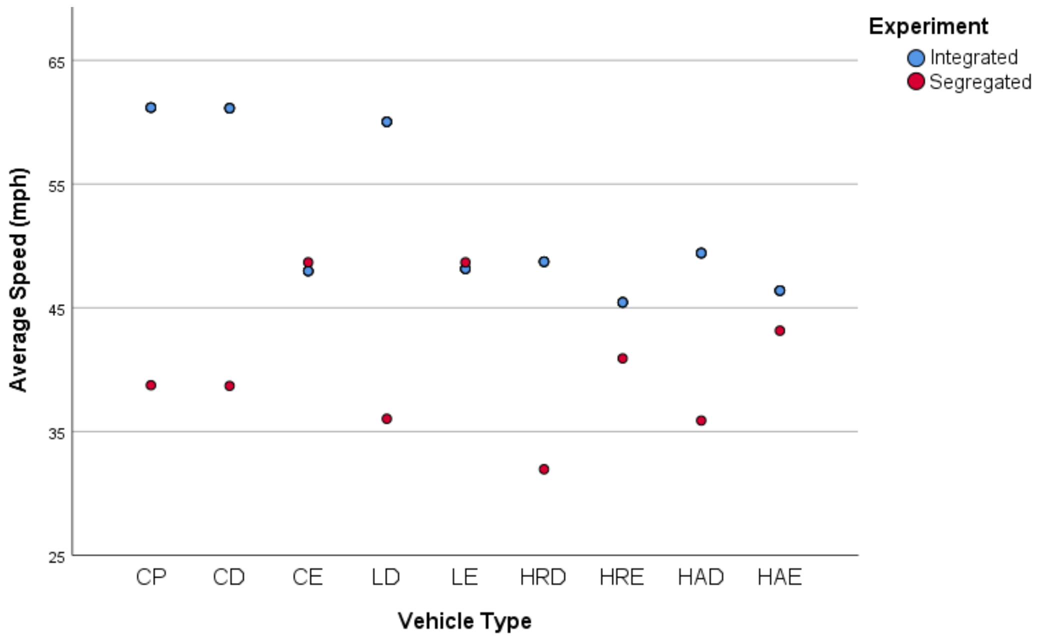
Figure 29 shows the average speed by vehicle type for the experiment, vehicle types that had a shorter travel time in Figure 27 previously, have an expectedly faster average speed in Figure 29. Again, EV speeds are slower across the board than their fossil fuelled counterparts due to the increased congestion and slower average speed of the charging lane.



CP (Car Petrol), CD (Car Diesel), CE (Car Electric), LD (LGV Diesel), LE (LGV Electric), HRD (HGV Rigid Diesel)
HRE (HGV Rigid Electric), HAD (HGV Articulated Diesel), HAE (HGV Articulated Electric)

Figure 29 – Average Speed by Vehicle Type

A common theme throughout this initial exploratory analysis was that restricting EVs to the charging lane resulted in slower vehicle speeds and journey times due to congestion. As a side comparison, a further experiment was simulated using same scenario settings laid out in Table 17, but the integrated inside charging lane became segregated. There is already an issue over capacity of existing road infrastructure, to then segregate a charging lane would reduce most motorway capacities from three lanes to just two; as seen with this experiment. As shown in Figure 30, containing the average speeds for both an integrated and segregated charging lane, unexpectedly EV speeds do not increase significantly. Whilst both CEs and LEs speeds increase, electric heavy freight speeds actually decrease. Further, there is a large impact to existing road traffic as the two remaining lanes become heavily congested and resultant average speeds decrease. Through detailed analysis of the traffic simulation data, the movement of vehicles onto the network and across the segregated charging lane becomes the main cause of congestion; vehicles will wait to move across the charging lane before speeding up to their desired speed.



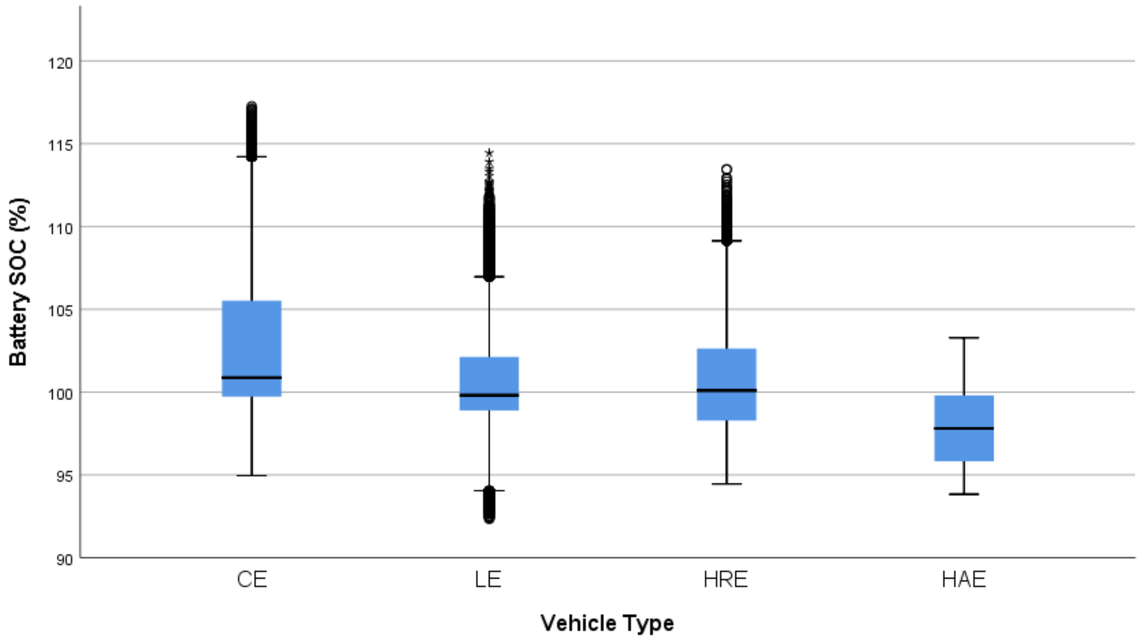
CP (Car Petrol), CD (Car Diesel), CE (Car Electric), LD (LGV Diesel), LE (LGV Electric), HRD (HGV Rigid Diesel)
HRE (HGV Rigid Electric), HAD (HGV Articulated Diesel), HAE (HGV Articulated Electric)

Figure 30 – Comparison of Average Speeds between Integrated and Segregated Charging Lanes

Whilst it is unlikely, it may be determined that such systems do require segregation for safety purposes, or could be used in scenarios where there is a requirement for HGV slow lanes in areas of significant uphill gradient. Either way, further analysis of this aspect would be required to measure the impact of segregating the charging lane, or if in fact additional segregated lanes should be added rather than reducing existing capacity.

Returning to the main experiment documented in Table 17. While, initial traffic statistics, travel time and speed, appear realistic, the remaining energy aspects must be evaluated. Assessing final

SOC by vehicle type (Figure 31) the medium power level has been shown to maintain vehicle SOC to near initial SOC for all but HAEs. The WPT system has the greatest effect on cars with the majority increasing in battery SOC over their trip. This is because the medium WPT system provides an energy transfer greater than the majority of cars use; further reinforcing the energy data shown in Table 18.

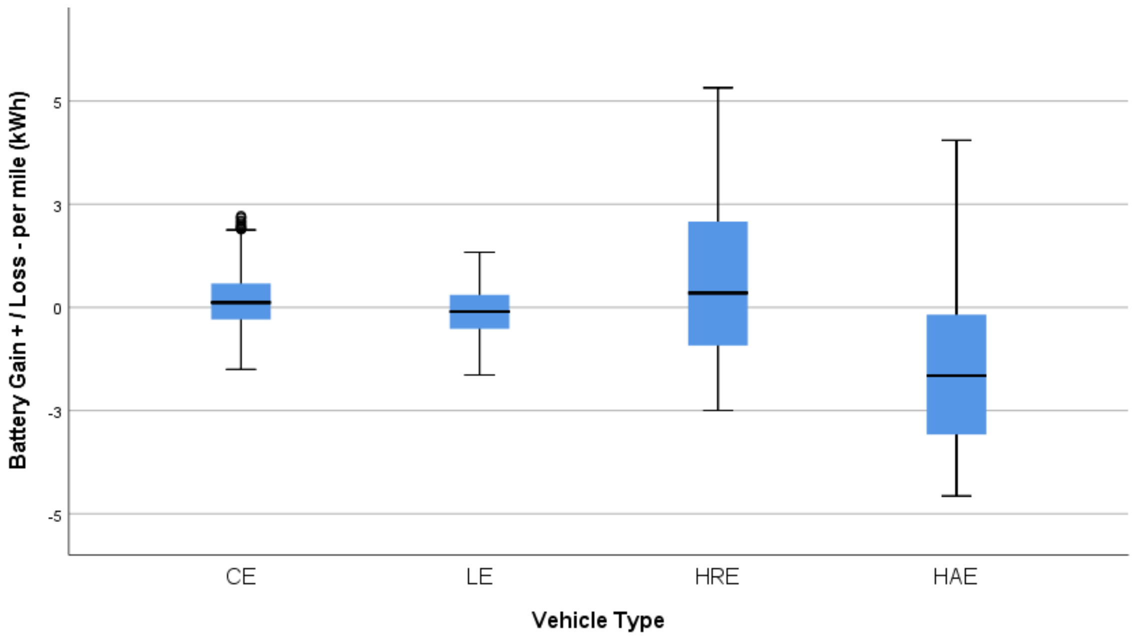


CE (Car Electric), LE (LGV Electric), HRE (HGV Rigid Electric), HAE (HGV Articulated Electric)

Figure 31 – Battery SOC by Vehicle Type

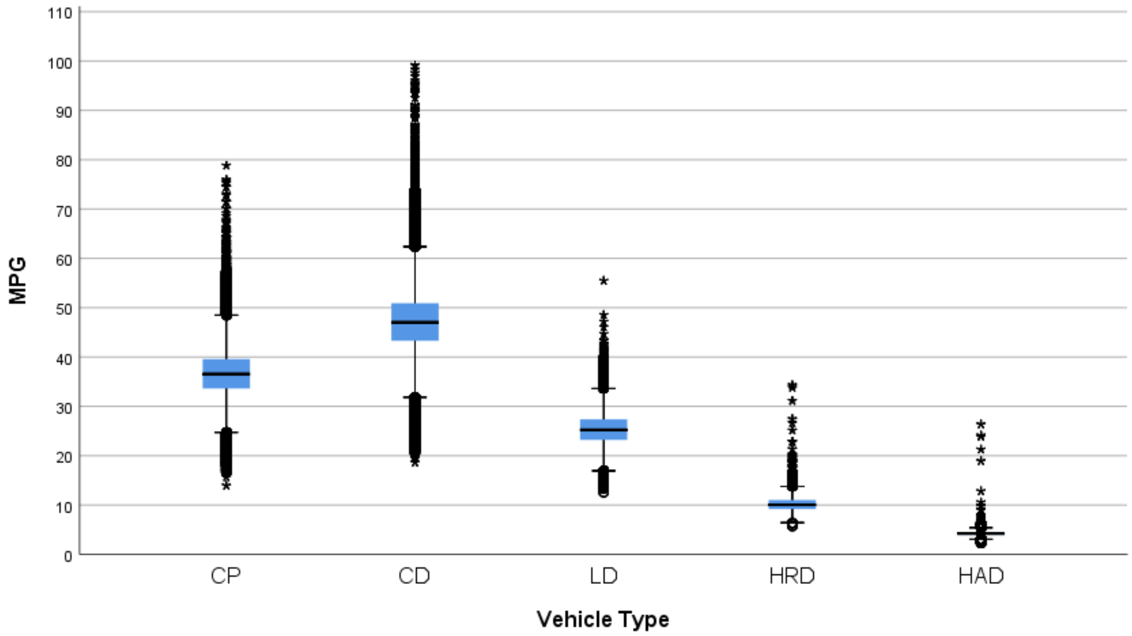
When assessing the outliers seen in Figure 31, as congestion occurs and vehicle speeds lower, travel times and consequently energy transfer increases. For example, the further most outlier for the HRE category in Figure 31 (vehicle: 12095) has a positive SOC gain of 40.4 kWh over the trip distance, yet average speed is just 31 mph; demonstrating the increased energy transfer when compared to the mean HRE (vehicle: 46460) has a positive SOC gain of 2.2 kWh with an average speed of 50 mph. Further, many HREs are in the model at the point of no congestion, and thus are able to travel at their desired (typical/average) speed which results in a negative SOC over the trip distance. Therefore, the medium WPT system does not supply sufficient energy for those vehicles in that scenario, signalling that the system is inadequate to maintain battery SOC. Either a higher power system could be implemented, greater technical system efficiencies achieved, or in fact acceptance that battery SOC cannot be maintained for all vehicles at every single moment in time.

When assessing the abilities of the WPT system to achieve zero battery miles, the battery gain or loss (kWh) per mile should be assessed. Scaling the data per mile allows for greater and more useful comparison between vehicle types and experiments, as both trip distances and scenario conditions will ultimately vary. Figure 32 demonstrates this more relatable unit of measurement; battery gain/loss (charge/discharge) per mile by vehicle type, rather than a percentage change like Figure 31. It is therefore demonstrable that even with a 150 kW charging system, HAEs are still consuming up to 4.7 kWh of energy per mile. Therefore, at the medium power level the WPT system is still not capable of achieving zero battery miles for all vehicle types at all times. For CEs, just over half are capable, for LEs the median is just below zero, and whilst the majority of HREs can achieve good charge gains, it is quite clear that HAEs are still seeing substantial battery usage.



CE (Car Electric), LE (LGV Electric), HRE (HGV Rigid Electric), HAE (HGV Articulated Electric)

Figure 32 – Battery Gain + / Loss - per mile by Vehicle Type

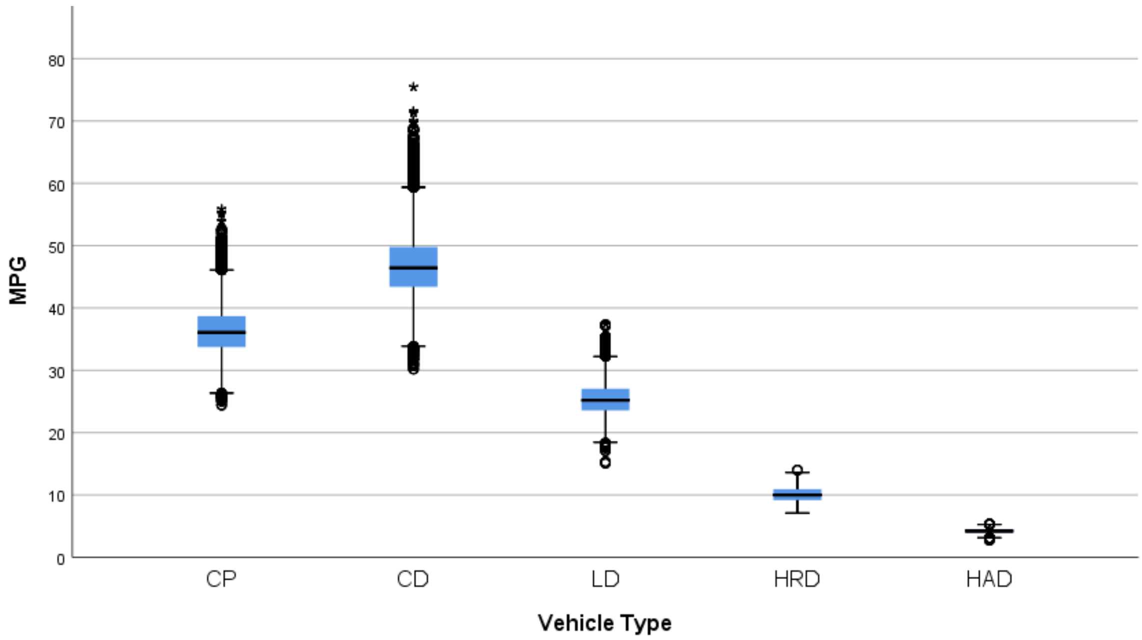


CP (Car Petrol), CD (Car Diesel), LD (LGV Diesel), HRD (HGV Rigid Diesel), HAD (HGV Articulated Diesel)

Figure 33 – MPG by Vehicle Type

In comparison, Figure 33 shows the fuel economy (MPG) for the various ICE vehicles. Typically, diesel vehicles have a greater fuel economy than petrol equivalents, and this trend is shown within this experiment. Further, as vehicle size/mass increases, fuel economy diminishes; again, a realistic real world result. Finally, MPG values are generally consistent with the calibration values sourced from literature (Table 15 and Table 16).

The reason for what appears to be excessively high MPG values is that vehicles enter the network at speed, and are only being assessed for what is a relatively short trip distance across the network, as opposed to its true movements where the network modelled forms a part of its greater OD trip. Therefore, vehicles don't experience standstill acceleration (unless heavily congested network) or the normal urban driving element required to access and depart the motorway. Vehicles can enter the network at speed, travel on what could be primarily downhill gradients (coasting) and then leave the network at the next junction; consequently using little energy input and resulting in a high MPG. Looking at one particular OD pair (Figure 34), M27 Eastbound to M3 Northbound, removes this issue with high MPG because of short trip distances between junctions. Although, as vehicles start at speed, MPG will inevitably be higher than a combined drive cycle as little acceleration is undertaken.

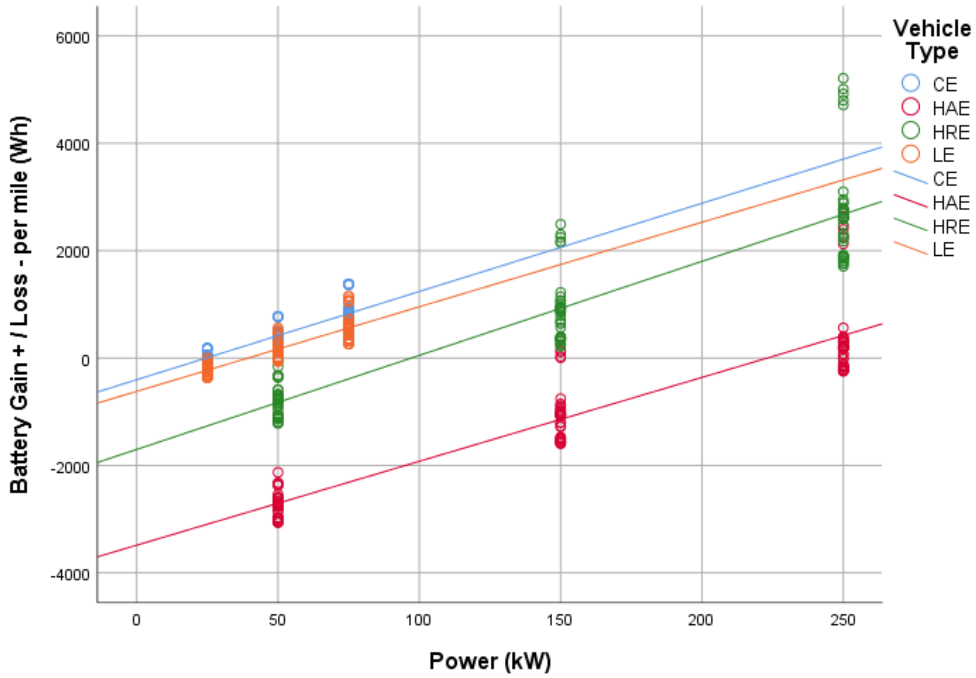


CP (Car Petrol), CD (Car Diesel), LD (LGV Diesel), HRD (HGV Rigid Diesel), HAD (HGV Articulated Diesel)

Figure 34 – MPG by Vehicle Type (M27 East to M3 North)

In summary, initial exploratory data analysis has identified that the model is producing realistic and expected results across all of the metrics assessed within this section. Thus, providing confidence in the traffic and energy models, as well as the various datasets generated by such models. The general trends, curves, and magnitudes of statistical data are considered realistic to what would be expected within real world conditions, further reinforcing the calibration and validation process.

The next stage was to aggregate the datasets and assess the data at the experiment level; specifically, all of the independent experiments outlined within Table 14 – Microscopic Experiments and Explanatory Variables Tested. Through plotting all 160 independent experiments undertaken on a single graph, some immediate curves can be drawn to assess the battery gain/loss per mile for different WPT power systems, see Figure 35.



CE (Car Electric), LE (LGV Electric), HRE (HGV Rigid Electric), HAE (HGV Articulated Electric)

Figure 35 – Battery Gain + / Loss - per mile by WPT Level

However, such an analysis does not consider differing scenario settings simulated; the range of battery gain/loss per mile can be over 3000 Wh at some power levels and vehicle types. Therefore, further analysis into the experiments explanatory variables is necessary; this consists of vehicle type, EV proportion, charging speed, charging lane location and WPT power level.

For example, the results of the experiments and explanatory variables could be used to ascertain response variables such as battery gain/loss per mile for a particular vehicle and WPT scenario set up. The eventual curve would see battery gain/loss per mile as the response variable, and average speed used as the explanatory variable (alongside the various vehicle and scenario settings). However, at present average speed is also an explanatory variable of the modelling process; Figure 36 gives an initial understanding of the current issue.

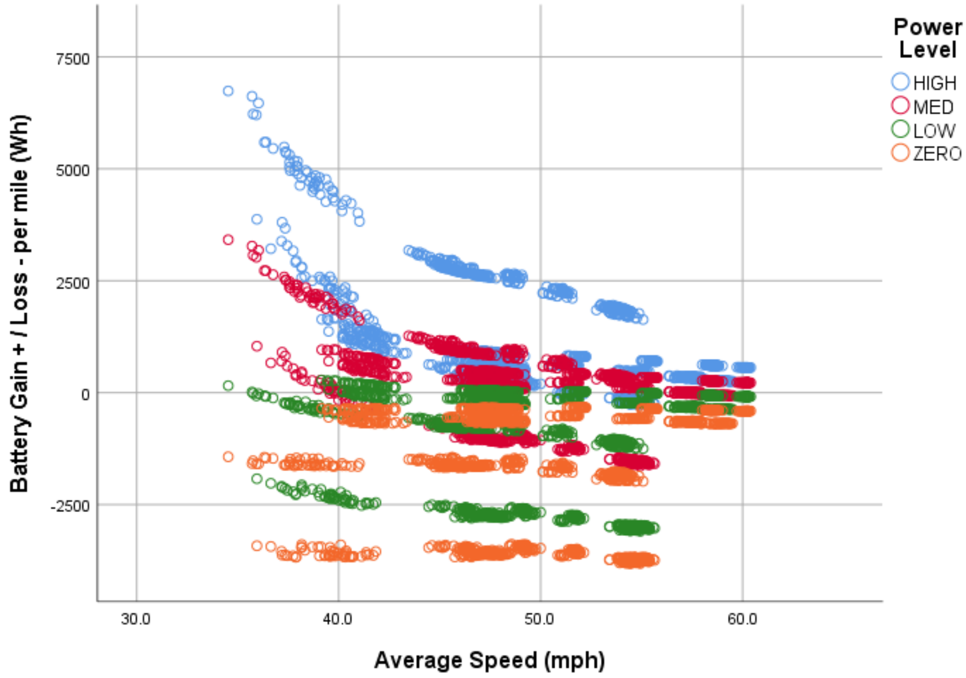


Figure 36 – Battery Gain + / Loss - per mile by Average Speed

Through plotting all 160 independent experiments on a single graph of battery gain/loss per mile against average speed, there is expectedly a lot of scatter, trends and randomness. Such a graph is complex and has a multitude of variables influencing the scatter plot. Some potential trends can be acknowledged: (i) as vehicle speeds increase, battery gain decreases. Vehicles with higher battery gains have a slower average speed, demonstrating that the slower average speed is increasing energy transfer. (ii) Different vehicle types are represented by the different curves above one another, as vehicle size increases, energy consumption is higher, thus on the graph battery loss is greater. (iii) As WPT power level increases, the greater it influences the battery gain/loss curve, the curves have a greater slope as power level increases, this is further shown at the ZERO power level where the curves are flat. (iv) There are two distinct clusters of data (with a marginal gap in the middle) whilst this initially appears to represent the charging lane location, when assessing the difference in charging lane locations (Figure 37) the gap remains present in the inside charging lane scenarios.

Further investigation demonstrates that the clustering is in fact caused by the EV proportion, as shown in Figure 38. As EV proportion increases, average speed decreases because of congestion occurring within the charging lane. This could be used to assess at what point EV proportion requires additional charging lane infrastructure, within these scenarios it suggests it starts to become an issue between 10-15%, but really begins to reduce the average speed of the charging lane beyond 15% EV proportion.

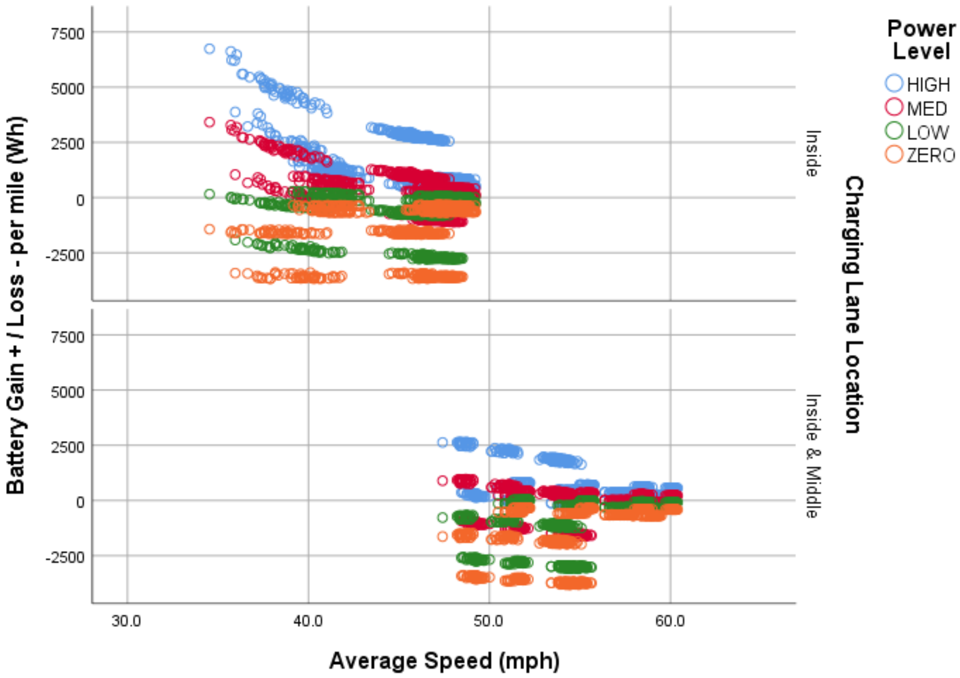


Figure 37 – Battery Gain + / Loss - per mile by Average Speed and Charging Lane Location

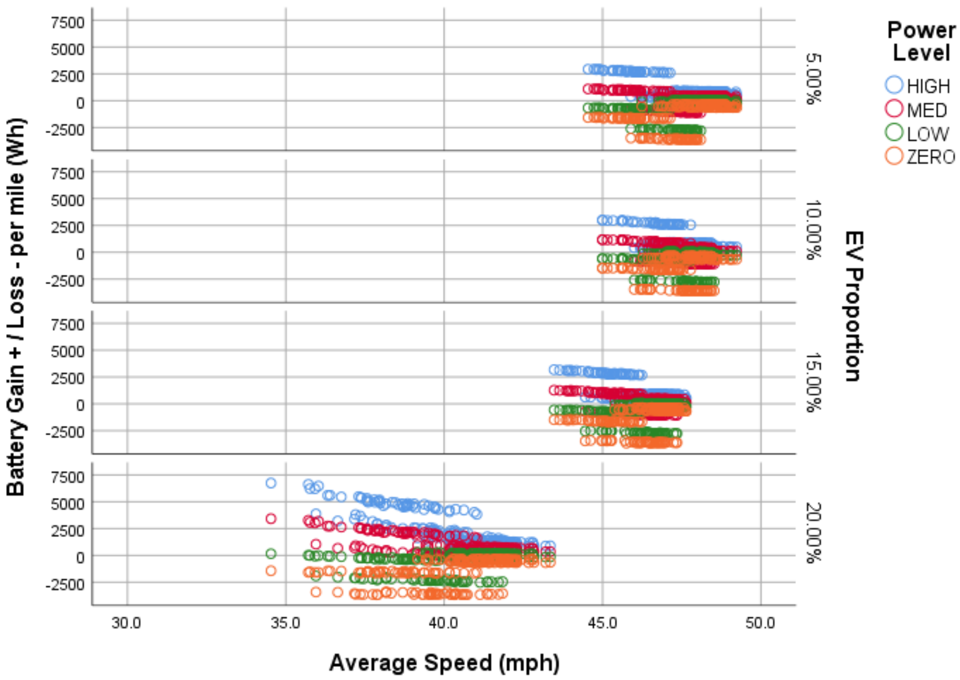


Figure 38 – Battery Gain + / Loss - per mile by Average Speed and EV Proportion (Inside Lane)

Returning to the original scatter plot (Figure 36). Further aspects that are not as easily defined are the charging speed limits, it would appear logical that as charging lane speed limits increase, average speed would also increase. Yet, Figure 39 shows that there are still clusters forming within the data, again a logical reason would be vehicle type, but again such clusters form within the data when plotted.

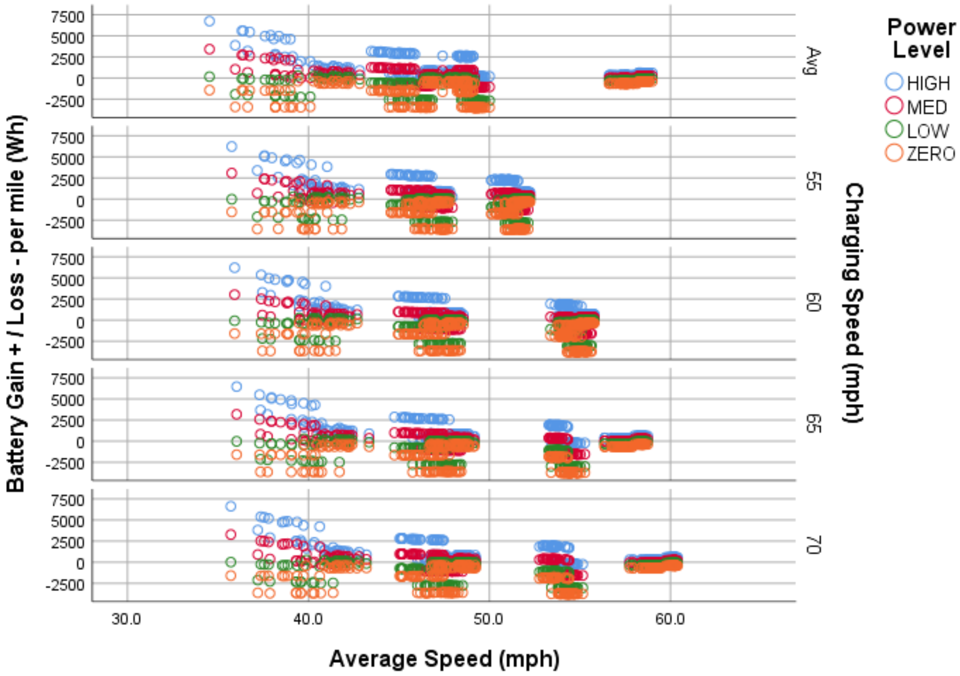


Figure 39 – Battery Gain + / Loss - per mile by Average Speed and Charging Lane Speed

Therefore, whilst these points go some way to explain the sorts of things that are occurring in Figure 36, there are numerous causes and effects occurring that are inherently linked to one another, causing a multitude of underlying trends. Clearly this is more complex and a different approach is required to assess such interactions. A sensible method would to form some sort of equation based model.

7.4 Mathematical Models

When determining any of the primary response variables (battery gain/loss per mile, ICEV fuel economy, emission production), the main explanatory variable that determines such response variables is average vehicle speed. For example, battery gain/loss per mile is a function of the explanatory variables (vehicle type, EV proportion, charging speed, charging lane location, WPT power level), as well as vehicle speed. Clearly, a two-step approach must be adopted to first develop an equation that determines average speed; which in turn is a response variable for the given network and scenarios modelled. From that, average speed can be used alongside the other explanatory variables to develop further mathematical models that determine the other primary response variables. It is the purpose of this section to document this work.

To provide some context to the work completed within the following subsections. A General Linear Model (GLM) Univariate process is used to provide ANOVA for the dependent variable, by the multiple explanatory factors and their pair wise combinations. This process assesses the effects the explanatory factors have on the dependent variable, both as individual entities as well as how they interact with one another. Only explanatory factors, and pair wise combinations of such factors, that prove statistically significant and can be explained will be included within the final models. The R^2 value can be increased to an absolute value of 1 if all factors and every single combination of factors are included (a full factorial model), yet a factor combination consisting of more than one pair becomes difficult to justify and can result in a model that is difficult to explain. Thus, it is far better to have a partial factorial model with a slightly lower R^2 value but is easily understood, defined and justified, rather than an unexplainable model with every combination of factors and a marginally higher R^2 value. Finally, there are no issues around multicollinearity, none of the explanatory factors (vehicle type, WPT power level, charging lane location, charging lane speed, EV proportion, and average speed where applicable) are correlated to one another, or could be estimated from the other explanatory factors. Values that could be strongly correlated to one another, like travel time and travel distance, are not explanatory variables.

7.4.1 Average Speed

As previously explained, a model to estimate average speed is first required as it will in turn be used as an explanatory variable in the later battery gain/loss, fuel economy and emission models.

It is important to note, the exact power of the WPT system will have no impact to the average speed of the vehicles. Therefore, it was not used within the model, leaving the remaining factors of: EV proportion, charging speed, charging lane location and vehicle type. The interaction between charging lane speed and EV proportion was shown not to be significant at the full factorial model ($p = 0.304$), thus was not included within the final model. Thus, a partial factorial model was applied, existing of the following combinations, significance and R^2 value:

Table 19 – Average Speed; Test of Between–Subject Effects (ANOVA)

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Corrected Model	59328.011[a]	87	681.931	1157.376	0.000
Intercept	4076209.563	1	4076209.563	6918155.814	0.000
EV Proportion	1562.882	3	520.961	884.176	0.000
Charging Speed	343.013	4	85.753	145.541	0.000
Vehicle Type	40410.828	8	5051.353	8573.173	0.000
Charging Lane	7855.314	1	7855.314	13332.064	0.000
EV Proportion * Charging Lane	1529.879	3	509.960	865.505	0.000
EV Proportion * Vehicle Type	280.863	24	11.703	19.862	0.000
Charging Speed * Charging Lane	190.655	4	47.664	80.895	0.000
Vehicle Type * Charging Lane	6095.868	8	761.984	1293.241	0.000
Charging Speed * Vehicle Type	1058.708	32	33.085	56.151	0.000
Error	796.605	1352	0.589		
Total	4136334.179	1440			
Corrected Total	60124.616	1439			

[a] R Squared = 0.987 (Adjusted R Squared = 0.986)

This process resulted in the following equation based upon the prior explanatory factors and combinations. As charging speed contained both numerical and categorical data (typical speed), it could not accurately be implemented to the model in a numerical/covariate form. Instead, a categorical input was required which resulted in a greater number of combinations and general complexity of the equation. The **average speed of the vehicle** can be expressed as:

$$v_{AVG} = v_{CL} + (Prop \times Prop_{EV})$$

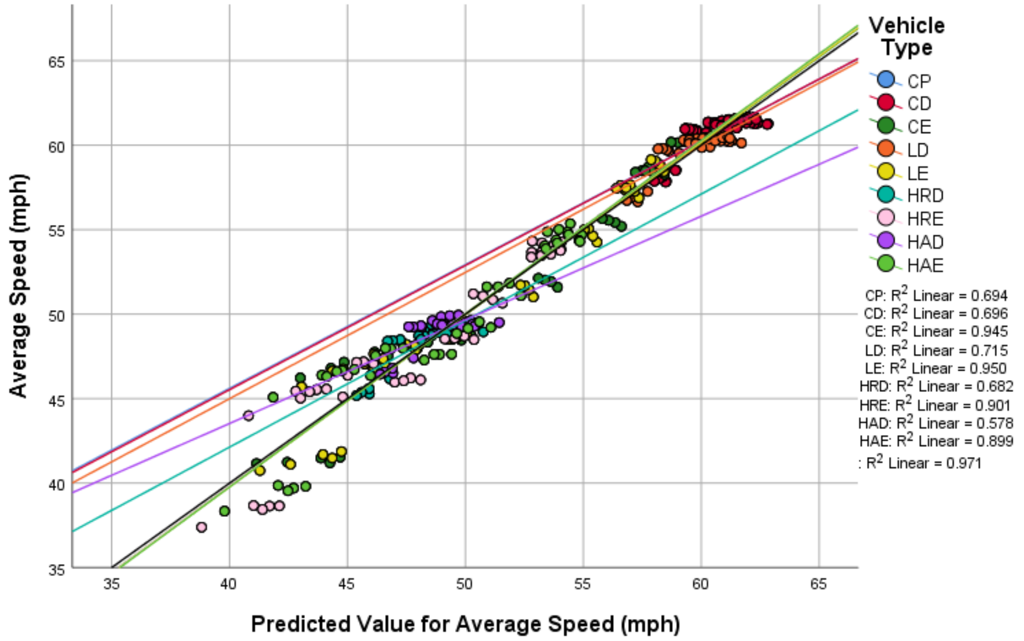
where, v_{CL} represents the charging lane speed coefficient, $Prop$ the proportion coefficient, and $Prop_{EV}$ the EV proportion of the experiment. Table 20 contains the relevant values and coefficients used within the above equation for each vehicle type, charging lane location and charging speed. To give an example scenario calculation, if the charging speed was fixed to 60 mph, the charging lane was located on the inside lane, and EV proportion was 10% then the following coefficients would be used:

$$v_{AVG} = 49.864 + (-37.087 \times 0.1)$$

Table 20 – Average Speed; Model Coefficients

Vehicle Type	Charging Speed	v_{CL} In.	v_{CL} In. & Mid.	$Prop$ In.	$Prop$ In. & Mid.
CE	55	48.563	54.18	-37.087	-5.421
	60	49.864	56.886		
	65	51.29	58.708		
	70	52.108	59.808		
	Typical	51.674	58.288		
CP	55	64.137	60.019	-26.009	5.657
	60	63.603	60.89		
	65	63.447	61.13		
	70	63.249	61.214		
	Typical	63.722	60.601		
CD	55	64.092	59.989	-25.937	5.729
	60	63.553	60.855		
	65	63.398	61.096		
	70	63.196	61.176		
	Typical	63.677	60.571		
LE	55	48.344	53.058	-35.285	-3.619
	60	49.645	55.764		
	65	51.018	57.533		
	70	51.801	58.598		
	Typical	51.409	57.12		
LD	55	63.03	58.985	-26.511	5.155
	60	62.51	59.87		
	65	62.346	60.102		
	70	62.145	60.183		
	Typical	62.608	59.56		
HRE	55	48.997	51.98	-39.903	-8.237
	60	50.093	54.481		
	65	49.674	54.458		
	70	49.377	54.443		
	Typical	46.795	50.775		
HRD	55	52.082	48.037	-26.449	5.217
	60	51.205	48.565		
	65	50.884	48.64		
	70	50.669	48.707		
	Typical	51.223	48.175		
HAE	55	50.318	52.835	-41.297	-9.631
	60	51.485	55.407		
	65	50.973	55.291		
	70	50.737	55.337		
	Typical	48.044	51.558		
HAD	55	52.648	48.227	-24.255	7.411
	60	51.753	48.737		
	65	51.428	48.808		
	70	51.234	48.896		
	Typical	51.783	48.359		

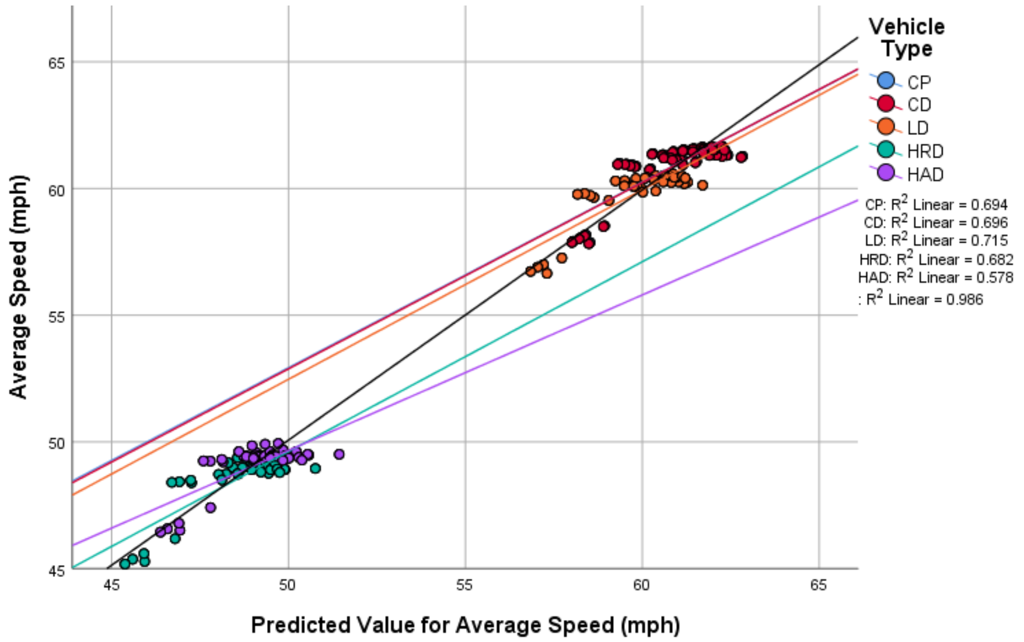
The final stage is to assess the mathematical models ability to predict average speed compared to the original dataset, Figure 40 plots average speed against predicted average speed.



CP (Car Petrol), CD (Car Diesel), CE (Car Electric), LD (LGV Diesel), LE (LGV Electric), HRD (HGV Rigid Diesel)
HRE (HGV Rigid Electric), HAD (HGV Articulated Diesel), HAE (HGV Articulated Electric)

Figure 40 – Average Speed by Predicted Value for Average Speed (All Vehicles)

Whilst EVs see a high correlation ($R^2 > 0.9$), ICEVs have a lower correlation with the heavy freight vehicles appearing worst; Figure 41 plots the correlation of just ICEVs.



CP (Car Petrol), CD (Car Diesel), LD (LGV Diesel), HRD (HGV Rigid Diesel), HAD (HGV Articulated Diesel)

Figure 41 – Average Speed by Predicted Value for Average Speed (ICEVs)

As seen in Figure 41, there are a number of points that are acting as points of high leverage, it is these points that are causing the lines to be pulled out of perfect correlation. Yet, R^2 values remain high ($R^2 > 0.578$) for all ICEVs and the model is capable of predicting average speed adequately. The reason that the correlation of EVs ($R^2 > 0.899$) is higher than ICEVs is because for the vast majority of experiments EV charging speed limits are restrained to specific values, thus can be more easily predicted based upon the input explanatory variables.

Whilst linked to the R^2 value of the GLM, a bivariate Pearson Correlation test showed that the predicted and actual average speed values have a significant linear relationship ($r = 0.985$, $p < 0.001$), demonstrating that the mathematical model is able to accurately predict average speed. Essentially, it is the relationship of the graphs (Figure 40 and Figure 41) that are of more importance here.

7.4.2 Battery Gain/Loss

Using average speed as an input, the battery gain/loss per mile model for EVs can be assessed; due to the relationships between explanatory factors, this proved a more difficult equation to formulate. A number of combinations were shown to not be statistically significant at the full factorial model level, these included charging speed and EV proportion ($p = 0.808$), vehicle type and EV proportion ($p = 0.933$), and vehicle type and charging lane ($p = 0.776$). The main explanatory variables, now including average speed and WPT power level, as well as the two way effects of each remaining combination were included. Thus, a partial factorial model was again applied, existing of the following combinations, significance and R^2 value:

Table 21 – Battery Gain/Loss per mile; Test of Between–Subject Effects (ANOVA)

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Corrected Model	840154015.212[a]	43	19538465.470	2964.779	0.000
Intercept	262082.636	1	262082.636	39.769	0.000
Vehicle Type	4277945.204	3	1425981.735	216.379	0.000
Charging Lane	725894.967	1	725894.967	110.148	0.000
Charging Speed	604084.643	4	151021.161	22.916	0.000
EV Proportion	15325.687	1	15325.687	2.326	0.128
Average Speed	22495.277	1	22495.277	3.413	0.065
WPT Power	13831146.041	1	13831146.041	2098.747	0.000
EVProp2 * Average Speed	25768.499	1	25768.499	3.910	0.049
Charging Lane * EV Proportion	161085.783	1	161085.783	24.443	0.000
EV Proportion * WPT Power	88254.488	1	88254.488	13.392	0.000
Charging Lane * Average Speed	640728.579	1	640728.579	97.225	0.000
Average Speed * WPT Power	8664120.216	1	8664120.216	1314.699	0.000
Vehicle Type * Average Speed	238548.451	3	79516.150	12.066	0.000
Charging Lane * Charging Speed	118017.484	4	29504.371	4.477	0.001
Charging Lane * WPT Power	1876161.271	1	1876161.271	284.690	0.000
Charging Speed * WPT Power	1106851.157	4	276712.789	41.989	0.000
Vehicle Type * Charging Speed	353886.017	12	29490.501	4.475	0.000
Vehicle Type * WPT Power	841188.022	3	280396.007	42.547	0.000
Error	2873324.248	436	6590.193		
Total	847181002.457	480			
Corrected Total	843027339.460	479			

[a] R Squared = 0.997 (Adjusted R Squared = 0.996)

The reason for a high R^2 value is that this equation is based upon prior kinematic and electrical equations within the energy model. However, this equation removes the necessity of microscopic simulation providing a simpler equation that can be used to predict battery gain/loss based upon the microscopic case study scenario and some explanatory factors.

This process resulted in the following equation using the prior explanatory factors and combinations. The **battery gain/loss per mile of the vehicle** can be expressed as:

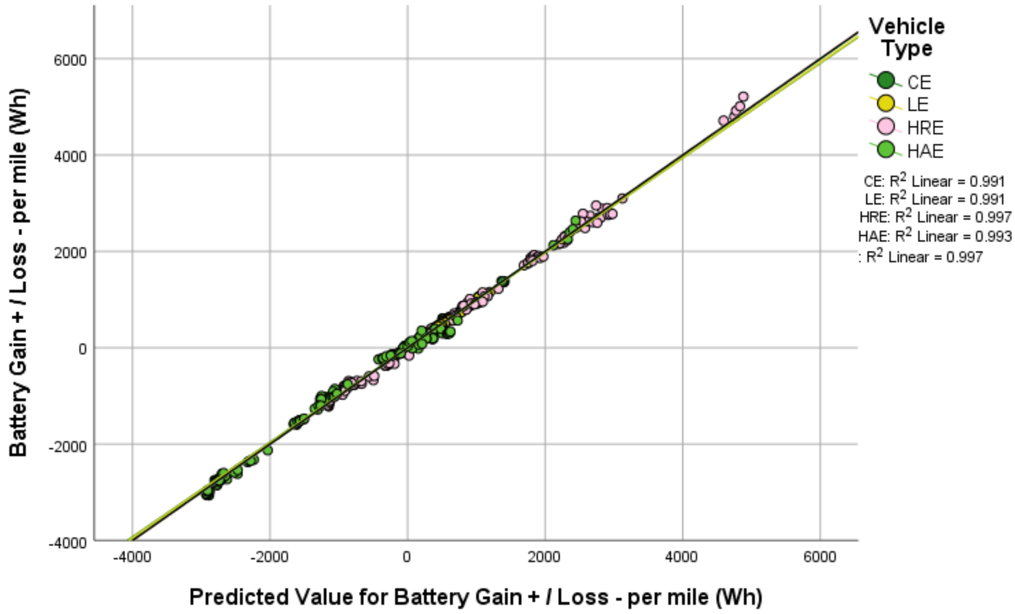
$$
\begin{aligned}
E_{batt} = v_{CL} + (P \times P_{WPT}) + (v \times v_{AVG}) + (Prop \times Prop_{EV}) \\
+ (-58.744 \times Prop_{EV} \times v_{AVG}) \\
+ (4.018 \times Prop_{EV} \times P_{WPT}) \\
+ (-0.918 \times v_{AVG} \times P_{WPT})
\end{aligned}
$$

where, P represents the WPT coefficient, P_{WPT} the WPT power level, v the average speed coefficient, v_{AVG} the average speed. The numerical values are fixed coefficients based upon the particular variable combination contained within the same brackets. Table 22 contains the relevant values and coefficients used within the above equation for each vehicle type, charging lane location and charging speed.

Table 22 – Battery Gain/Loss per mile; Model Coefficients

Vehicle Type	**Charging Speed**	v_{CL}		P		v		$Prop$	
		In.	**In. & Mid.**	**In.**	**In. & Mid.**	**In.**	**In. & Mid.**	**In.**	**In. & Mid.**
	55	179.447	-2734.58	60.652	64.421				
	60	88.706	-2822.74	62.083	65.852				
CE	65	98.569	-2861.36	62.02	65.789	-9.99	43.764	1702.372	3077.567
	70	91.852	-2887.36	62.002	65.771				
	Typical	208.808	-2783.61	59.857	63.626				
	55	6.615	-2907.42	59.53	63.299				
	60	-113.181	-3024.63	60.961	64.73				
LE	65	-133.156	-3093.08	60.898	64.667	-9.576	44.178	1702.372	3077.567
	70	-164.458	-3143.67	60.88	64.649				
	Typical	-34.14	-3026.56	58.735	62.504				
	55	-335.352	-3249.38	58.633	62.402				
	60	-541.262	-3452.71	60.064	63.833				
HRE	65	-504.986	-3464.91	60.001	63.77	-24.22	29.534	1702.372	3077.567
	70	-496.554	-3475.77	59.983	63.752				
	Typical	-189.568	-3181.99	57.838	61.607				
	55	-2698.16	-5612.19	57.583	61.352				
	60	-2861.98	-5773.42	59.014	62.783				
HAE	65	-2842.71	-5802.63	58.951	62.72	-12.523	41.231	1702.372	3077.567
	70	-2833.48	-5812.69	58.933	62.702				
	Typical	-2563.09	-5555.51	56.788	60.557				

Again, the mathematical models ability to predict battery gain/loss when compared to the original dataset was assessed, Figure 42 plots this correlation.



CE (Car Electric), LE (LGV Electric), HRE (HGV Rigid Electric), HAE (HGV Articulated Electric)

Figure 42 – Battery Gain/Loss by Predicted Value for Battery Gain/Loss

The mathematical model appears to have a good linear correlation in predicting battery gain/loss, this is confirmed when testing for significance using Pearson's Correlation ($r = 0.998$, $p < 0.001$), with R^2 values for all vehicle types > 0.991.

7.4.3 Fuel Economy

The fuel economy MPG model for ICEVs was formulated using average speed as an input, alongside the other explanatory factors. The WPT power level will not have an effect on the MPG for ICEVs, thus was not used within the model. In addition, the effect between EV proportion and average speed was not statistically significant ($p = 0.100$), and was therefore not included. Thus, a partial factorial model was again applied, existing of the following combinations, significance and R^2 value:

Table 23 – Fuel Economy; Test of Between–Subject Effects (ANOVA)

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Corrected Model	196728.524[a]	53	3711.859	552041.099	0.000
Intercept	7.511	1	7.511	1117.067	0.000
Vehicle Type	13.187	4	3.297	490.306	0.000
Charging Lane	0.398	1	0.398	59.136	0.000
Charging Speed	0.266	4	0.066	9.880	0.000
EV Proportion	4.967	1	4.967	738.731	0.000
Average Speed	0.310	1	0.310	46.161	0.000
Charging Lane * EV Proportion	9.662	1	9.662	1437.019	0.000
Charging Speed * EV Proportion	0.979	4	0.245	36.418	0.000
Vehicle Type * EV Proportion	0.959	4	0.240	35.643	0.000
Charging Lane * Average Speed	0.397	1	0.397	59.106	0.000
Charging Speed * Average Speed	0.266	4	0.067	9.896	0.000
Vehicle Type * Average Speed	5.864	4	1.466	218.028	0.000
Charging Lane * Charging Speed	0.356	4	0.089	13.232	0.000
Vehicle Type * Charging Lane	1.404	4	0.351	52.200	0.000
Vehicle Type * Charging Speed	1.283	16	0.080	11.922	0.000
Error	5.016	746	0.007		
Total	722199.391	800			
Corrected Total	196733.540	799			

[a] R Squared = 1.000 (Adjusted R Squared = 1.000)

Whilst a very high R^2 is seen, there is some marginal error in the model. Again, the prior algebraic equations within the energy model are the cause for the expectantly high R^2 value, this equation is amalgamating the previous microscopic work.

This process resulted in the following equation based upon the prior explanatory factors and combinations. The **MPG of the vehicle** can be expressed as:

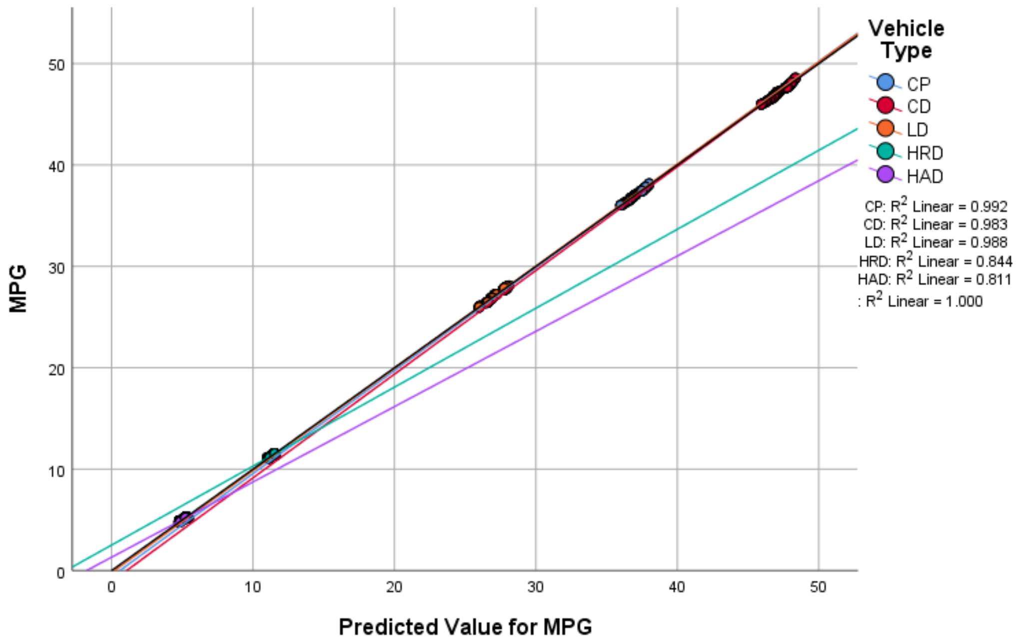
$$E_{MPG} = v_{CL} + (v \times v_{AVG}) + (Prop \times Prop_{EV})$$

Table 24 contains the relevant values and coefficients used within the above equation for each vehicle type, charging lane location and charging speed.

Table 24 – Fuel Economy; Model Coefficients

Vehicle Type	Charging Speed	v_{CL}		v		$Prop$	
		In.	In. & Mid.	In.	In. & Mid.	In.	In. & Mid.
	55	31.571	47.461	0.091	-0.164	-3.586	2.243
	60	29.946	45.893	0.118	-0.137	-3.213	2.616
CP	65	31.886	47.813	0.086	-0.169	-4.182	1.647
	70	33.442	49.272	0.06	-0.195	-5.045	0.784
	Typical	34.165	49.977	0.049	-0.206	-5.226	0.603
	55	38.761	54.796	0.14	-0.115	-3.324	2.505
	60	37.107	53.199	0.167	-0.088	-2.951	2.878
CD	65	38.991	55.063	0.135	-0.12	-3.92	1.909
	70	40.519	56.494	0.109	-0.146	-4.783	1.046
	Typical	41.246	57.203	0.098	-0.157	-4.964	0.865
	55	20.072	35.831	0.119	-0.136	-4.575	1.254
	60	18.552	34.368	0.146	-0.109	-4.202	1.627
LD	65	20.519	36.315	0.114	-0.141	-5.171	0.658
	70	22.152	37.851	0.088	-0.167	-6.034	-0.205
	Typical	22.786	38.467	0.077	-0.178	-6.215	-0.386
	55	17.708	29.95	-0.123	-0.378	-4.957	0.872
	60	16.326	28.625	-0.096	-0.351	-4.584	1.245
HRD	65	17.998	30.277	-0.128	-0.383	-5.553	0.276
	70	19.388	31.57	-0.154	-0.409	-6.416	-0.587
	Typical	19.974	32.138	-0.165	-0.42	-6.597	-0.768
	55	11.029	23.278	-0.11	-0.365	-5.312	0.517
	60	9.641	21.947	-0.083	-0.338	-4.939	0.89
HAD	65	11.308	23.594	-0.115	-0.37	-5.908	-0.079
	70	12.714	24.903	-0.141	-0.396	-6.771	-0.942
	Typical	13.292	25.463	-0.152	-0.407	-6.952	-1.123

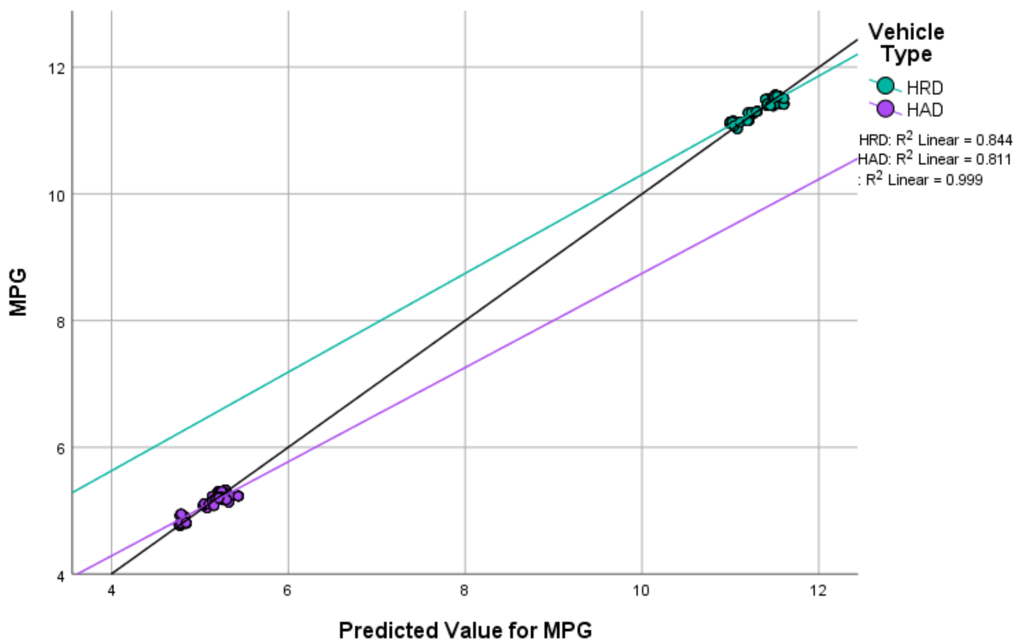
Again, the mathematical models ability to predict fuel economy when compared to the original dataset was assessed, Figure 43 plots this correlation.



CP (Car Petrol), CD (Car Diesel), LD (LGV Diesel), HRD (HGV Rigid Diesel), HAD (HGV Articulated Diesel)

Figure 43 – Fuel Economy by Predicted Value for Fuel Economy (All ICEVs)

Whilst, cars and LGVs appear to have a good correlation, there appears to be some error in the HGV values. The MPG for HGVs is contained over a very finite range, typically all points are within a range of 1 MPG, thus at higher (unrealistic) MPG values the model performs less well at predicting MPG; this is further shown in Figure 44.



HRD (HGV Rigid Diesel), HAD (HGV Articulated Diesel)

Figure 44 – Fuel Economy by Predicted Value for Fuel Economy (ICE HGVs)

The points are clustered very close together, therefore the models ability to predict values outside of their own range is not wrong, it is just unknown; as such values have been shown to be unrealistic within this case study and modelling process. When formerly testing for linear correlation, a Pearson's Correlation test demonstrated that the MPG model is statistically significant in predicting MPG ($r = 1.000$, $p < 0.001$). Whilst R^2 values for HGVs are marginally lower than other vehicles, all are > 0.811.

7.4.4 Emissions

Finally, the emissions model was formulated for both fossil and electrical fuelled vehicles. The effect WPT charging has on EV emissions was not assessed within this body of work for a number of reasons. Most notably was that emissions were based on likely average CO_2e values per kWh of electricity, or litre of fossil fuel (Department for Business, Energy & Industrial Strategy, 2019) (Department for Transport, 2019). Therefore, assessing the precise accurate impact of an estimated emission value over various scenarios is impractical. At this stage the impact of the WPT charging system on emissions was not assessed, and the ZERO power scenario was used for all EVs. Therefore, the WPT power level was not included within the model, nor was the interaction between charge speed and several other factors: EV proportion ($p = 0.719$), average speed ($p = 0.714$), or charge lane ($p = 0.702$); none of which were statistically significant when formerly assessed. Thus, a partial factorial model was applied, existing of the following combinations, significance and R^2 value:

Table 25 – Emissions; Test of Between–Subject Effects (ANOVA)

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Corrected Model	197129119.528[a]	74	2663907.021	67281.115	0.000
Intercept	16793.921	1	16793.921	424.157	0.000
Vehicle Type	85851.312	8	10731.414	271.039	0.000
Charging Lane	3222.084	1	3222.084	81.379	0.000
Charging Speed	7996.014	4	1999.004	50.488	0.000
EV Proportion	577.326	1	577.326	14.581	0.000
Average Speed	74.940	1	74.940	1.893	0.170
EV Proportion * Average Speed	634.143	1	634.143	16.016	0.000
Charging Lane * EV Proportion	2835.541	1	2835.541	71.616	0.000
Vehicle Type * EV Proportion	7731.530	8	966.441	24.409	0.000
Charging Lane * Average Speed	3424.008	1	3424.008	86.479	0.000
Vehicle Type * Average Speed	5259.810	8	657.476	16.606	0.000
Vehicle Type * Charging Lane	11796.438	8	1474.555	37.242	0.000
Vehicle Type * Charging Speed	22513.029	32	703.532	17.769	0.000
Error	11284.199	285	39.594		
Total	384984285.100	360			
Corrected Total	197140403.727	359			

[a] R Squared = 1.000 (Adjusted R Squared = 1.000)

Whilst not significant by itself, average speed was left within the model as it was significant in its various combinations. Due to the model being a function of the algebraic equations within the energy model, the equation is expectedly very good at predicting emissions; with some error shown in Table 25.

This process resulted in the following equation based upon the prior explanatory factors and combinations. The **emissions of the vehicle** can be expressed as:

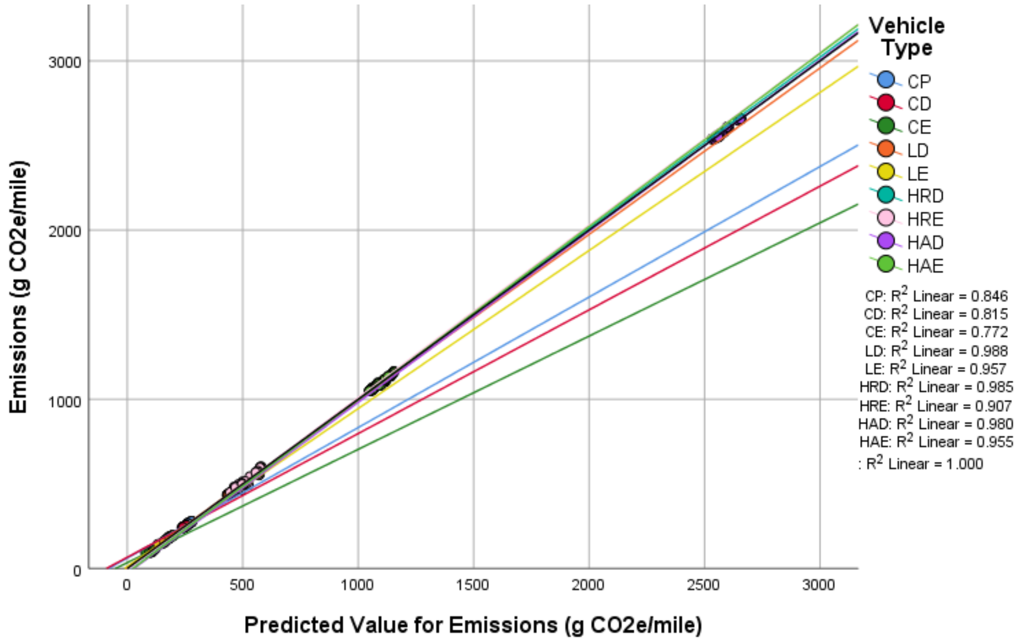
$$N_{emissions} = v_{CL} + (P \times P_{WPT}) + (v \times v_{AVG}) + (Prop \times Prop_{EV}) + (14.036 \times Prop_{EV} \times v_{AVG})$$

Table 26 contains the relevant values and coefficients used within the above equation for each vehicle type, charging lane location and charging speed.

Table 26 – Emissions; Model Coefficients

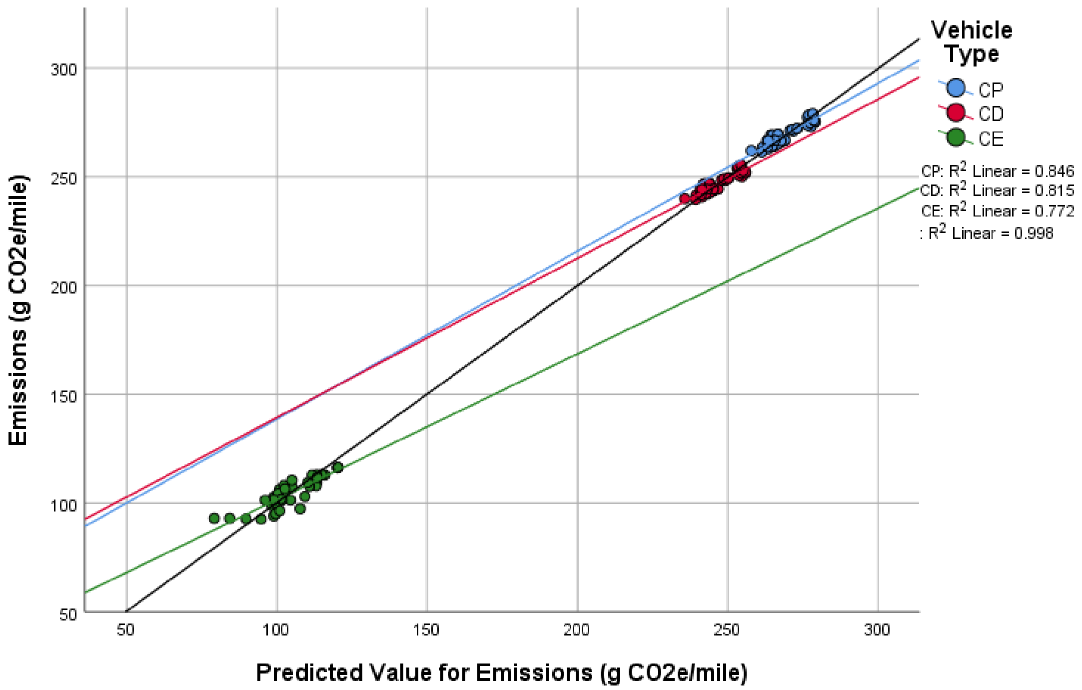
Vehicle Type	Charging Speed	v_{CL}		v		$Prop$	
		In.	In. & Mid.	In.	In. & Mid.	In.	In. & Mid.
CE	55	309.05	21.919	-4.414	1.527	-676.323	-843.943
	60	310.77	23.639				
	65	312.684	25.553				
	70	315.388	28.257				
	Typical	314.473	27.342				
CP	55	291.51	-63.227	-0.528	5.413	-731.825	-899.445
	60	290.254	-64.483				
	65	290.958	-63.779				
	70	292.53	-62.207				
	Typical	292.726	-62.011				
CD	55	256.343	-97.682	-0.322	5.619	-733.317	-900.937
	60	255.138	-98.887				
	65	255.759	-98.266				
	70	257.212	-96.813				
	Typical	257.437	-96.588				
LE	55	346.559	57.133	-4.115	1.826	-653.188	-820.808
	60	357.68	68.254				
	65	369.323	79.897				
	70	379.929	90.503				
	Typical	374.871	85.445				
LD	55	624.361	267.295	-3.113	2.828	-698.319	-865.939
	60	623.032	265.966				
	65	624.282	267.216				
	70	626.203	269.137				
	Typical	626.648	269.582				
HRE	55	570.244	331.537	-1.855	4.086	-695.247	-862.867
	60	601.754	363.047				
	65	600.031	361.324				
	70	599.257	360.55				
	Typical	549.151	310.444				
HRD	55	999.459	707.586	1.022	6.963	-492.94	-660.56
	60	1002.296	710.423				
	65	999.705	707.832				
	70	999.024	707.151				
	Typical	997.471	705.598				
HAE	55	1288.309	1035.239	-4.187	1.754	-743.584	-911.204
	60	1318.506	1065.436				
	65	1319.938	1066.868				
	70	1319.907	1066.837				
	Typical	1260.527	1007.457				
HAD	55	3415.767	3103.114	-17.542	-11.601	-355.387	-523.007
	60	3419.263	3106.61				
	65	3413.543	3100.89				
	70	3410.609	3097.956				
	Typical	3410.508	3097.855				

The final stage was again to assess the models capability in predicting emissions compared to the original dataset, Figure 45 plots this correlation.



CP (Car Petrol), CD (Car Diesel), CE (Car Electric), LD (LGV Diesel), LE (LGV Electric), HRD (HGV Rigid Diesel) HRE (HGV Rigid Electric), HAD (HGV Articulated Diesel), HAE (HGV Articulated Electric)

Figure 45 – Emissions by Predicted Value for Emissions (All Vehicles)



CP (Car Petrol), CD (Car Diesel), CE (Car Electric)

Figure 46 – Emissions by Predicted Value for Emissions (Cars)

Typically, a good correlation is seen. Whilst there appears to be an issue for car classifications, some points of high leverage (see Figure 46) are causing the curves to flatten. It is important to note, emissions are an output of the model and are based upon the explanatory factors and scenario modelled. Throughout all of the experiments, there is a finite range in emissions for each car classification, Figure 46 shows the curves extending beyond a magnitude of difference compared to where the original plots are clustered. Therefore, how the model behaves at that level it very much uncertain. Essentially, the model will not see such car emission values within this, and many other, case study scenarios; such values are unrealistic.

Generally, the emission model sees R^2 values > 0.772 with the vast majority being > 0.9. A Pearson's Correlation test identified that the model is statistically significant with a good linear correlation ($r = 1.000$, $p < 0.001$).

7.5 Chapter Conclusions

This chapter first assessed the realism of the data generated from the traffic and energy models developed within this research. It was found that the models were well calibrated to existing literature, and in combination with initial exploratory data analysis, sufficient confidence in the data was gained. The exploratory process identified that there were a multitude of interactions, causes and effects, occurring within the experimental data; assessing each exploratory factor as an individual entity proved problematic. Therefore, a GLM was proposed that saw the development of a series of mathematical models that could be used to first predict average speed, from which the battery gain/loss, fuel economy, and emissions of each WPT scenario could be estimated. The resultant models were shown to have a good linear correlation and general ability to accurately predict the relevant attribute. Therefore, it was not necessary to explore neural network approaches as outlined as a potential route within the methodology.

Whilst a very detailed investigation could be undertaken to assess a particular scenario or experiment modelled within the microscopic work, the exact effect of each individual experiment, scenario or configuration was not the purpose of this study. Such an exercise would be excessively detailed, specific to just a single WPT configuration, and provide little context to the wider system. Instead, the formulation of mathematical models are considered the main results of this microscopic work. Such mathematical models are able to inform a higher, macroscopic, level study where a network of greater distance could be assessed; whilst still retaining the detailed microscopic vehicle interactions. The tools have been developed that enable a user to apply their own WPT scenario and assess both its traffic impact and energy considerations. The following chapter demonstrates the application of such tools, and how they can be used to assess a series of scenarios to further understand the potential of WPT for dynamic charging of EVs.

Chapter 8 Macroscopic Model

8.1 Introduction

This body of work has seen the investigation of WPT charging for EVs, the development of a microscopic traffic model, consequential energy model, and then the formulation of equations from such models. These mathematical models capture the relationships between factors modelled and represent an aggregated approach to capture microscopic effects at a higher, macroscopic level, without the need to run such detailed microscopic simulations.

It is the purpose of this section to document the application of such tools and how they can be applied to a user's own scenario or experiment configuration. In order to do so, a number of modelling assumptions were required and this chapter serves as a first look at how the tools developed in this thesis could be used at the SRN level. Importantly, it is the prior microscopic simulation work that forms the core of this thesis, the following macroscopic work serves as an additional illustration. The main underlying assumption of this macroscopic study is that it is based upon the prior microscopic case study; not all regions of the macroscopic study will see similar traffic and energy dynamics to that of the microscopic study. Importantly, the exact values obtained with respect to route equipment will inevitably have some error in place because of the scaling of the microscopic results to the entirety of the macroscopic route.

A particular macroscopic case study is outlined, areas of investigation documented and several likely WPT infrastructure deployment scenarios investigated. Essentially, both the traffic impact and energy criteria are assessed throughout this study. The mathematical models formulated within the prior chapter are first used to assess the average speed of the particular infrastructure configuration, the value of which is then used within the battery gain/loss model to investigate the energy criterion. A number of assumptions and limitations do exist with this methodology, all of which are documented throughout this chapter.

The key purpose of this chapter was to apply the tools developed within this thesis and to investigate higher level, macroscopic, issues. Typically, how much charging infrastructure is required to facilitate some end of route scenarios; for example, for the vehicle to reach the end of the route, or to maintain a particular SOC.

8.2 Macroscopic Case Study

The following sections outline the macroscopic case study scenario; including the areas of investigation as well as the traffic and vehicle data used within this study.

8.2.1 Scenario Outline

It is likely that WPT charging systems will initially be deployed at the interurban SRN level, as opposed to urban locations. Therefore, the scenario used was an interurban route such as a vehicle travelling from city to city, or a freight vehicle travelling between distribution hubs. From initial exploratory analysis, it indicated that vehicles would be capable of a circa 200 mile range; given the vehicle specifications documented within this thesis. Therefore, a trip distance of 200 miles was modelled, as some vehicles will be reliant upon sufficient charging infrastructure to undertake such a distance. The specific case study route was from Greater London to Greater Manchester, using both the M40 and M6 respectively, shown in Figure 47. This case study was selected because it aligns well to the likely first use case being a common freight trunk route, is of a significant distance that would require at least one recharge stop, and will generally result in a situation that is realistic.

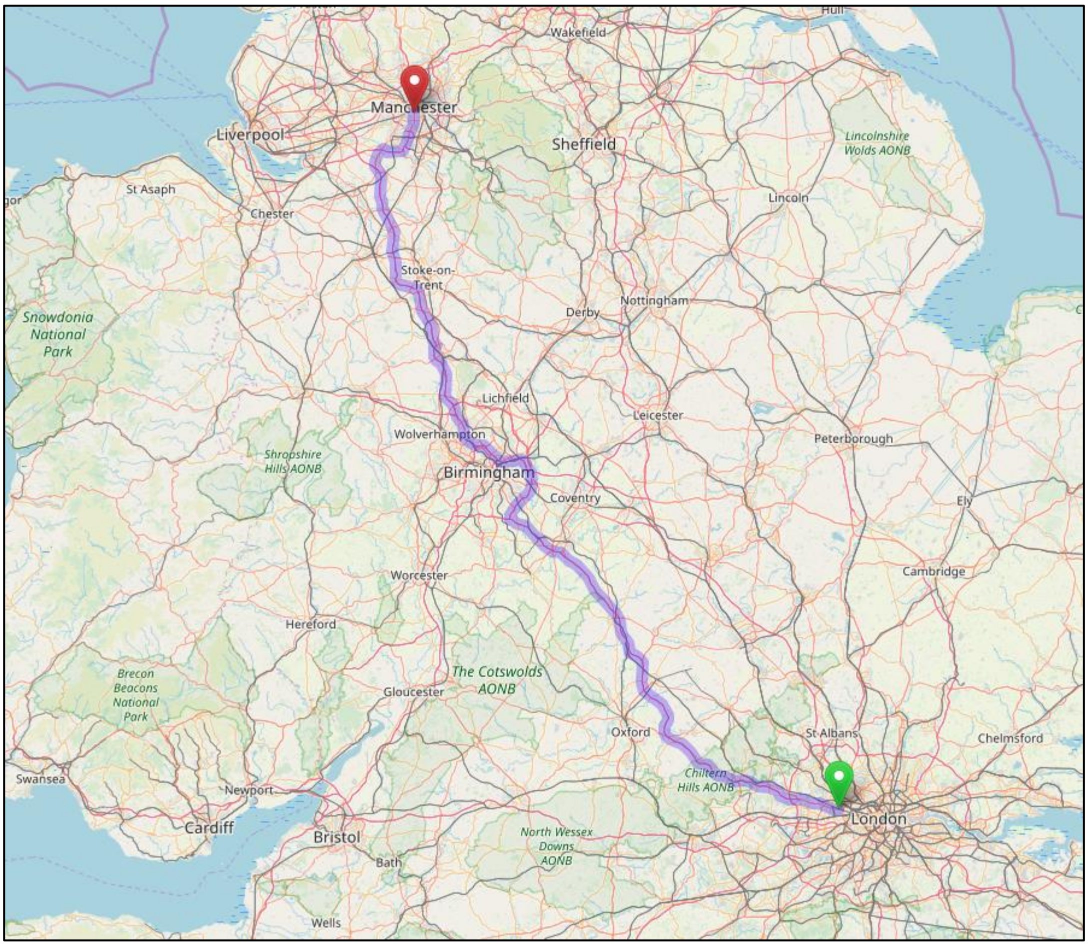


Figure 47 – Macroscopic Case Study Location

It is important to note, one limitation of this approach is that the prior microscopic simulation work was centred around the M3 corridor from Southampton to Winchester. Thus, consequential data is relatable to that specific scenario, road gradients, and importantly lane configurations. That route was primarily a three lane carriageway, whilst sections of the motorways between London and Manchester are not always three lanes. So how well the model replicates the results of motorways with greater than three lanes, or in fact dual carriageways, is unknown and is an area of further research. The microscopic model should ultimately be applied to other lane configurations and those models can in turn be applied where appropriate at the macroscopic level.

8.2.2 Areas of Investigation

Due to physical constraints, cost implications and sheer impracticalities, at the point of deployment the entire route will not be equipped with charging infrastructure. The main area of investigation at this stage was to assess how much of the route must be equipped with WPT charging infrastructure to facilitate three potential end results; an assumption was made that EVs would have an initial SOC of 100%:

1. Achieve route distance
2. Maintain half initial SOC over route (50%)
3. Maintain initial SOC over route (100%)

Thus, the investigatory variable is the length of route equipment required to achieve the trip distance, or to achieve an end SOC, in this case maintaining 50% or 100% of the initial SOC. The latter maintain entire SOC result would be a zero battery usage or energy neutral scenario, where vehicles would enter and leave the SRN with the same SOC. The exact positioning of the infrastructure was not investigated at this stage. Generally, the exact position should be done within the microscopic simulation to see the individual effects on traffic flow and detailed interactions of placing charging infrastructure near junctions and gradients. Therefore, the route was equipped as a percentage, for example a 10% coverage would see one in every ten miles being equipped, and so forth. For areas of no charging infrastructure, the energy consumption of vehicles in the base ZERO power scenario will be used.

Three scenarios are investigated, each of which appears possible according to literature and prior research. The average speed model was first used to ascertain typical vehicle speeds and the general traffic impact of the charging infrastructure and scenario configuration. Before which the battery gain/loss model was implemented to assess the effect of the charging system. A base experiment with no WPT charging capability was used, the data for which was taken directly from the respective microscopic simulations. Table 27 outlines the base scenario and each of the three WPT infrastructure configurations modelled; the main factors tested are highlighted in green.

Table 27 – Macroscopic Experiments and Factors Tested

Experiment	**Factor**	**Value**
0 (Base)	EV Proportion	10%
	Charging Lane	None
	Charging Speed	N/A
	WPT Power Level	N/A
1	EV Proportion	10%
	Charging Lane	Integrated Inside Lane
	Charging Speed	Typical/Average
	WPT Power Level	Low, Medium, High
2	EV Proportion	10%
	Charging Lane	Integrated Inside and Middle Lane
	Charging Speed	Typical/Average
	WPT Power Level	Low, Medium, High
3	EV Proportion	10%
	Charging Lane	Integrated Inside Lane
	Charging Speed	60 mph
	WPT Power Level	Low, Medium, High

Alongside the base experiment, the three main experiments investigate three main infrastructure configurations: placing the charging lane in the inside lane, equipping both the inside and middle lane, and equipping the inside lane but limiting charging speed to 60mph.

8.2.3 Traffic Demand and Vehicle Specifications

Whilst the microscopic simulation work concerned itself with time varying vehicle flows throughout a 24-hour period, this macroscopic study focuses on individual vehicle trips and will assess how a single vehicle travels over the route. This methodology was possible because the detailed vehicle interactions were considered at the microscopic stage; thus, are encapsulated within the mathematical models and data used. Scaling of the macroscopic study to include a greater number of vehicles would provide the same result as shown with a single vehicle. In terms of vehicle specifications, the vehicle data remains the same as used in the microscopic study.

8.3 Traffic Impact

Throughout this report, focus has been placed upon energy gain/loss per mile of EVs; the impact to existing traffic has seen little analysis. It is the purpose of this section to investigate the traffic impact of different WPT charging infrastructure scenarios, importantly to both users and non-users of the charging system; thus, ICEV's must be considered to ascertain the impact to existing traffic. The physical infrastructure configuration and how users access such systems will ultimately vary the traffic conditions of the network. Implementing fixed charging speeds, single or multiple charging lanes, and differing EV proportions will all affect traffic conditions. The unit used to investigate the traffic impact is average speed. Charging infrastructure scenarios that effectively worsen traffic flow will see a decrease in average speed, whilst scenarios that improve traffic flow will see a corresponding increase in average speed. The detailed interactions at vehicle junctions, gradients and other general points of congestion are considered within the data, but are not physically visible due to the sheer number of vehicles within the microscopic simulation. Yet, simple assumptions can often be made to understand why average speed worsens or improves.

The average speed formula expressed in Section 7.4.1 was used to create Table 28 comparing average speeds of the different macroscopic experiments; EVs are highlighted in green.

Table 28 – Average Speed (mph) Comparison of Macroscopic Experiments

Vehicle Type	Exp. 0	Exp. 1	Exp. 2	Exp. 3
CP	61.6	63.5	60.7	63.3
CD	61.6	63.4	60.6	63.3
CE	61.6	48.0	57.7	46.2
LD	60.6	60.0	56.9	63.0
LE	60.2	47.9	56.8	46.1
HRD	49.1	48.6	48.7	48.6
HRE	49.0	42.8	50.0	46.1
HAD	49.6	49.4	49.1	49.3
HAE	49.8	43.9	50.6	47.4

CP (Car Petrol), CD (Car Diesel), CE (Car Electric), LD (LGV Diesel), LE (LGV Electric), HRD (HGV Rigid Diesel)
HRE (HGV Rigid Electric), HAD (HGV Articulated Diesel), HAE (HGV Articulated Electric)

At the base experiment, speeds between vehicle fuel sources and indeed some classes are expectedly similar as both share comparable vehicle specifications and driver behaviour characteristics. Clearly, a few things are going on when the infrastructure set up changes. Initially it can be seen that the base experiment generally has higher average speeds when compared to those with charging systems. Introducing a charging lane to the inside lane (Exp. 1) sees average speed drop for EVs due to such vehicles being constrained to the inside charging lane. Yet, for petrol and diesel cars, average speeds increase because of the spare capacity now in the two non-charging lanes. Further, the number of lorries in the middle lane reduces as all electric freight vehicles are now in the inside charging lane; they are no longer overtaking.

Increasing the charging lane to both the inside and middle lane (Exp. 2) sees speeds increase for EVs, and generally decline for all ICEVs. At an EV proportion of 10%, two lanes may be unnecessary; most EVs are able to travel at speeds close to the base scenario. By constraining charging speed (Exp. 3), the speeds of vehicles in the charging lane become more homogenised, and the difference in speeds between CE/LE and HRE/HAE is lessened, potentially improving safety. However, there is still a significant difference in speed between the charging lane and non-charging lanes, as would also be the case between HGVs and lighter vehicles in the non-charging lanes.

In summary, the use of two charging lanes (Exp. 2) has the biggest impact to existing ICEV traffic as would be expected; yet increases EV speeds the most of any scenario due to the ability for EVs to now overtake whilst charging. In comparison, a single charging lane (Exp. 1 and Exp. 3) has little impact to existing traffic flow; and in some cases increases average speeds because of the spare capacity in the two non-charged lanes. Yet, the impact to EV speeds is substantial when compared to the base experiment (Exp. 0). Constraining vehicle charging speed, effectively smooths the speeds seen in the charging lane, and could be an option to minimise the traffic impact of charging both cars and freight vehicles using the same charging infrastructure.

8.4 Energy Impact

This section assesses the energy consumption of vehicles and potential energy gain from the use of WPT charging systems. Now that average speed has been ascertained for each experiment, the battery gain/loss equation expressed in Section 7.4.2 was used to determine the battery gain/loss for each vehicle type, in each experiment. The results of which are shown in Table 29, negative values represent energy consumption, whilst positive values (highlighted in green) indicate the spare capacity and thus charge received to the battery per mile travelled.

Importantly, such values are per mile and assume that the vehicle is charging for the entire mile. Further, the values do not consider the urban portion of most motorway trips, and the inevitable acceleration and deceleration associated with starting and ending such a journey. Hence, are purely in motion values obtained at motorway speeds; something that should be considered if comparing to other data sources, even the prior drive cycle data. Typically, EVs are more efficient at slower speeds with regular start/stops when compared to higher motorway speeds. It is important note, the WPT power levels documented within Table 7 – Wireless Power Transfer Model Specifications were used; such values vary depending on the vehicle type. For example, medium WPT for CE/LE is a 50 kW system, but for HRE/HAEs a 150 kW system; a reason why power gain seen in Table 29 is larger for HGV categories.

Table 29 – Battery Gain + / Loss – (Wh/mile) Comparison of Macroscopic Experiments

Vehicle Type	Exp. 0	Exp. 1				Exp. 2				Exp. 3			
	Zero	Zero	Low	Med	High	Zero	Low	Med	High	Zero	Low	Med	High
CE	-404	-382	-22.4	427	832	-290	-13	263	540	-474	28	530	1031
LE	-674	-604	-225	154	533	-543	-274	-5	264	-655	-179	297	773
HRE	-1507	-1307	-360	1535	3430	-1691	-886	725	2336	-1758	-851	964	2778
HAE	-3482	-3201	-2356	-667	1022	-3459	-2733	-1283	168	-3564	-2769	-1178	412

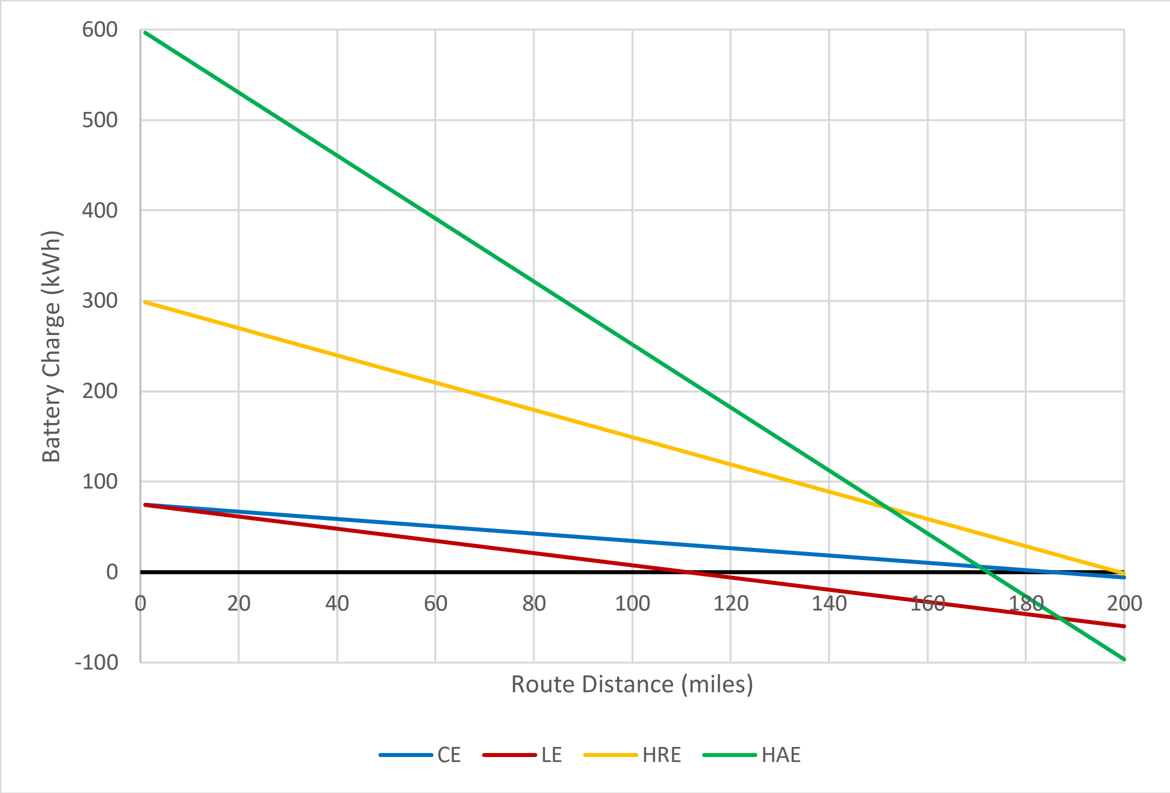
CE (Car Electric), LE (LGV Electric), HRE (HGV Rigid Electric), HAE (HGV Articulated Electric)

There are some interesting trends that appear in Table 29. Not least, battery loss for the base experiment without charging (Exp. 0) appears high for all categories when compared to the drive cycle data in Section 7.2 – Calibration and Validation of Models. This results in no vehicle classification being able to achieve the entire 200 mile route distance without having to recharge at some point; the energy consumption of each vehicle is shown in Figure 48. As expected from initial exploratory analysis and macroscopic route selection, both cars and rigid HGVs fall just short of the 200 mile route, with articulated HGVs achieving a 171 mile distance and LGVs just 110 miles.

The drive cycles used previously in the calibration process are predetermined cycles that feature a combination of both urban and interurban driving, one reason for higher consumption values in this scenario is likely the higher transit speeds when compared to the WLTP cycle. Unlike ICEVs where higher constant speeds generally result in greater fuel efficiencies, the faster EVs go the higher the energy consumption.

Whilst electric freight vehicles have higher energy consumption values when compared to CEs and LEs, they also have significantly larger battery capacities. Although they only just fall short of the 200 mile route distance, minimal WPT infrastructure would be required in this scenario to allow them to achieve full route distance. If such freight vehicles were to be fitted with smaller batteries than specified within these studies, the amount of WPT infrastructure would increase accordingly.

Table 29 also demonstrated for CEs, Exp. 2 had a lower energy consumption (-290 Wh/mile) compared to the other experiments (-404, -382, -474 Wh/mile). Yet, the higher average speeds of Exp. 2, due to the reduced congestion of two charging lanes and ability to overtake whilst charging, results in less charge received by the EVs. This in turn results in a higher route coverage required,



CE (Car Electric), LE (LGV Electric), HRE (HGV Rigid Electric), HAE (HGV Articulated Electric)

Figure 48 – Vehicle Energy Consumption over Route (no charging)

when compared to other WPT configurations with a lower average speed. There is a constant balance between minimising journey time, maximising energy transfer, and minimising infrastructure requirements. What is not seen in Table 29 is the negative impact of having two charging lanes on ICEVs, the average speed of ICEVs is lower because the majority of which is now located in the outside lane of the carriageway, this was seen in Table 28 within the prior traffic impact section.

Restricting EV charging speed to 60mph (Exp. 3) would in theory allow for greater energy transfer due to the longer time the vehicles are now being charged, the data in Table 29 reflects this trend. Yet, the consumption values of Exp. 3 zero charge scenario are greater than the base scenario. Referring to the microscopic stage, it is known that this is due to congestion of the inside lane as faster vehicles attempt to move into and across the slower charging lane. This is an important aspect of informing the macroscopic study with microscopic simulation work, without first knowing the detailed interactions at the micro level, such results can be unexplainable at the macro level. Clearly, average speed has a significant impact on battery gain/loss.

There is a larger discussion topic around driver behaviour on and off of the charging system. The zero scenario for experiments one through three have different energy consumption values to the base scenario. For example, Exp. 2 has a battery loss of 290 Wh/mile for CEs, at the base experiment this is actually 404 Wh/mile, a considerable difference. This is because the WPT infrastructure is still in place for the experiment and thus traffic flow dynamics continue even though no charging is commenced; the infrastructure is effectively impacting driver speeds, as previously discussed. Any likely future scenario would see WPT systems deployed to just partial sections of the SRN at any one point, so the area of investigation is how quickly driver behaviour would revert back and forth to normal driving as charging infrastructure begins or ends. Within this study, this is represented by average speed; so it is unknown if, or how quickly, vehicle speeds will change back to normal driving speeds shown in the base experiment (Exp. 0). It is considered that if vehicle speeds are constrained for charging (Exp. 3) then this will likely occur quite quickly, yet will repeatedly see additional deceleration and acceleration to and from the charging speed. However, for scenarios where purely congestion is occurring, driving patterns may continue as they had been within the area of charging infrastructure for quite some time, or until traffic flow stabilises. Further areas of concern are then raised when the motorway effectively switches back and forth between electrified and non-electrified sections, five miles charged, five miles non charged, and so forth. The driver behaviour and safety impacts of such a scenario are noteworthy points of future work.

Returning to the areas of investigation; specifically, the amount of WPT infrastructure required to achieve three end results: achieve route distance, maintain 50% SOC, maintain 100% SOC. Such aspects are subsequently explored.

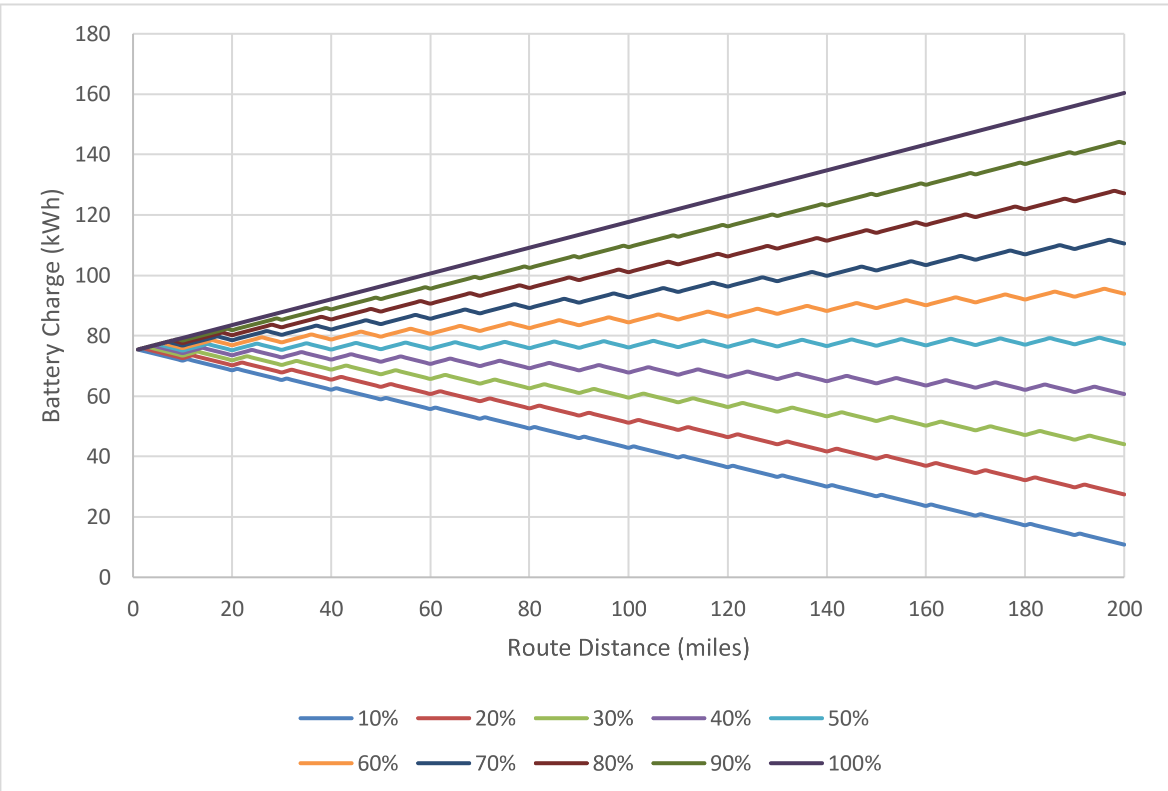
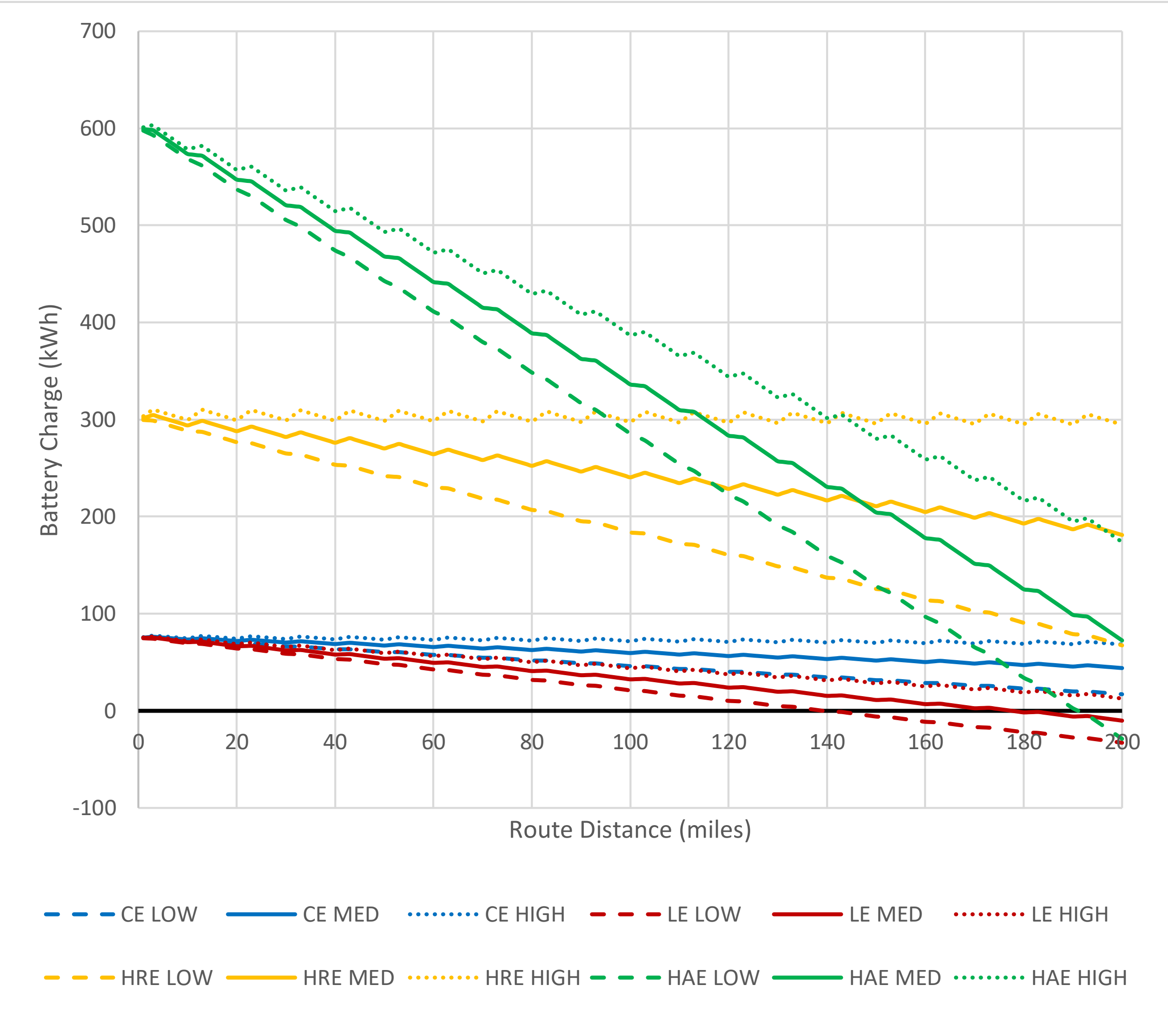


Figure 49 – Vehicle Energy Consumption over Route (CE, Medium WPT) [Exp. 1]

The energy consumption of a single CE, over a partially equipped 200 mile route is plotted in Figure 49, a medium WPT system is used, with a configuration outlined by Exp. 1; WPT deployment is varied between 10% and 100% of the route. It is shown that circa 50% of the route maintains initial battery SOC, whilst a mere 10% enables the vehicle to achieve the entire route distance; both of which assuming an initial 100% SOC. Deployment levels beyond 50% could be deemed unnecessary as depending upon initial SOC and battery capacity, spare energy may not be utilised. There is a question over whether such WPT systems should be designed to effectively: charge vehicles, to supplement vehicle range, or in fact to maintain battery SOC at all times. The amount of infrastructure and energy required for each scenario would vary significantly. At this stage of technology and deployment levels, it would seem appropriate to provide additional capacity and not see the systems as replacement charging systems. Yet, a partially equipped route would require the system to provide excess power so that surplus energy can be used later on unequipped sections. For example, charge high for one mile, use that excess energy for the next nine miles of the unequipped route.



CE (Car Electric), LE (LGV Electric), HRE (HGV Rigid Electric), HAE (HGV Articulated Electric)

Figure 50 – Vehicle Energy Consumption over Route (30% coverage, varying WPT level) [Exp. 1]

Investigating further at 30% route coverage, the effects of different power systems and vehicle types can be seen in Figure 50 for Exp. 1. Such a graph shows the detail that can be explored within this macroscopic study. The greater range between power levels for HGVs appears dominant because of the higher range in power levels for such vehicles (50-250 kW) when compared to the systems used for CEs and LEs (25-75 kW). Only some power levels are sufficient for vehicles to reach the end of the route without additional static based charging.

Table 30 – Percentage of Route Equipment to achieve End Scenario [Exp. 1]

Vehicle Type	Route Distance			50% SOC			100% SOC		
	Low	Med	High	Low	Med	High	Low	Med	High
CE	7.6%	3.5%	2.3%	56.7%	26.1%	17.5%	-	48.6%	32.7%
LE	66.6%	36.1%	24.8%	-	58.8%	40.3%	-	81.4%	55.8%
HRE	0.6%	0.2%	0.1%	66.0%	24.9%	15.3%	-	49.5%	30.5%
HAE	42.8%	17.1%	10.7%	-	70.4%	44.0%	-	-	77.3%

Table 31 – Percentage of Route Equipment to achieve End Scenario [Exp. 2]

Vehicle Type	Route Distance			50% SOC			100% SOC		
	Low	Med	High	Low	Med	High	Low	Med	High
CE	7.4%	4.4%	3.1%	55.4%	32.5%	22.9%	-	60.6%	42.8%
LE	74.8%	44.7%	31.9%	-	72.7%	51.9%	-	-	71.9%
HRE	1.1%	0.3%	0.2%	-	33.9%	19.7%	-	67.5%	39.2%
HAE	64.4%	21.9%	13.2%	-	90.1%	54.3%	-	-	95.4%

Table 32 – Percentage of Route Equipment to achieve End Scenario [Exp. 3]

Vehicle Type	Route Distance			50% SOC			100% SOC		
	Low	Med	High	Low	Med	High	Low	Med	High
CE	6.7%	3.1%	2.0%	50.1%	23.2%	15.1%	93.5%	43.3%	28.2%
LE	60.4%	30.8%	20.7%	98.3%	50.1%	33.6%	-	69.4%	46.6%
HRE	1.1%	0.3%	0.2%	-	30.6%	17.7%	-	61.0%	35.2%
HAE	67.6%	20.9%	12.4%	-	86.0%	50.9%	-	-	89.4%

CE (Car Electric), LE (LGV Electric), HRE (HGV Rigid Electric), HAE (HGV Articulated Electric)

Further investigation is required to assess the exact amount of infrastructure required to facilitate each of the three end of route results. The macroscopic route was mathematically modelled and the information contained within Table 30 to Table 32 summarises the amount of charging infrastructure required to facilitate each of the three end of route situations, for each of the three different charging infrastructure configurations (Exp. 1-3). For scenarios where the WPT system, even with 100% route coverage, was not capable of facilitating the desired end result, the value is left blank. A colour gradient has been applied with progressively darker colours used to highlight the greater amount of WPT route equipment required.

The amount of infrastructure required varies significantly dependent upon the vehicle type, power of the WPT system, and the desired end result. In order to maintain the initial SOC over the SRN, high power systems are generally required, as well as high levels of route coverage. For many vehicle types, low and medium power systems are often not enough to facilitate vehicles maintaining SOC over the route. Whilst no vehicle was capable of achieving the route distance without supplementary charging (Figure 48); due to the large battery capacities of some vehicles, those only required small amounts of charge to achieve the route distance. This is most obvious with the HRE category, typically less than one percent of route equipment is required. This analysis could also be used to assess the size of onboard battery storage, quite possibly a 300 kWh battery is over specified when compared to the energy consumption of the HRE.

As SOC was used as the measurement metric, the amount of WPT infrastructure is heavily reliant upon initial SOC, the size of battery, and the vehicles energy consumption. Varying such parameters will ultimately vary route equipment requirements. Larger onboard storage effectively reduces the amount of infrastructure required. So, if a particular vehicle has greater battery storage, less infrastructure is required. Yet, in order to reduce battery sizes, more charging infrastructure is necessary.

Whilst the end result of achieving the route distance is a worthy subject of investigation, it is not considered best practice. Generally, some contingency should be added into the system to allow for the urban component of each trip, other route choices, adverse traffic or weather conditions, or lack of access to the WPT system due to technical problems or lack of capacity. An end result that depletes battery capacity to zero is not ideal for the vehicles battery, drivers psychology, and does not allow for other problems that may occur which potentially risk the vehicle not reaching the end destination. Focusing on maintaining SOC over the route negates the reliance upon battery capacity and focuses more on the energy consumption of that vehicle over the route.

When comparing between scenarios, limiting charging speed to 60mph (Exp. 3) required the least amount of charging infrastructure; not least because of the extended amount of time vehicles are now charging for. Yet, the impact of which is seen in journey times; average speeds (Table 28) are expectedly lower for EVs in Exp. 3 when compared to other experiments. This demonstrates how both energy and traffic aspects should be considered in combination.

When assessing Exp. 2, marginally more charging infrastructure is required when compared to Exp. 1 to achieve the same end result. However, this is in combination to the fact that Exp. 2 uses two charging lanes, thus infrastructure requirements are doubled at the higher percentage stated in Exp. 2. Thus, for this scenario at a 10% EV proportion, it demonstrates that there is not sufficient demand to justify the deployment of two charging lanes. Vehicles are able to travel faster due to the extra charging lane, hence charging infrastructure requirements increase due to the higher average speeds, and resultingly higher energy consumption values.

Looking at a particular scenario in Exp. 1, to maintain 50% SOC over the route distance, at a medium power level uses between 24.9 and 70.4% of charging infrastructure dependent upon the particular vehicle type. Considerably more infrastructure is required for HAEs, the data suggests that the high power charging system could be used for such vehicles, while the remaining vehicle categories could use the medium power system. This would bring infrastructure requirements down to between 24.9 and 44% percent for the same scenario. This is a further aspect that could be investigated, power levels should be balanced so that an equilibrium is found between power and route equipment. If, as in this scenario, CEs require 24.9% of route equipment and HAEs require 44%, there is an unbalanced amount of infrastructure required. Manipulating the exact power of the charging system to equalise the amount of infrastructure required for all vehicle categories appears logical.

8.5 Chapter Conclusions

The purpose of this chapter was to demonstrate the application of the mathematical models developed within the prior microscopic simulation chapter. The application of this macroscopic methodology demonstrates how such tools can be used to investigate the amount of WPT charging infrastructure required to facilitate a desired end of route scenario; be it to reach the end of the route or to maintain a particular SOC. It was clear that the analysis of such scenarios must consider both energy and traffic aspects in parallel to truly see the effect the charging infrastructure has on both criteria. Typically, some compromise is always necessary between journey time, energy transfer, and infrastructure requirements.

This study demonstrated the benefits of using the microscopic simulation to inform the macroscopic work. Rather than just assuming a value of energy consumption or charge per mile, as seen with other approaches from literature, a more accurate and realistic estimate could be gained by using the mathematical models to estimate average speed and then in turn battery gain/loss per mile. Such resultant data contained all of the detailed vehicle interactions seen at the microscopic level. Yet, it was shown that consideration should be given to fully understanding the microscopic effects and not rely merely on the macroscopic data. The same methodology outlined within this chapter could be applied to other variables such as ICEV fuel consumption and vehicle emissions using the respective models formulated previously.

It was identified that the power of the WPT system should be balanced between vehicle types in order to balance out the amount of infrastructure required between vehicle types. Thus, avoiding a scenario where one vehicle type requires more or less charging infrastructure than another vehicle type. Albeit, factors such as route choice and trip distance become further aspects to consider. It would be ideal to optimise the system and power levels so that all vehicles use the same amount of infrastructure but at different power levels.

There were some limitations of this study, most of which repeat the same limitations of the microscopic based models of the prior chapter. Such models are based on a particular motorway section with three lanes, a specific gradient profile, and featured a number of junctions in close proximity. In order to compensate for other motorway sections with a greater number of lanes, dual carriageways, or indeed urban elements, the microscopic modelling could be expanded to produce a number of mathematical models dependent upon the particular section of SRN used within the macroscopic work. It is unknown at this stage how well the mathematical models represent different carriageway configurations. Thus, it is important such limitations should be considered when assessing the macroscopic study results, this chapter serves at a first look at such aspects. The development of additional models for different regions of the macroscopic route would improve the validity of the study but would significantly increase the amount of modelling work required.

Whilst the focus of this thesis has been the microscopic modelling and investigation, this chapter has demonstrated the ability to apply the tools developed to a macroscopic study in order to begin to assess the amount of infrastructure required to facilitate some desired end of route results.

Chapter 9 Conclusions

The use of WPT for charging of EVs is seen to be a disruptive technology that has the ability to mitigate many of the current issues facing EVs; limitations of battery technology, lack of EV range, the significant need for static based charging systems. Whilst much is understood about WPT charging systems at the technological level, little work has been made to model such systems within the traffic domain. The aim of this research was to investigate the issues related with transitioning dynamic WPT systems for EVs from technical demonstrators to full scale deployments.

Through an extensive review of literature, the current state of the art was identified, issues with implementation recognised, and the lack of previous traffic consideration acknowledged. This research saw the development of a microscopic traffic model to address such an issue, and to explore the WPT charging situation further. The development of the microscopic traffic model and the specific case study were outlined in Chapter 5. This research focused on the development of a kinematic based energy model, Chapter 6 documented this process and how the model was expanded to consider the energy consumption, energy transfer from WPT systems, emission production, as well as fossil fuel consumption of ICEVs. The traffic and energy models were shown to produce realistic results under the calibration, validation and exploratory analysis processes undertaken within Chapter 7. A large array of experiments were simulated within the traffic model, and subsequently the energy model. The main explanatory factors were: vehicle type, WPT power level, charging lane location, charging lane speed, and EV proportion.

Whilst the research could have assessed individual precise scenarios to assess the impact of the WPT system within both traffic and energy domains, the exact effect of each individual experiment, scenario or configuration was not the purpose of this study and would provide little context to the wider system. Instead, the microscopic results were amalgamated through the formulation of four mathematical models. Such models were capable of estimating the traffic impact of the WPT scenario, specifically through an average speed model, from which the battery gain/loss, fuel economy, and emission values could be estimated. Thus, this approach could inform a higher, macroscopic, level study where a network of greater distance could be assessed; whilst still retaining the detailed microscopic vehicle interactions. Such a macroscopic study is capable of investigating higher level issues, such as the required amount of charging infrastructure for a given scenario. Chapter 8 saw the application of the tools developed within this thesis, and how they can be used to assess a series of WPT scenarios in order to understand the potential of WPT for dynamic charging of EVs at the SRN level.

9.1 Contributions of the Research

At start of this thesis, the research aimed to contribute in four main areas:

1. **To understand and quantify the current technical potential of WPT systems**

Through initial background literature reviews and extensive traffic and energy modelling, it was shown that WPT technology is both capable of dynamic charging of EVs and more often than not able to provide power in excess of EV energy consumption given little WPT infrastructure.

This body of work has shown that the gap in knowledge was not technologically driven, instead, it was an implementation issue in understanding how systems would be deployed and utilised within the road network.

2. **To develop a series of modelling tools that assess the detailed traffic and energy aspects of WPT charging systems**

The detailed vehicle interactions were assessed using microscopic simulation, it was identified that the WPT system would impact driver journey times through affecting their average speed. Depending upon the vehicle type, EV proportion, charging speed and charging lane location, this had a varying impact to traffic dynamics as well as the energy transfer potential of the WPT charging system. Mathematical models were formulated based upon the microscopic simulation work, such models amalgamate the various experiments, independent WPT factors and detailed vehicle interactions with both other vehicles and the WPT infrastructure.

This has shown for the first time how the specific WPT road layout will affect driver journey times, as well as the detailed vehicle interactions with one another and the charging system. Previous studies such as the one by Deflorio and Castello (2017) only went as far as producing a basic kinematic energy model with a limited range of WPT factors and vehicles. This thesis has gone beyond previous studies in both its depth of investigation at the microscopic stage as well as formulating a series of mathematical models. Such models can be used to determine likely vehicle speeds, energy consumption, energy transfer and emission values given a users specific WPT charging configuration; importantly, without the need for detailed microscopic simulation work.

3. **To quantify the energy transfer potential of WPT in real-life situations**

The development of a kinetic based energy model was a significant component of this work, the model was shown to be realistic in estimating vehicle energy consumption, WPT charger to vehicle energy transfer, as well as environmental emission elements. Such models were applied to real world theoretical traffic networks and case studies.

This has shown for the first time realistic values for both EV energy consumption as well as energy that can be transferred to the vehicle from dynamic WPT charging systems. Previous studies such as the one by Emre and colleagues (2018) only focused on a single EV, over a single route, at several fixed vehicle speeds. This thesis has presented a far more detailed microscopic analysis of EV energy consumption and the energy transfer potential of dynamic WPT charging systems.

4. **To understand the level of WPT infrastructure required to provide a feasible system**

A macroscopic case study was undertaken to apply the tools developed throughout this thesis, the main purpose of this study was to assess the amount of WPT infrastructure required to achieve some end of route scenarios; depending upon the scenario configuration, WPT infrastructure requirements were shown to vary.

This has shown for the first time the level of WPT route equipment that may be required at the SRN level to provide a feasible charging system.

9.2 Policy Implications

This research would benefit a number of key stakeholders; including Highways England, System Manufacturers, Distribution Network Operators as well as at the National Government level.

For the first time this report has demonstrated the detailed microscopic vehicle interactions of dynamic WPT charging systems. System manufacturers are able to apply the mathematical models developed within this research to their own WPT system specifications to understand the potential real-life energy consumption and transfer capabilities, essentially capturing the traffic aspects that have not been considered previously in research. Systems can be further developed on the basis of this and an understanding of what a feasible system may be in terms of real-life usability. Distribution Network Operators can also apply this research to understand future energy and power requirements of dynamic WPT charging systems, and apply such data to areas of the grid that may require reinforcement to support such systems.

The environmental benefits of such systems have been shown to reduce point of use emissions as well as more generally reduce vehicle emission levels across the board, thus such schemes would benefit from national government investment strategies targeting emission reductions. The greatest impact of this would be in areas already highlighted as high pollution points of the SRN and alternative means of reducing emissions are being implemented such as reduced speed limits. Importantly, such routes require a high proportion of EV users to have the most benefit, as well as routes that traditional EVs or electric freight would not be capable of achieving without additional on-route charging. Further, providing a national dynamic charging system would reduce issues around limited EV range and potentially increase the market take up of EVs.

Finally, to ensure successful deployment and development of a feasible dynamic charging system across the SRN, the road based system must be standardised. Such a scenario would allow third parties to develop their own vehicle based systems that can work and receive power from these standardised road coils and communication protocols. Without such policy implementation then the technology and deployment of WPT systems is hampered.

9.3 Limitations

A number of limitations were identified and discussed throughout this body of work. The main limitation of this research was the focus placed upon a single motorway link for the microscopic study, the resulting data, eventual mathematical models, and macroscopic study are all associated to the features, road layout, and general traffic characteristics of that particular SRN link. Adjusting any of the values, assumptions or WPT technicalities at the microscopic stage would inevitably change the subsequent mathematical models and would require reanalysis at the microscopic level. Yet, to reach the required depth of detail in the microscopic work, a single case study was selected that represented a good proportion of the SRN and featured a varied road layout. A further limitation was the inability to quantify driver behaviour for both EVs and WPT charging, such elements could not be definitively defined and represent a significant research undertaking in their own right.

9.4 Further Work

This thesis has addressed the initial research aim and objectives, yet additional questions and topics of research have been identified as a result of this work. The following points summarise the general themes for future work:

Driver Behaviour of EVs and WPT equipped vehicles:

Whilst this topic was reviewed and issues surrounding such a topic were explored, a certain driver behaviour was assumed for the purposes of this modelling work. Yet, how drivers will utilise WPT charging systems, their behaviour on and off of the network, and their interaction with other non-charging vehicles are all aspects that require further research and quantification. As does the behavioural differences of drivers when comparing ICEVs and EVs. A combination of studies, both physical and simulator based, would be a good first step to exploring such issues; but significant work is required within this field to begin to both understand and quantify such aspects.

Expansion of Mathematical Models:

The development of further microscopic, and consequential mathematical, models for different road configurations could be undertaken. This would see multiple models being applied at the macroscopic stage to include different lane quantities, configurations, junctions or road features. The development of an urban model would further complement this work.

Specific WPT Technical Layout:

Whilst this thesis has developed tools and begun to explore the amount of infrastructure required under different WPT configurations. The specific layout of WPT infrastructure has not yet been investigated. The exact positioning of charging coils within the SRN and specific road layout configurations could be investigated at the microscopic level to see their effect on junctions and other road features. However, this stage is also dependent upon the regional supply capabilities of the electricity grid.

Electricity Grid Analysis:

The electricity grid capabilities to support and facilitate EV charging has seen notable investigation thus far in literature. Yet, how the grid can support dynamic charging of EVs is a necessary area of further research. Issues include how SRN infrastructure crosses Distribution Network Operator (DNO) borders, is often located in interurban locations away from usual supply areas, general upgrades to capacity with added flexibility in supply, and the grids ability to cope with peak demand during morning and evening commutes. A power demand and grid analysis investigation could be undertaken that maps and overlays the power grid supply with WPT demand requirements.

System Optimisation:

The microscopic and macroscopic modelling approaches could be used to optimise the infrastructure and vehicle design in combination. The use of smaller onboard battery capacities could be facilitated by WPT charging systems, yet would require a greater proportion of WPT infrastructure and investment. The question becomes which route is best for investment, as well as considering the economic, political, traffic, energy and environmental impacts of either direction.

9.5 Final Conclusions

This thesis has culminated in a novel method, and respective tools, to model WPT charging systems for EVs. A greater understanding has been gained to the current potential of WPT systems, and whilst WPT technology has been shown to be technically possible for the dynamic charging of EVs, it cannot be assumed. Such scenarios require extensive analysis before physical deployment of infrastructure, the issues explored within this thesis and the tools developed as a result of such can be used to undertake this analysis and optimisation.

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