Forecasting the Impact of Growing Shares of Hybrid and Electric Vehicles on Future Emissions of Carbon Dioxide and Air Quality Pollutants

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The candidate confirms that the work submitted is her own, except where work which has formed part of jointly authored publications has been included. The contribution of the candidate and the other authors to this work has been explicitly indicated below. The candidate confirms that appropriate credit has been given within the thesis where reference has been made to the work of others.

Parts of Chapters 3, 4 and 5 in this thesis are based on work as follows, which has either been published in academic journals or was presented as part of conference proceedings:

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ABSTRACT

Electric vehicles such as hybrid, plug-in hybrid and battery electric vehicles are a low-pollution low-carbon alternative to conventional petrol and diesel vehicles. They currently only represent a fraction of the vehicle fleet, but demand and supply is rapidly accelerating. It is important to understand the changes in relative costs of electric vehicles, to inform scenarios of the future vehicle fleet mix and subsequent impacts on expected trends in emissions of carbon dioxide and air quality pollutants. This is of interest to policymakers worldwide who are under pressure to cut carbon emissions and improve urban air quality.

Barriers to adoption of hybrid and electric vehicles still exist including the high initial cost. Total Cost of Ownership considers all vehicle costs to ascertain whether the cheaper running costs of electric vehicles can offset the higher initial cost. By modelling hybrid vehicle ownership costs from 2000 to 2015 in different geographic vehicle markets a link between cost and adoption is proven. This research found that ownership costs of hybrid and electric vehicles are falling compared to conventional vehicles, with costs already cheaper in the UK, USA and Japan with the current subsidies available, and findings that by 2030, subsidies could be phased out.

This study uses three future fleet scenarios resulting from an extended generalized bass model. This model includes a fleet turnover unit with an age based scrappage curve to create scenarios of hybrid and electric vehicle uptake, which also includes the on-road fleet share of petrol and diesel vehicles by Euro standard. These scenarios characterize three different futures: Business as Usual, Battery Bonanza (where the current 2040 target of 100% hybrid and electric vehicle market share is met) and Diesel Persists, where battery price, fuel price and subsidy level vary depending upon market conditions.

Hybrid and electric vehicles have lower operational CO_2 and NO_x emissions; however, most modelling studies to date are based on either single vehicle models or high-level estimates. This thesis assesses the impact the evolving fleet has on trends in tail-pipe emissions of CO_2 and NO_X from 2015 to 2040 over a typical UK urban road network. A coupled microscopic traffic and instantaneous emission-modelling framework that can properly account for the impact of traffic congestion was used to assess vehicle emissions over 24-hours of a typical day for the three future vehicle fleet scenarios. This thesis concludes that the adoption of hybrid and electric vehicles could reduce network level emissions of CO_2 and NO_x by up to 31.6% and 95% respectively by 2040, with greater effects during congested conditions.

CONTENTS

LIST OF FIGURES

LIST OF TABLES

LIST OF ABBREVIATIONS

ACEA	European Automobile Manufacturer's Association
AFV	Alternatively Fuelled Vehicle
AIMSUN	Advanced Interactive Microscopic Simulator for Urban and non-urban Networks
ANPR	Automatic Number Plate Recognition
API	Advanced Programming Interface
ATC	Automatic Traffic Count
BEIS	Department for Business, Energy and Industrial Strategy
BEV	Battery Electric Vehicle
BIK	Benefit in Kind
BNEF	Bloomberg New Energy Finance
CAZ	Clean Air Zone
CCS	Combined Charging System
CHAdeMO	Charge de Move
CNG	Compressed Natural Gas
CO	Carbon Monoxide
CO_2	Carbon Dioxide
COPERT	Computer Programme to calculate Emissions from Road Transport
DECC	Department for Energy and Climate Change
DEFRA	Department for Environment, Food and Rural Affairs
DfT	Department for Transport
DMV	Department of Motor Vehicles (US)
DPF	Diesel Particulate Filter
EC	European Commission
EEA	European Environment Agency
EFT	Emissions Factors Toolkit (EFT v8.0.1)
EGR	Exhaust Gas Recirculation
EPA	United States Environmental Protection Agency
EPSRC	Engineering and Physical Sciences Research Council
EV	Electric Vehicles
FHWA	Federal Highway Administration
GPS	Global Positioning System
HBEFA	HandBook on Emission Factors for road transport (HBEFA v3.1)
HEV	Hybrid Electric Vehicle
HFC	Hydrogen Fuel Cell
HGV	Heavy Goods Vehicle
HOV lane	High Occupancy Vehicle lane
HSD	Hybrid Synergy Drive
ICCT	The International Council on Clean Transportation
ICEV	Internal Combustion Engine Vehicle
IEA	International Energy Agency
IPCC	International Panel on Climate Change
ITS	Institute for Transport Studies, University of Leeds
JAMA	Japan Automobile Manufacturers Association
LCC	Leeds City Council
LCV	Light Commercial Vehicle
LEZ	Low Emission Zone
LiDAR	Light Detection And Ranging

LNT	Lean NOx Trap
LPG	Liquid Petroleum Gas
MaaS	Mobility as a Service
MCC	Manual Classified Counts
MOVES	Motor Vehicle Emission Simulator (MOVES v2010b)
MPV	Multi-Purpose Vehicle
MSRP	Manufacturer Suggested Retail Price
NAEI	National Atmospheric Emission Inventory
NEDC	New European Driving Cycle
NEV	New Energy Vehicle
NO_x	Nitrogen Oxides including Nitrogen Monoxide (NO) and Nitrogen Dioxide (NO_2)
OBS	Horiba On Board emission measurement System (OBS-1300)
ONS	Office of National Statistics
PAMS	Portable Activity Measurement System
PEMS	Portable Emission Measurement System
PEV	Plug-in Electric Vehicle
PHEM	Passenger car and Heavy-duty Emission Model (v11.7.5)
PHEV	Plug-in Hybrid Electric Vehicle
PLDV	Passenger Light Duty Vehicle
PM	Particulate Matter
PN	Particulate Number
PWC	Price Waterhouse Cooper
RAC	Royal Automobile Club
RDE	Real Driving Emissions
REEV	Range Extended Electric Vehicle
Rpm	revolutions per minute
SCR	Selective Catalytic Reduction
SMMT	Society of Motor Manufacturers and Traders
SOES	Sheffield Omnibus Enthusiasts Society
SUV	Sports Utility Vehicle
TAG	Transport Analysis Guidelines
TCO	Total Cost of Ownership
TfL	Transport for London
TNO	Netherlands Organisation for Applied Scientific Research
TSS	Transport Simulation Systems
TU-Graz	Technical University of Graz
VED	Vehicle Excise Duty
VKM	Vehicle Kilometres Travelled
VSP	Vehicle Specific Power
V2G	Vehicle to Grid
WLTP	World Light Duty Testing Procedure
WTP	Willingness to Pay
ULEZ	Ultra-Low Emission Zone
ZeEUS	Zero Emission Urban Bus System

CHAPTER 1: INTRODUCTION

1.1 MOTIVATION

Anthropogenic climate change poses a threat to the future of human civilisation. Already the consequences of global warming are evident with greater numbers of extreme weather events, rising sea levels and food security concerns (Intergovernmental Panel on Climate Change, 2016). Limiting average global surface temperature rise to only 2 degrees (on pre-industrial levels) by the end of the 21st century, is regarded as an ambitious target. Even if warming is limited to this threshold, flora and fauna will be affected by the serious consequences of ocean acidification, permafrost melting, and increased periods of draught (Climate Analytics, 2018). Reducing greenhouse gas emissions is therefore imperative to stabilising the climate and minimising these dire consequences.

Transport as a whole accounts for approximately 22% of global carbon dioxide emissions (IEA, 2017), but represents a higher percentage in developed countries such as the UK (34%) and USA (28%) (Department for Business, Energy and Industrial Strategy, 2018; United States Environmental Protection Agency, 2018b). Transport sector carbon dioxide emissions are still growing; mainly due to the increasing ownership of vehicles in emerging economies such as China and India as well as the lack of improvement in the efficiency of both light and heavy duty vehicles in real driving conditions (International Council on Clean Transportation, 2016; International Council on Clean Transportation, 2017; United States Environmental Protection Agency, 2018a). Even though the size of the car fleet has stabilised in most developed countries, the transport sector is facing the challenge of decarbonisation.

Many cities across the world are breaking air quality standards; ambient air pollution is estimated to cost more than 4.2 million lives a year (World Health Organisation, 2018). In much of the developed world, tailpipe emissions from road transport are the main source of this pollution; partly due to the dieselisation of the car fleet, and due to city topography (European Environment Agency, 2012). The effect of urban air pollution on human health is only starting to be understood, with links to asthma, neurological problems and cancer under investigation (Guarnier and Balmes, 2014; Hamra et al., 2014; Clifford et al., 2016). The EU has annual legally binding limits of Nitrogen dioxide (NO_2) and Particulate Matter (PM_{10} and $PM_{2.5}$); however, many major European cities such as London exceed these restrictions within a number of weeks (Carrington, 2018). To cut pollution levels, many cities are implementing policies such as Ultra Low Emissions Zones, diesel vehicle bans and congestion charges (Rotaris et al., 2010; Moody and Tate, 2017; Möhner, 2018).

Hybrid and electric vehicles present a low-carbon low-pollution alternative to conventional petrol and diesel vehicles (Hutchinson et al., 2014). Despite their advantages, these vehicle types face several challenges to large scale adoption: historically high upfront costs have presented the greatest barrier, but range anxiety for full Electric Vehicles linked to lack of publically available charging infrastructure, distrust of new technology, lack of model choice and supply constraints all contribute to their relatively low adoption rates in most vehicle markets (Coffman et al., 2017).

With cost often quoted as the key barrier to hybrid and electric vehicle adoption, analysing ownership costs across multiple geographic regions enables an assessment of the link between ownership costs and adoption. Conclusions can therefore be drawn about future adoption scenarios, which can inform how the urban traffic mix may develop. Estimating vehicle emissions at a network level using a traffic microsimulation model coupled with a vehicle emissions model enables a high resolution estimation of how the changing vehicle fleet composition affects congested urban areas such as the Headingley network in Leeds.

1.2 AIM

The overall aim of this research is to assess the impact of different vehicle fleet scenarios stemming from changing ownership costs of hybrid and electric vehicles, on vehicle emissions for a representative urban traffic network. The background to this topic is discussed in depth (Chapter 2) followed by an examination of the economic case for hybrid and electric vehicles in the past (Chapter 3) and the future (Chapter 4), across different geographic regions, years, and ownership types. These cost estimates then feed through to inform a range of vehicle fleet turnover and evolution scenarios (Chapter 5). The impact of these different scenarios on the vehicle emissions over an urban network is estimated (Chapter 6). The thesis concludes with policy suggestions in the wider transport framework (Chapter 7).

1.3 OBJECTIVES

To address the overall aim, the research will focus on the following objectives:

OB1. To assess how vehicle ownership costs for hybrid and electric vehicles have changed over time in different geographic regions.

OB2. To project future vehicle ownership costs by size segment.

OB3. To develop future vehicle fleet scenarios to account for different adoption pathways.

OB4. To assess the impact of different adoption scenarios on vehicle emissions and energy consumed over an illustrative area of the Leeds urban traffic network.

1.4 METHODOLOGICAL APPROACH

The first objective, OB1, will be achieved by building a Total Cost of Ownership model for UK, California and Japan, for the time period spanning 1997 to 2015. This model will consider hybrid, plug-in hybrid, battery electric, petrol, and diesel cars. Using a panel regression model, the link between cost and market share will be analysed.

The second objective, OB2, will be achieved by projecting the Total Cost of Ownership model for the UK from 2015 to 2040. This projection will be split by vehicle size segment with additional analysis of historic ownership costs by ownership type. Three different scenarios will be considered to account for different external market conditions and changes in policy.

Objective OB3 will be accomplished by developing a market diffusion model examining fleet composition under different future scenarios including vehicle Total Cost of Ownership.

Objective OB4 will be addressed by coupling a microsimulation traffic model with an instantaneous vehicle emissions model to replicate variations in real driving behaviour of the current and future vehicle fleet scenarios. This coupled microsimulation traffic and emissions model will be used to estimate real-driving vehicle emissions over an urban road network.

1.5 RESEARCH QUESTIONS

The research questions given here illustrate the main questions this thesis will endeavour to answer using the methods outlined in section 1.4.

R1. Are hybrid and electric vehicles cheaper now than when they were first introduced to the mass market?

R2. How do vehicle ownership costs change over different size segments and how does this link to market share?

R3. How might the evolution of vehicle costs influence the future road vehicle fleet?

R4. How would a future vehicle fleet containing more hybrid and electric vehicles affect vehicle emissions at a road network scale?

1.6 THESIS CHAPTER OUTLINE

Chapter 2 of the thesis aims to describe the transport policy environment and technological space in which this thesis is situated. Providing background information regarding trends in vehicle purchasing such as electrification, dieselisation, and average kerbside weight increases, puts the aims and objectives of this research in context. In this chapter the current state of the EV market, factors affecting adoption of EVs, and EV policy incentives are discussed.

Chapter 3 is an investigation of historic Total Cost of Ownership of hybrid and electric vehicles. The vehicle Total Cost of Ownership accounts for all consumer related vehicle costs and therefore this calculation can determine whether subsidies and lower running costs can offset the associated price premium. This section compares the Total Cost of Ownership of hybrid and electric vehicles across different vehicle markets and for an extensive timespan to ascertain whether ownership cost and market share are strongly linked.

Chapter 4 is an investigation of historic and future Total Cost of Ownership of hybrid and electric vehicles for the UK vehicle market. The Total Cost of Ownership calculations in this chapter consider different vehicle size segments for different ownership types (private and company). The content of this chapter builds on work from the previous chapter where historic vehicle costs were compared across different regions but focused on the mid-sized vehicle segment and the private vehicle owner.

Chapter 5 uses electrification of the private vehicle sector from 2015 to 2040 as a case study for investigating the limitations and potential of the market diffusion modelling approach. In Chapter 3 hybrid vehicle Total Cost of Ownership was found to be strongly correlated with market share, therefore the modelling in this chapter takes vehicle Total Cost of Ownership scenarios (from Chapter 4) into account when modelling scenarios of the composition of future vehicle registrations.

Chapter 6 uses the Leeds road network as a case study to examine the effect of a changing future road fleet mix on network-level vehicle emissions. To do this, the vehicle adoption scenarios are used from chapter 5, along with a traffic survey of the Leeds network from 2015, to estimate the road traffic composition from 2015 to 2040. A microsimulation traffic model of Leeds is employed (Version 1 built by Wyatt (2017) in AIMSUN and improved upon for this work (Version 2) by extending this to a 24-hour model and using primary data collection to improve the vehicle dynamics in the model), to estimate realistic vehicle trajectories for all vehicle types. This input is collated into a second-by-second vehicle emissions model: the

‘Simulink H/EV Energy and Emissions Model’ (adapted from Richard Riley’s doctoral thesis (2016) to model Hybrid, Plug-in hybrid and Battery Electric Vehicle fuel consumption) and the PHEM model (developed by TU Graz (Hausberger, 2017)) is used for all other vehicles. This multi-stage methodology allows for analysis temporally over the 24-hour modelling period and spatially over the network with a breakdown of the contribution to emissions split by vehicle type and emissions Euro standard. It is important to understand the emissions contribution of vehicles over 24-hours as the annual average air quality standard of 40 $\mu g.m^{-3}$ is currently exceeded in Leeds and many streets in urban centres across the UK. Finally, this analysis is benchmarked against the widely used Emissions Factors Toolkit model (EFT v8.0.1) (DEFRA, 2018).

Chapter 7 brings all the strands of the thesis together to describe some general conclusions in the wider context of the decarbonisation of the transport sector. In this chapter, the research questions outlined here will be answered, and the degree to which the aims and objectives are met will be discussed. The limitations of the research are discussed and extensions to the thesis are identified. The electrification of the fleet has the potential to provide several benefits; however, there is technological push and policy pull, which is needed for significant electrification of the vehicle fleet.

CHAPTER 2: THE PAST EXPERIENCES AND FUTURE OPPORTUNITIES FOR THE ROAD FLEET

2.1 INTRODUCTION

Since the 1990s, there have been several distinct trends in car registrations across Europe: these include electrification, dieselisation and average kerbside weight increases. Policy changes have pushed trends, but development of technology has provided encouragement. Overall, across Europe the number of new vehicle registrations has risen slowly from 163.6 million in 1990 to 254.2 million in 2015 (Statista, 2018). There is still diversity in vehicle age, type and average vehicle size across different countries, with the composition of the vehicle fleet changing depending on country level policy (ICCT, 2017b). The number of hybrid and electric vehicles has risen slowly across Europe and the rest of the world, with some countries such as Norway and Japan leading the way in adoption of these vehicle types. There are still challenges in scaling up electric vehicle adoption to meet the future targets of 100% of new car and LCV registrations that several European countries such as the UK, France and Slovenia have announced (IEA, 2018a).

This chapter aims to describe the transport policy environment and technological space in which this thesis is situated. Providing background information regarding trends in vehicle purchasing, policy changes on a national and international level puts the aims and objectives of this research (as detailed in Chapter 1) in context. There are several options to decarbonise the road fleet, but electrification is argued as an appealing avenue because of the opportunity to utilise the increasing share of renewable energy, the lower emissions of pollutants such as NO_x, and the recent advances in battery technology. There are several key barriers to achieving 100% market share of hybrid and electric vehicles including high initial capital cost, lack of accessibility to charging infrastructure, and range anxiety of fully electric vehicles, which are discussed in this chapter. Effectively addressing these barriers across different markets segments offers the opportunity to catalyse uptake of hybrid and electric vehicles across different vehicle markets. Finally, it is recognised that there are other future mobility sector revolutions on the horizon, such as autonomous vehicles and Mobility as a Service, which could change vehicle ownership models and transport demand.

2.2 ELECTRIFICATION OF THE ROAD TRANSPORT

2.2.1 An Overview of Hybrid and Electric Vehicle Markets

Hybrid and electric vehicle numbers are rising across the world (see Figure 2-1 for global sales of hybrid and electric vehicles in key vehicle markets), with over 12 million hybrid vehicles and 3 million electric vehicles sold to date (Daily News, 2018; IEA, 2018a). The vehicle markets with the highest hybrid market share are Japan and California with over 20% and 4.6% respectively (Yang and Bandivadekar, 2017; Pyper, 2018) – these regions are investigated further in Chapter 3. For electric vehicles, Norway and Sweden are global leaders as defined by high electric vehicle market share. China is the global leader in absolute numbers of battery electric vehicle sales, accounting for over half of all electric vehicles sold globally each year, however, market share is just over 2% (IEA, 2018a).

Hybrid[1] Electric Vehicles (HEVs) refers to non plug-in vehicles that have hybrid vehicle features. These include regenerative braking, engine stop-start and all electric drive, thereby increasing the efficiency of the vehicle especially at low speeds (Hutchinson et al., 2014). Although collectively referred to as hybrids, these vehicles are not all built using the same architecture. HEVs fall within two categories: series or parallel. In a series configuration, either the battery or the petrol/diesel engine provides power to the electric motor, whereas in a parallel configuration either source can provide mechanical power simultaneously. There is also a series/parallel fusion such as either the engine or electric motor can provide power independently or together (Hutchinson et al., 2014). The Toyota Prius – the hybrid vehicle which holds highest market share in the world - utilises Toyota's Hybrid Synergy Drive (HSD) system which is categorised as a parallel hybrid (Yang and Bandivadekar, 2017; Pyper, 2018). Note that over 88% of new hybrid vehicles sold on the US market in 2017 use the HSD system (WardsAuto, 2018). As Toyota cars dominate the market this thesis uses the Prius as the representative HEV for the market in the coming chapters.

The Toyota Prius was the first hybrid to be developed, it was released in 1997 exclusively to the Japanese market with a Manufacturer Suggested Retail Price (MSRP) significantly lower than production cost (Pinkse et al., 2014). Toyota used this first limited release as an opportunity for further Prius on-road testing. Despite initial problems with the battery, the vehicle was released in other markets in the year 2000 (Sallee, 2011). The Toyota Prius was initially only manufactured in Japan, with production opening in China in 2005 and Thailand in 2010. To counteract consumer doubts over reliability of battery technology, Toyota offered a five year mechanical warranty with options to lease rather than purchase the vehicle outright (Toyota GB, 2018). By 2008 cumulative global Prius sales passed the one million mark, and by

[1] Note that the same definition of hybrids e.g. non plug-in vehicles using regenerative braking and a larger battery for increased efficiency, will be used throughout this thesis.

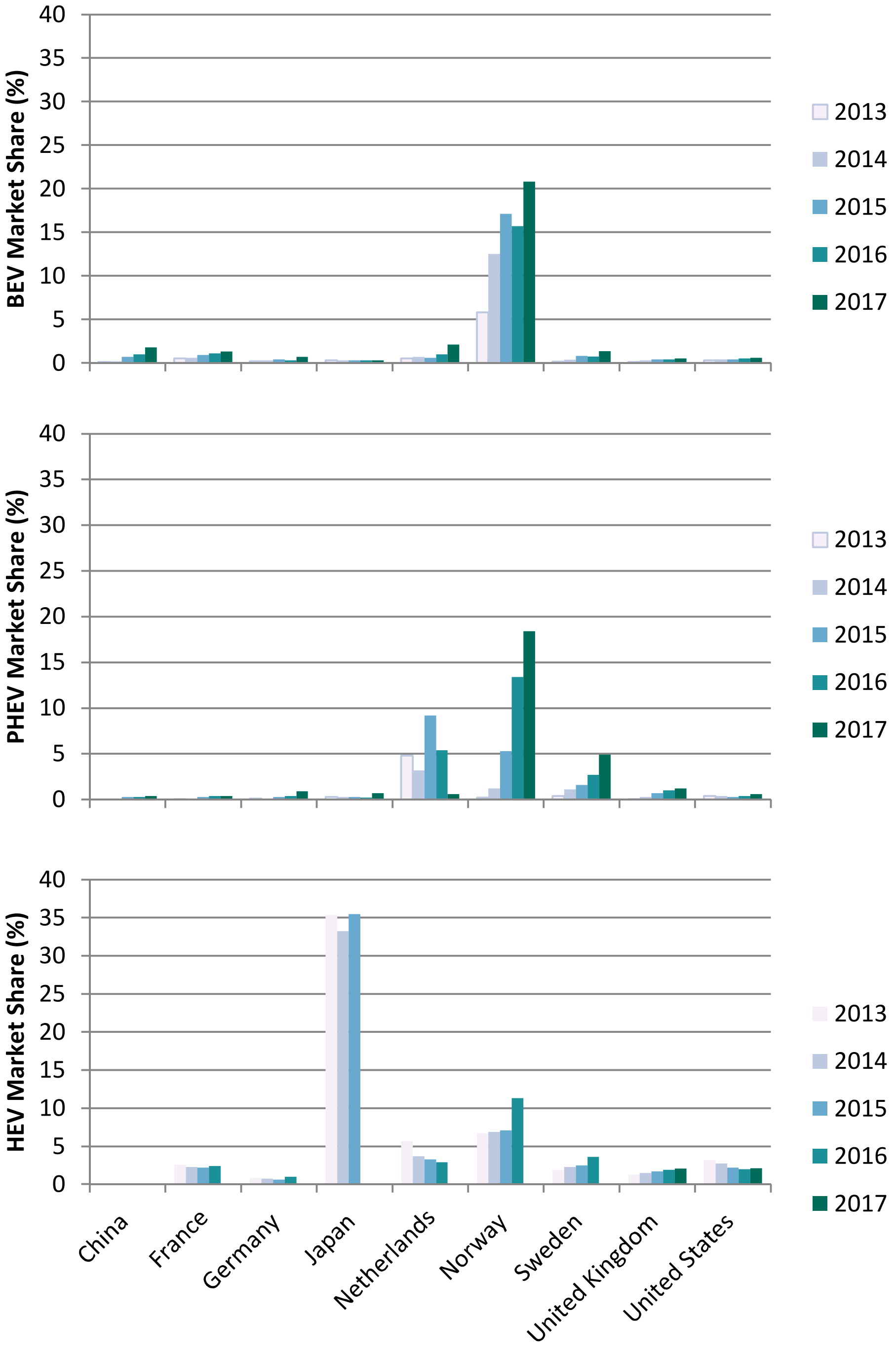

Figure 2-1: *Market share of battery electric vehicles (top), plug-in hybrid electric vehicles (middle) and hybrid electric vehicles (bottom) 2013-2017 for several key countries (note data was unavailable for the complete HEV time series, specifically China (2013-2017), France (2017), Germany (2017), Japan (2016 and 2017), The Netherlands (2017), Norway (2017) and Sweden (2017)) (IHS Markit, 2017; ICCT, 2017b; Society of Motor Manufacturers and Traders, 2017; IEA, 2018a).*

2017 Toyota hybrid vehicles had exceeded 10 million cumulative sales (Toyota GB, 2018). In the last few years, Toyota has expanded the HSD system into other vehicles, such as the Auris, Yaris and Aqua. With a wide choice of Toyota hybrids, this could account for declining Prius market share in Japan. Since the first Toyota Prius model was released, Toyota have continuously advanced the Prius such that real world vehicle fuel efficiency has increased by 25% (Spritmoniter, 2018).

Hybrid vehicle market share has taken around 15 years to become established (see Fig 2-1 for market share of hybrid and electric vehicles in different vehicle markets). This is partly because of certain distinct barriers to adoption of this new technology that include lack of consumer confidence in this novel vehicle technology and the increased capital cost (Sallee, 2011). The early EV market has learnt some lessons from the initial deployment of hybrids: for example extended warranties are commonplace in the EV market (Kia, Hyundai and Tesla all offer powertrain and battery coverage for more than 8 years (Gorzelany, 2019)), and the profit margins on new EVs are considerably lower than ICEVs (Wu et al., 2015). However, it is difficult to ascertain whether the EV market will grow quicker than the hybrid vehicle market because there are additional challenges of lower vehicle range and requirements in changes in driver behaviour for vehicle charging. These additional barriers make it challenging to predict whether the EV market will grow more quickly than the HEV market has done.

Electric Vehicles (EVs) refer collectively to both Plug-in Hybrid Electric Vehicles (PHEV) and Battery Electric Vehicles (BEV)[2]. In this thesis Range Extended Electric Vehicles (REEV) will be categorised under PHEV for simplicity, these vehicles (such as the Chevrolet Volt) are officially series PHEVs as the petrol/diesel engine can only charge the battery rather than power the wheels directly, REEVs only represent a small percentage of the EV market. EVs were released onto the mass market circa 2010, much later than HEVs, but the number of models available has expanded as market share has grown. In 2011 there were 6 BEV models and 2 PHEV models available in the USA, in 2017 this had expanded to 25 BEV models and 26 PHEV models as other manufacturers diversified into electric mobility (Richter, 2018). Tesla was founded in 2003, and contrary to other BEV manufacturers (such as BMW, Mitsubishi and Nissan), specialises in only manufacturing and retailing BEVs (Tesla, 2018a). Tesla revolutionised the EV market, making EVs a desirable commodity as opposed to the small unfashionable vehicles (such as the Renault Twizzy) available previously. Additionally, their intellectual property is open source, thereby recognising that by sharing knowledge the industry could advance

[2] This is the definition adopted throughout this thesis, although it is not uniformly agreed upon throughout the literature. The term PEVs e.g. Plug-in Electric Vehicles, will not be used in this thesis, as it is deemed the same definition as that adopted for EVs.

forward as a whole. In many markets, such as the USA, Tesla is the bestselling BEV marque (Shahan, 2018). In the UK, as in Norway, the Nissan Leaf is the most popular BEV with over 23 000 registrations between 2010 and 2018 (this is the key reason the Nissan Leaf is deemed representative of the BEV market in the latter chapters of this thesis), whereas the Mitsubishi Outlander is the most popular PHEV with 34 800 total UK registrations (Kane, 2018). Globally, BEVs account for two thirds of EV sales, mainly due to the high numbers deployed in China (IEA, 2018a).

2.2.2 Policy Push: Incentives for Hybrid and Electric Vehicle Purchase

Historically, there has been policy push and technological pull that has enabled hybrid and electric vehicle numbers to grow in vehicle markets across the world. Incentives to persuade consumers to adopt a more sustainable option fall into two distinct categories, financial and non-financial, and can be executed at either an international, national, or a city-level basis (see Table 2-1 for examples of incentives introduced to stimulate EV adoption, the financial incentives in major vehicle markets will be discussed in detail in Chapter 3.) By examining incentives that have been introduced in different vehicle markets and assessing their effect on EV adoption, we can inform how fiscal incentives can be optimally designed.

Financial incentives for HEVs are limited, and mainly include reduced vehicle taxes due to widespread use of taxation systems graduated by rated CO_2 of the vehicle (e.g. the manufacturer tested CO_2 figure published in g CO_2/km). In some regions such as California, HEVs had access to Higher Occupancy Vehicle (HOV) lanes when market share was low (Shewmake and Jarvis, 2014) - as discussed further in Chapter 3. Financial incentives for EVs exist across the world and research has shown that fiscal incentives increase adoption (Jenn et al., 2013; Bjerkan, K.Y., Nørbech, T.E., Nordtømme, 2016; Jenn et al., 2018) - in Chapter 3 the link between ownership costs and adoption will be explored further to build upon this body of literature. The initial capital cost of a hybrid or electric vehicle is typically greater than a conventional vehicle. By offering a fiscal incentive such as reduced registration tax or a direct subsidy on purchase cost of new vehicles, this barrier can be reduced (as explored in Chapter 3 and 4). For example, electric cars in Norway are exempt from acquisition tax (approximately £9000), and the 25% VAT usually payable on car purchases (Figenbaum et al., 2015). Norway is the most generous country in the world for EV subsidies, but with high vehicle taxes it is viable to reduce taxes for EV adopters rather than increase them for petrol/diesel ICEV owners. In other countries, it is not deemed politically viable to increase taxes for petrol/diesel ICEVs to incentivise adoption of low emission vehicles.

Table 2-1: *Types of EV incentives. This table is not exhaustive, but illustrates the types of policies available and the wide geographic spread, indicating that countries across the globe are committing to electrification of the transport fleet. (Zhang et al., 2014; Van Der Steen et al., 2015; Zhou, 2017; Van den Steen, 2018; Perkowski, 2018; Cokayne, 2018).*

Category	Type of Incentive	Level	Examples of introduction
Financial	Purchase rebate	National	UK, USA, China, India, Canada
	Registration tax exemption/reduced rates	National	Belgium, Denmark, Finland, Ireland
	Annual tax exemption	National	UK, Germany, The Netherlands
	Purchases tax exemption	National	Norway, Colombia, Uruguay, and Ecuador
	Parking charge exemption	City	Dundee, London, Oslo
	Free charging	City	Dundee
	Exemption/Reduction from import taxes	National	Ecuador, Uruguay, Costa Rica and Colombia, South Africa
	Reduced electricity tariffs for charging EVs	National/ City	Mexico and Santiago (Chili)
Non-financial	High Occupancy Vehicle lane access, Bus lane access	State/ City	California, Norway
	Low Emission Zone access	City	London
	Mandating minimum percentage of parking spaces for EVs in public parking lots	National/ City	Mexico, and recently in Guayaquil (Ecuador)
	Obliging new construction sites, public buildings and workplaces to implement charging points	National/ City	London
	Manufacturer fleet ave. CO_2 emission limit	International	EU

Hybrid and electric vehicles are more expensive because of the high capacity battery and the novel powertrain, but annual running costs are much lower (as discussed in Chapter 3 and 4). A number of studies have found this to factor into purchase decisions (Egbue and Long, 2012; Burgess et al., 2013; Carley et al., 2013; Hoen and Koetse, 2014; Barth et al., 2015; Bjerkan et al., 2016). However, it is understood that consumers are not entirely economically rational in their decision behaviours (Turrentine and Kurani, 2007; Hardman and Tal, 2016). In fact, fiscal incentives have been found to increase purchases of EVs despite consumers not undertaking TCO calculations themselves to ascertain their savings (Vetter, 2016). Therefore, the size of these fiscal incentives has been found not to be directly proportional to the effect on rates of adoption. A review of the studies investigating the effectiveness of fiscal incentives on the adoption of electric vehicles by Hardman et al. (2017) showed that 32 of the 35 studies published on this topic have positive results. The fiscal incentives considered in the studies range from tax exemptions, purchase price reductions, and tax credits across different countries such as the USA, Norway, Canada and Sweden. Despite the link found between fiscal incentives and adoption of EVs, there is still criticism in the literature that some of these incentives, specifically tax rebates, are structured inefficiently or not communicated sufficiently. Evidence shows that rebates are more effective than tax credits (Hardman et al., 2017). This is likely to result from the phenomenon of 'hyperbolic discounting' where consumers value smaller financial incentives sooner than larger rewards later. The literature indicates that point of sale grants and VAT exemptions for BEVs are the most effective fiscal incentives (Yang et al., 2016).

Incentives have been found to incentivise EV purchases in both the private and company car market (Nilsson and Nykvist, 2016). The literature indicates that in the business car market adoption of EVs tends to be more economically rational (Skippon and Chappell, 2019). Vehicle selection decisions have been found to be based upon operational suitability and costs of ownership (Mau and Woisetschläger, 2018). Other factors which have been found to influence fleet purchasing decisions include organisational innovativeness, expectation of environmental benefits and positive effect on employee motivation (Sierzchula, 2014; Globisch et al., 2018).

Discount rates are used to account for the present value on costs and benefits that will occur later. There are two key types of discount rates: private and social. Private discount rates are used to account for preferences such as time, risk and pro-environmental preferences; predictable (ir)rational behaviour, (e.g. bounded rationality and behavioural biases); and external barriers to energy efficiency such as lack of information or capital (Schleich et al., 2016). Private discount rates for vehicle purchases reported in the literature range from 1.9%

to 11.6% for new car purchases (Meghan et al., 2016). With a large number of factors affecting private discount rates, Schleich et al (2016) has identified that this is an area that needs more research. Social discount rates on the other hand consider the importance of the welfare of future generations compared to the present (Nordhaus, 2006). Social discount rates are usually lower than private discount rates (Schleich et al., 2016). Essentially both individual and social discount rates are built up from individual time preference based on factors such as growth in living standards, catastrophic risk and pure time preference that vary between individuals. A factor in all discount rate setting is opportunity cost – the comparison with rates of return available elsewhere.

The lower operational cost of EVs is likely to produce a behavioural rebound effect (Whitehead et al., 2015). The direct rebound effect translates to additional annual mileage of the EV driver, whereas the indirect rebound effect takes the form of additional expenditures due to the annual financial saving and is more difficult to estimate. Whitehead et al (2015) found that the rebound effect on annual mileage for EV adopters is up to 12.2%. Holtsmark and Skonhoft (2014) found that EV drivers drive more miles at the expense of public transport and cycling. Similarly, Hultkratz and Liu (2012) found that free 'green car' access to the Swedish toll road increased traffic volumes. The rebound effect would mitigate some of the cost benefits of switching to an EV.

A large body of literature examines the key motivations and factors affecting adoption of EVs (see Li et al. (2017) for a systematic review of the literature concerning the motivations and factors behind EV adoption). The results from these numerous studies are largely based on stated preference or revealed preference surveys. Several themes emerge from these studies, indicating that in the purchase of a hybrid or electric vehicle many other factors come into play, these can largely be categorised into three categories. Demographic factors such as age, gender and education have been found to affect EV adoption (Hidrue et al., 2011; Egbue and Long, 2012; Bjerkan, K.Y., Nørbech, T.E., Nordtømme, 2016). Situational factors such as driving range, cost, and charging infrastructure concerns also have been found to play a role in whether individuals choose an EV (Hackbarth and Madlener, 2016; Barth, M., Jugert, P., Fritsche, 2016; Adepetu and Keshav, 2017). Psychological factors such as pro-environmentalism, technology oriented lifestyle and subjective social norms also affect this decision (Madlener, 2012; Axsen et al., 2012; Axsen et al., 2013). Many potential consumers are not aware of the benefits of switching to HEVs or EVs, therefore information programs have been found to be important for stimulating adoption (Krause et al., 2013; Van Der Steen et al., 2015; Kester et al., 2018). Although this thesis focuses on vehicle ownership costs, it is important to acknowledge these other factors that have been identified in the literature.

The factors that affect the decision to purchase an EV are unique to distinct groups of people, therefore when investigating adoption of EVs, it is also important to consider market segmentation. For example, it has been found that incentives are not needed for high end BEVs but are more effective for low end BEVs (Hardman et al., 2017). Research has found that different segments of the market might be attracted or repelled from EVs for different reasons. For example, Anable et al. (2016) found that there are eight segments which are distinguished by characteristics such as the degree to which EVs are viewed as being consistent with personal identity, the level of anxiety concerning the operation of EVs, the perceived difficulty in EV recharging, the willingness to pay to reduce the environmental damage of car use and the symbolic motivations they assign to EV ownership. Other studies such as Axsen et al. (2015) provide perspectives of consumer based on preference and lifestyle heterogeneity, indicating that the segment most enthusiastic about EV adoption tends to display strong environmental awareness coupled with a high enthusiasm for the technology. Nayum et al. (2016) indicates that EV adopters are particularly distinct from the mainstream market and tend to represent individuals who are highly educated with very high household incomes. Market segmentation is also important when considering the effect of vehicle leasing on adoption of EVs. Liao et al. (2018) found by using a stated preference survey that at an aggregate level vehicle leasing does not affect EV adoption. However, by considering the vehicle market in five classes based on preference profiles, 13% of respondents changed their preference towards EVs, with approximately half indicating a positive shift and half with a negative shift.

2.2.3 Technology Pull: Battery Technology Development

Battery technology underpins how EVs perform; the cost, performance, and availability of batteries is important for the future electrification of the transport sector. Most conventional car batteries are currently lead-acid. Lead acid batteries are a cheaper battery technology mainly due to market maturity, but their characteristics are not sufficient for use in EVs. In many 2-wheelers, due to a short range and light body, lead acid batteries are still used to minimise cost.

At present, Lithium Ion Batteries are the desirable technology for EVs because of high energy density, long lifespan, rechargability and low rates of self-discharge. These attributes have led to nearly all high-performance EVs utilising Lithium Ion Batteries (Wang and Wu, 2017). For

EVs, Lithium Ion Battery chemistry is anticipated to be dominant in the medium term, with potential development of Lithium Air, Lithium Sulphur and solid-state Lithium batteries in the long term. Such battery technologies could offer higher density, greater capacities, and lower combustion risks with greater charge cycle life but they are still in the development stages (Vandervell, 2017; IEA, 2018a; Lambert, 2018a).

Current battery capacities for cars range from 40 kWh for the Nissan Leaf (note this recently increased in September 2018 from 24 kWh), to 100 kWh for the Tesla Model X (Tesla, 2018a; Nissan, 2018)[3]. The cost of Lithium batteries has fallen from an average battery pack price of $1,000/kWh in 2010 to $209/kWh in 2017. Average energy density of EV batteries is also improving at around 5-7% per year (BNEF, 2018).

The cost reduction of Lithium Ion EV batteries has been found to follow a learning curve (Goldie-Scott, 2019). That is to say, that with each doubling of cumulative manufacture the cost of the battery pack reduces by a certain percentage. This results in large price reductions in the early stages of deployment, which diminishes as the market matures. This learning can be attributed to improvements in three key areas: first, gains in the production process from worker productivity and overall manager experience; the second to changes in the product itself such as re-design, standardisation and innovation of the technology; the third to changes in input prices for materials and labour (Rubin et al., 2015; Samadi, 2018).

Learning rates have been used across different technologies and industries (Yeh and Rubin, 2012). Most learning rates in the literature employ a one-factor approach, in this case only one independent variable (usually the installed capacity or cumulative manufactured capacity) is used to explain cost changes over time (Samadi, 2018). A very small number use a two-factor approach factoring in other parameters such as R&D spending, economies of scale and other public policies (Samadi, 2018). Although the multi-factor approach is more appealing in calculating the 'true' learning rate, these learning rates are difficult to calculate due to data limitations (Rubin et al., 2015; Samadi, 2018). The estimates of learning rates for Lithium-Ion EV battery packs vary from 6% to 18% (Nykvist and Nilsson, 2015; Schmidt et al., 2017). Comparing this to other industries, estimates for solar PV range from 8% to 17%, onshore wind from -3% to 12% and offshore wind from -5% to 10% (Rubin et al., 2015; Samadi, 2018). From this, the learning rates for Lithium-Ion EV battery packs are currently most comparable to solar PV.

[3] Rivian have announced they are manufacturing a 180 kWh Electric SUV that will shortly be available (see https://products.rivian.com/suv/).

An extensive literature examines the future of EV battery costs. Many of these studies consider the benchmark of $100/kWh. Tesla estimates that this could be reached for their battery packs in 2020 (Holland, 2018). McKinsey (2018) uses market expertise to estimate this to be reached between 2020 and 2030. Beckermans et al. (2017) uses combine process-based cost modelling with learning curves finding that the 100$/kWh sales barrier will be reached between 2020 and 2025. Nykvist et al. (2019) analyse historic costs to find that by combining the 'best' cost estimates and the average learning rate the benchmark will be reached in 2025. The battery cost projections from BNEF (Bloomberg New Energy Finance), the industry authority that produces the annual battery price survey, estimate that using a learning rate of 18% the 100$/kWh will be reached before 2024 (Goldie-Scott, 2019).

As the demand for EVs grows, the manufacturing capacity of batteries must grow with it. In the last few years, customers wishing to make the transition to electric have had issues with wait times due to demand outpacing supply (Manthey, 2018). To remedy this, EV manufacturers such as Tesla have built their own "Gigafactories" to ensure supply issues of batteries and electric motors do not disrupt vehicle sales (Tesla, 2014).

At present, there are relatively few batteries for second life applications because there is a delay of over a decade between vehicle deployment and scrappage. There is discussion over whether EV batteries could have a second life as electricity grid storage especially in the future when there is a plethora of cheap spent batteries. However, it is unlikely that large numbers of non-uniform batteries consisting of out-dated battery technology would present an opportunity rather than a risk for this application. Some manufacturers are using spent batteries to balance power demand on charging hubs (ZapMap, 2018). In these situations, the power draw for rapid chargers (≈120 kW) could present a challenge for the grid in certain areas (e.g. rural motorway service stations). Therefore, employing a second life battery to stabilise this load when more than one vehicle plugs in to charge can be a cheap and beneficial option compared to grid expansion.

Once the battery is spent, ideally all the battery materials would be recycled such that the constituent parts would be recoverable at a low energy and environmental cost. Recycling of Lithium Ion Batteries is in its infancy as EV sales are ramping up and very few EVs have reached the end of their useful life. The problem of EV battery recycling is often cited as one of the key sustainability issues surrounding the electrification of the transport sector (Gaines, 2018).

This thesis focuses on the car market, however, there are opportunities for larger vehicles such as buses and trucks to electrify. The weight of the higher capacity batteries in these larger vehicles is much greater than a traditional drivetrain, to counter this, materials such as aluminium and carbon fibre are often used in the body. In Europe the ZeEUS project (Zero Emission Urban Bus System) has deployed electric bus demonstration projects across ten cities but at present over 80% of electric buses deployed worldwide are in China (IEA, 2018a). The bestselling urban bus has a battery capacity of around 330 kWh for a range of approximately 250 km; this vehicle is manufactured by the Chinese company BYD (IEA, 2018a). Tesla and DAF are amongst the latest companies to announce plans to start selling electric Heavy Goods Vehicles (HGVs) (Tesla, 2018b; DAF, 2018). HGVs face the additional challenge of needing to transport heavy loads over long distances. There are substantial air quality benefits within an urban setting of deploying electric buses and delivery trucks. As batteries fall in price and increase in energy density, the applications in larger vehicles will become more prevalent.

2.2.4 Charging Infrastructure: Catalyst or Magnet?

Range anxiety is closely linked to lack of accessibility to public charging infrastructure (Sierzchula et al., 2014). EV charging infrastructure has three main characteristics: level – e.g. power output, type – e.g. socket and connector type, and mode – e.g. communication protocol (see Table 2-2 for details of charging characteristics by type). At present EV charging is not standardised across the world. There are three different types of DC fast charger: Tesla supercharger, CHAdeMo (CHArge de Move) dominant in Japan and the USA – note that the Tesla standard is compatible with CHAdeMO, and CCS (Combined Charging System) in Europe. It is anticipated that DC fast charging standards will not be standardised in the coming years potentially impeding electric vehicle market growth (fleetcarma, 2018).

Different levels of charging infrastructure have a rated power that correlates to the time taken to recharge the EV battery: this broadly falls into three categories: slow, fast, and rapid (see Table 2.2). It is anticipated that despite advances in charging speed, EVs will primarily be charged overnight from slow chargers with additional top-up charging either at work or during a long journey (IEA, 2018a). This could create the opportunity for a smart grid, where EVs are charged according to times when there is surplus energy on the grid. Vehicle to Grid (V2G) is a possible extension of this smart grid opportunity, where EVs could be used as demand side management for additional grid storage when there is excess renewable energy supply or drained when there is a demand surge (Liu et al., 2013). This also raises questions surrounding the accessibility of charging for households that do not have their own private land.

Coverage of public charging infrastructure is growing across the world. It is estimated that in 2017 public charge points grew from 2.3 to 3.5 million. In the UK this number expanded from

Table 2-2: *Charging speed table (IEA, 2018a; Lily, 2018).*

Category	Level	Power	Approximate Time (to charge to 80%)	Connectors
Slow	Level 1	≤ 3.7 kW (AC)	6-12 hrs	3-Pin: 3 kW (AC) Type 1: 3 kW (AC) Type 2: 3 kW (AC) Commando: 3 kW (AC)
Fast	Level 2	> 3.7 kW and ≤ 22 kW (AC)	3-5 hrs	Type 2: 7-22 kW (AC) Type 1: 7 kW (AC) Commando: 7-22 kW (AC)
Rapid	Level 3	> 22 kW and ≤ 43.5 kW (AC) < 200 kW (DC)	20-40 mins	CHAdeMO: 50 kW (DC) CCS: 50 kW (DC) Type 2: 43 kW (AC) Tesla Type 2: 120 kW (DC)

10 152 to 14 800 (Zap-Map, 2018); where nearly two thirds of these public charge points are slow chargers. In Norway – the country with the highest percentage of EVs in the road fleet, there are comparatively few public EV chargers available (0.05 public chargers per EV in Norway compared to 0.1 for the UK) (IEA, 2018a). This means we can draw the conclusion that a large network of public EV charging points is not strictly a precursor for high EV market share.

The introduction of greater capacity batteries could stem issues of range anxiety and reduce pressure on public charge points. Higher capacity batteries would give vehicles a greater range but would increase the initial cost. As battery density increases and costs fall, EV range will increase such that opportunity charging may become less needed. The introduction of battery swapping could negate the need for public charging infrastructure. If EV owners were able to switch their depleted battery for a fully charged one, this could solve issues of long charging times and the need for public charging infrastructure. At present there are several barriers to this solution, namely that this would require standardisation across battery types and a high penetration of EVs in the fleet. EV batteries are not designed to be easily removed; this would need to be a priority for EV manufacturers who would need to tailor their vehicles accordingly.

Battery factories are already facing challenges scaling up to meet demand, this option would require surplus batteries. Realistically, this is not an option in the short term and by the time this is viable it is highly likely that charging infrastructure would have evolved to meet EV needs.

2.3 ELECTRIFICATION IN THE CONTEXT OF EUROPEAN VEHICLE POLICY AND THE MARKET CONDITIONS

2.3.1 Vehicle Testing: Rated CO_2, Policy and Legislation

Across Europe, every country has its own laws regarding vehicle taxation (ACEA, 2018). The EU has overarching legislation encompassing vehicle testing and urban air pollution that underpins both national decisions on vehicle taxation and city level policies on transport. In many countries across Europe, vehicle taxes are graduated by the rated CO_2 of the vehicle (e.g. the manufacturer tested CO_2 figure published in g CO_2/km) (ACEA, 2018), therefore there has been increasing pressure on manufacturers to reduce rated CO_2 or risk losing market share (Transport&Environment, 2014). As a result, rated CO_2 emissions of new registrations have fallen by over 25% since 2000 (Mock et al., 2017). However, the difference between on-road testing and rated CO_2 has increased from around 5% to 40% (Mock et al., 2017). This discrepancy has been a result of manufacturers exploiting loopholes in vehicle testing procedure such as reducing rolling resistance, minimising vehicle weight, and increasing the aerodynamics of the vehicle (Transport&Environment, 2014). Until recently, manufacturers in the EU have assessed cars for their CO_2 emissions on the New European Drive Cycle (NEDC). The NEDC test cycle was widely criticised for not adequately representing real driving behaviour, and therefore when vehicle manufacturers optimise their engine map for this drive cycle they are not optimising their engines for real world driving (Stewart et al., 2015). Because of this increasing discrepancy, especially with diesel vehicles (Cames and Helmers, 2013), new European vehicle testing legislation was passed in 2015. The key changes include the introduction of a new vehicle test cycle – the World Light Duty Testing Procedure (WLTP) drive cycle from September 2018 – designed to be representative of real driving behaviour, and a Real Driving Emissions test from September 2019 (European Commission, 2018b).

The introduction of the WLTP test cycle has already affected manufacturers who rely on the company car market. Low emissions vehicles such as the Mitsubishi Outlander have been reassessed with higher CO_2 emissions on the WLTP drive cycle than the NEDC drive cycle. For this reason manufacturers are redesigning these vehicles with slightly larger batteries (13.8

kWh instead of 12 kWh in the case of the Mitsubishi Outlander) so that the rated CO_2 falls below 50 g/km – the cut off point for lower company car tax rates (Autovista Group, 2018) (see Appendix 4-B for company car tax rates in the UK).

From 2000 to 2015, average kerbside weight of new car registrations increased by 10%, this in turn affects vehicle fuel economy (ICCT, 2017b). The key reasons for this result from the body requirements for crash testing approval as well as the increasing electrification of accessories in the vehicle that would have historically been manually adjusted (e.g. windows and seats). New materials could be used to reduce body weight such as carbon fibre and magnesium, but this change would increase vehicle costs (Lewis et al., 2014). Additionally, if policy were ever introduced to account for cradle to grave vehicle emissions (as opposed to purely tailpipe emissions), such a shift would be untenable as these materials have higher embodied emissions (Schmidt et al., 2004).

Manufacturer fleet average emissions were legislated for in 2014 (European Commission, 2018d). This law mandates that the average rated CO_2 of all cars sold by a manufacturer (of a size greater than annual production of more than 300 000 vehicles per year) must be below 95 g CO2/km by 2020 (European Commission, 2018d). There are certain caveats to this law, such as every BEV sold counts as five BEVs sold, referred to as super credits. This legislation reduces the incentive to sell low carbon vehicles, sanctioning OEMs to continue to sell their less fuel efficient luxury vehicles.

Vehicle emission Euro standards were introduced in 1995 to curb tailpipe pollutant emissions. For each of the progressing Euro standards (see Table 2-3 for details of vehicle Euro standards), a smaller ceiling was placed on the maximum amount of each specific tailpipe pollutants (e.g. NO_x, PM etc) that could be emitted over the standard NEDC test cycle. Different Euro standard limits apply to cars, LCVs, buses and HGVs split further by weight class (Dephi, 2017). The increasingly stringent limits have been designed to solve the problems of urban air pollution across European cities, especially from diesel vehicles - the highest polluter of harmful emissions such as NO_x (Moody and Tate, 2017) – note that network level vehicle emissions are investigated in Chapter 6 of this thesis.

In diesel vehicles, NO_x is produced when the air-fuel mixture is combusted in the engine. The amount of NO_x varies with peak combustion temperature: the higher the temperature the greater the rate of NO_x formation. Higher temperatures occur with higher engine loads, therefore by lowering the combustion temperature and using after-treatment devices, NO_x can be minimised. Most modern diesel vehicles utilise exhaust-gas recirculation (EGR) systems into

Table 2-3: *Limits for different pollutants over all Euro standards (Note petrol standard/diesel standard when two values given) (Dephi, 2017).*

	EU1	EU2	EU3	EU4	EU5a	EU5b	EU6b	EU6c/dT/d
Type Approval	July 92	Jan 96	Jan 00	Jan 05	-	Sep 11	Sep 14	-/Sep17/Jan 20
New vehicles	Jan 93	Jan 97	Jan 01	Jan 06	-	Jan 13	Sep 15	Sep 18/Sep 19/Jan21
THC (mg/km)	-	-	210/-	100/-	100	100	100	100
NMHC (mg/km)	-	-	-	-	68/-	68/-	68/-	68/-
NO_x (mg/km)	-	-	150/500	80/250	60/180	60/180	60/80	60/80
CO (mg/km)					1000	1000	1000	1000
HC+ NO_x (mg/km)	970	500/700	-/560	-/300	-/230	-/230	-/170	-/170
PM (mg/km)	-/140	-/80	-/50	-/25	5.0	4.5	4.5	4.5
PN# (e11 Nb/km)	-	-	-	-	-	-	6.0	6.0

their vehicle design. EGR systems recycle a portion of the exhaust gas back into the combustion chamber; this reduces the oxygen content and increases the water vapour content of the combustion mixture reducing peak combustion temperature. Two methods are used in diesel vehicles to control NO_x after the exhaust has exited the engine. A lean NO_x trap (LNT) uses a catalyst to store NO_x from the exhaust temporarily. By increasing the proportion of the fuel in the air-fuel mixture, the exhaust gas has less oxygen and more unburned hydrocarbons. The stored NO_x at the catalyst then reacts with hydrocarbons in the exhaust to produce nitrogen and water and/or CO_2. Selective catalytic reduction (SCR) systems reduce NO_x over a catalyst using ammonia as the reductant (ICCT, 2019). LNT systems are generally cheaper and less effective than EGR or SCR systems (ICCT, 2017a).

Studies such as Hagman (2015) have found that when testing diesel cars in real driving conditions, they emit 20 to 40 times more NO_x than petrol cars with similar sized engine. Even diesel cars which have passed the Euro 6 limit have been found to be producing more than ten times the limit when tested in real world environments (Baldino et al., 2017). There are several reasons for this including: decline of emission-control system components over the vehicle's lifetime; using the vehicle's ECU for deliberate cheating on vehicle certification tests; removing or tampering with components of the emission-control system; or utilising a certification test that is unreflective of operating conditions encountered in real on-road driving (ICCT, 2019). This is one of the reasons that despite increasingly stringent policy, NO_x levels on key urban arterials have remained static over the last decade. City level policies such as Low Emission Zones, Clean Air Zones, and congestion charging have been introduced to attempt to curb pollutant emissions from diesel vehicles (Holman et al., 2015). Because of the issues of transport related air pollution and carbon dioxide emission outlined in this section, this thesis explores how more hybrid and electric vehicles in the vehicle fleet, along with an increasing number of Euro 6 petrol and diesel vehicles, can lead to reductions in CO_2 and NO_x emissions at a network level.

The research in this thesis focuses primarily on vehicle exhaust CO_2 and NO_x emissions. Particulate emissions originate from both the exhaust and the brakes. As technology improves to deal with PM emissions from the exhaust, non-exhaust emissions from the tyre wear, brake wear, road surface wear and resuspension of road dust will most likely become the primary cause of these vehicle emissions (Thorpe and Harrison, 2008). With the electrification of the road fleet, there is evidence that EVs have higher PM emissions from regenerative braking than ICEVs (Timmers and Achten, 2016). Non-tailpipe emissions (e.g. emissions from tyres and brakes) are challenging to model accurately and therefore have not been considered within

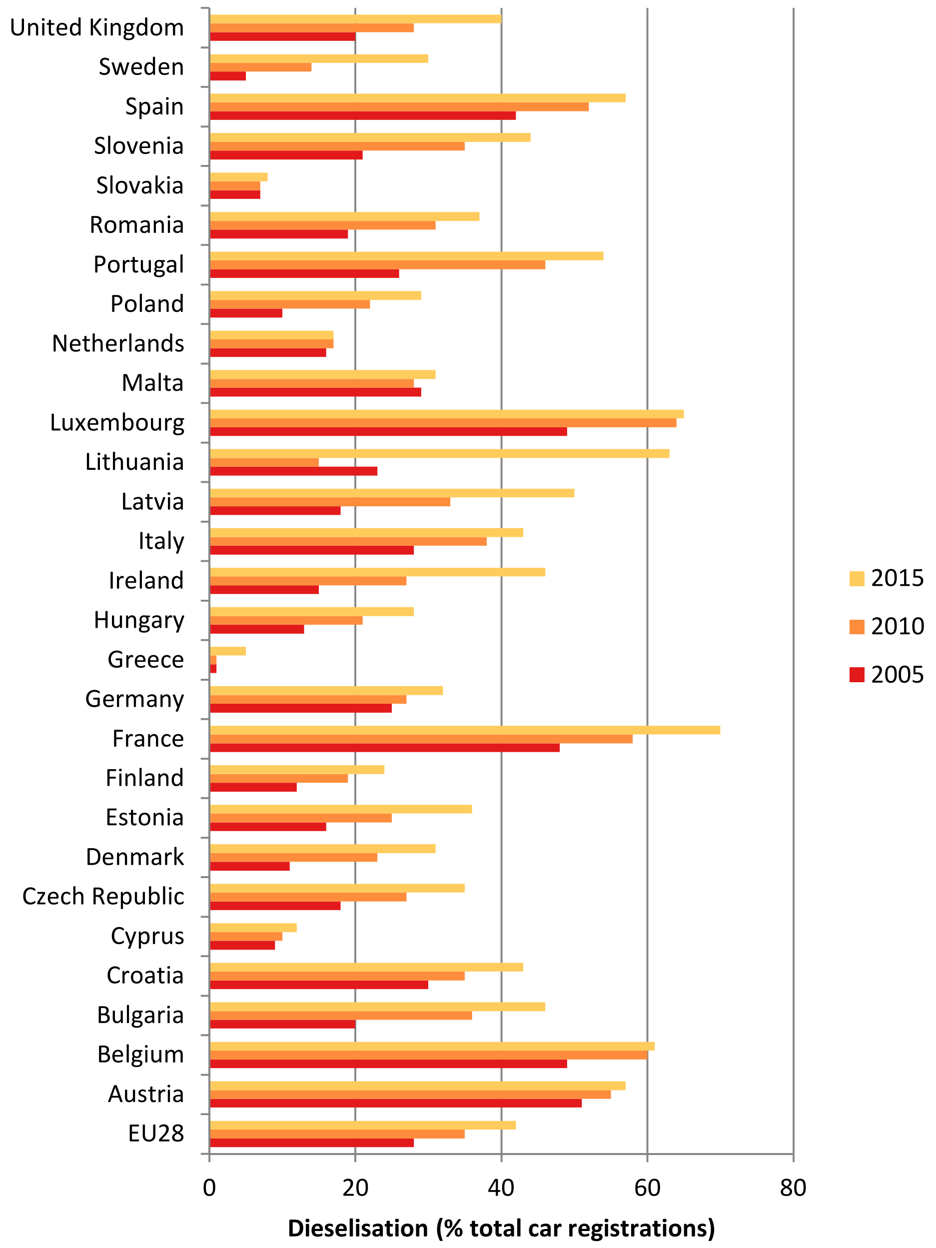

Figure 2-2: *Dieselisation (percentage of total registrations) comparing European countries (European Environment Agency, 2018).*

the scope of this thesis.

2.3.1 The Rise of Diesel Cars

The initial development and adoption of diesel cars in the 1990s originated from their higher fuel efficiency; diesel cars produce approximately 15% less CO_2 than a like-for-like petrol car (Hagman, Rolf; Gjerstad and Amundsen, 2015). However, research has shown that if OEMs had invested in reducing petrol vehicle fuel efficiency as they had in diesel vehicle fuel efficiency then the average CO_2 emissions of petrol vehicles would have improved by similar percentage

Table 2-4: ***Country level commitments to move from ICEVs to EVs (IEA, 2018a). PLDV denotes Passenger Light Duty Vehicle.***

Country	ICEV car ban	EV target
China		5 million EVs by 2020, including 4.6 million PLDVs, 0.2 million buses and 0.2 million trucks. New energy vehicle (NEV) mandate: 12% NEV credit sales of passenger cars by 2020. NEV sales share: 7-10% by 2020, 15-20% by 2025 and 40-50% by 2030.
Finland		250 000 EVs by 2030.
France	2040	
India		30% electric car sales by 2030. 100% BEV sales for urban buses by 2030.
Ireland	2030	
Japan		20-30% electric car sales by 2030.
The Netherlands	2030	10% electric car market share by 2020. 100% electric public bus sales by 2025 and 100% electric public bus stock by 2030.
New Zealand		64 000 EVs by 2021
Norway	2025 (PLDVs, LCVs and urban buses)	75% EV sales in long-distance buses and 50% in trucks by 2030.
Korea		200 000 EVs in PLDVs by 2020.
Slovenia	2030	
UK	2040 (Scotland 2032)	396 000 to 431 000 electric cars by 2020.
United States (selected states)		3 300 000 EVs in eight states combined by 2025. ZEV mandate in ten states: 22% ZEV credit sales in passenger cars and light-duty trucks by 2025. California: 1.5 million ZEVs and 15% of effective sales by 2025, and 5 million ZEVs by 2030.

as that seen by diesel vehicles (Cames and Helmers, 2013). The greater cost of the diesel engine – approximately £1500 – is offset by increased fuel efficiency within approximately 10 000 miles (Wu et al., 2015), this is backed up by the analysis in Chapter 3 and 4 of this thesis. Hence, diesel vehicles are usually purchased as high mileage vehicles and represent a greater percentage of road traffic (Society of Motor Manufacturers and Traders, 2017). Diesel cars also tend to be higher power and weight than conventional petrol cars: between 2001 and 2011, the average petrol engine power increased by 7.5% but the figure for diesel is much higher at 22% (ICCT, 2017b).

Dieselisation of the car fleet is a problem across most of Europe with the market share of diesel cars ranging between 30-80% at its peak in 2016 (see Figure 2-2 for diesel car market share across European countries). Conversely, in the USA and Japan, market share of diesel cars is below 0.1% (Cames and Helmers, 2013). Stemming from a push to reduce CO_2 emissions from the transport sector, in the EU diesel vehicle purchases were incentivised with lower fuel and vehicle taxes. Four key reasons have been identified for the different levels of dieselisation across Europe; the impact of national car/supplier industry, the degree of ecological modernization, fuel tourism, and states with preferential relations with industry (Cames and Helmers, 2013). All these factors play a part in how persistent diesel car sales have been in a particular region. Without a strong car industry, but with poor ecological modernisation momentum, in the UK diesel vehicle market share has persisted even in recent years.

The dieselisation of the car fleet in the UK is more prevalent in the size segments that are dominated by company or business car purchases. For example, market share of diesel cars in the executive size segment (where the split of private to business registrations is 29% to 71%) rose to 81% in 2018, whereas in the mini size segment diesel cars only represent 15% of new registrations (this is discussed further in Section 2.3.3 where the UK vehicle market is analysed in depth). The rise of diesels in the small vehicle size segments is more concerning as the types of catalysts used in smaller vehicles, such as Lean NO_x Trap (LNT) as opposed to Exhaust Gas Recirculation (EGR) or Selective Catalytic Reduction (SCR), tend to be cheaper and less effective at removing NO_x from tailpipe emissions (ICCT, 2017a).

In 2017, the diesel market share of new car sales dropped from 47% to 42% as a result of changing public opinion. New European legislation has been introduced to ensure that Diesel Particulate Filters (DPFs) are properly tested during a vehicle's MOT (Evans, 2018). The high cost for DPF replacement means that it often is not cost effective for older vehicles to replace their broken DPFs, therefore these high polluting vehicles are more likely to be scrapped, and consumers are less likely to risk purchasing older diesel vehicles. The VW scandal also affected consumers trust in the auto industry (Markowitz et al., 2017). In 2015 VW was fined $4.3 billion by the US government for fitting emissions test cheating software in their vehicles, it is estimated that the cost of fixing cars, buying back cars, clean air fines, penalties and compensation cost the company over $20 billion. There is still ongoing cases in Europe where consumers have brought civil lawsuits against the company (BBC, 2018).

Consumers have lost trust in diesel vehicles and government advice (as evidenced by market share peaking). Many environmentally conscious consumers chose a diesel vehicle in the early 2000s to reduce their emissions and within a decade the official advice had reversed, condemning diesel vehicles and increasing prices accordingly (Cames and Helmers, 2013). As a result, some countries have stated they will stop new registrations of conventional diesel (and in some cases petrol) cars by a certain year (see Table 2-4 for summary of announcements of national EV deployment goals), this comes hand in hand with targets for EV sales. Additionally, OEMs have started to move away from diesel cars: Fiat Chrysler have announced they will phase out diesel models by 2022, Toyota have committed to stop selling diesel cars in Europe by 2018 and Subaru will withdraw diesel car production and sales by 2020 (IEA, 2018a).

2.3.1 The UK Vehicle Market in Detail

This thesis focuses on the UK vehicle market, but many of the conclusions drawn will be similar for other countries in Europe. The spread of market share across different vehicle size segments is similar for the UK and the rest of the EU, with the majority of the same models of HEV, PHEV and BEV available (Thiel et al., 2015) (see Appendix 2-A for details of size segments for USA, UK and EU). By analysing historic hybrid and electric vehicle sales conclusions can be drawn about future adoption of these vehicle types across the fleet (see Figure 2-3 for UK car market share split by purchase and fuel type). The mid-sized (C/D) car segments account for the majority of historic HEV sales (64%). The Toyota Prius was originally a medium car (C) segment (2000-2004), moving into the large car (D) segment after its redesign in 2004. In the last decade Toyota have diversified their hybrid range to include a wide range of models all utilising the HSD system originally developed for the Toyota Prius. This is one of the reasons for plateauing sales of the Toyota Prius, despite total Toyota hybrid market share increasing every month. Since the Toyota Yaris Hybrid came onto the market in 2011, the supermini (B) segment shows significant HEV sales (2.4% market share).

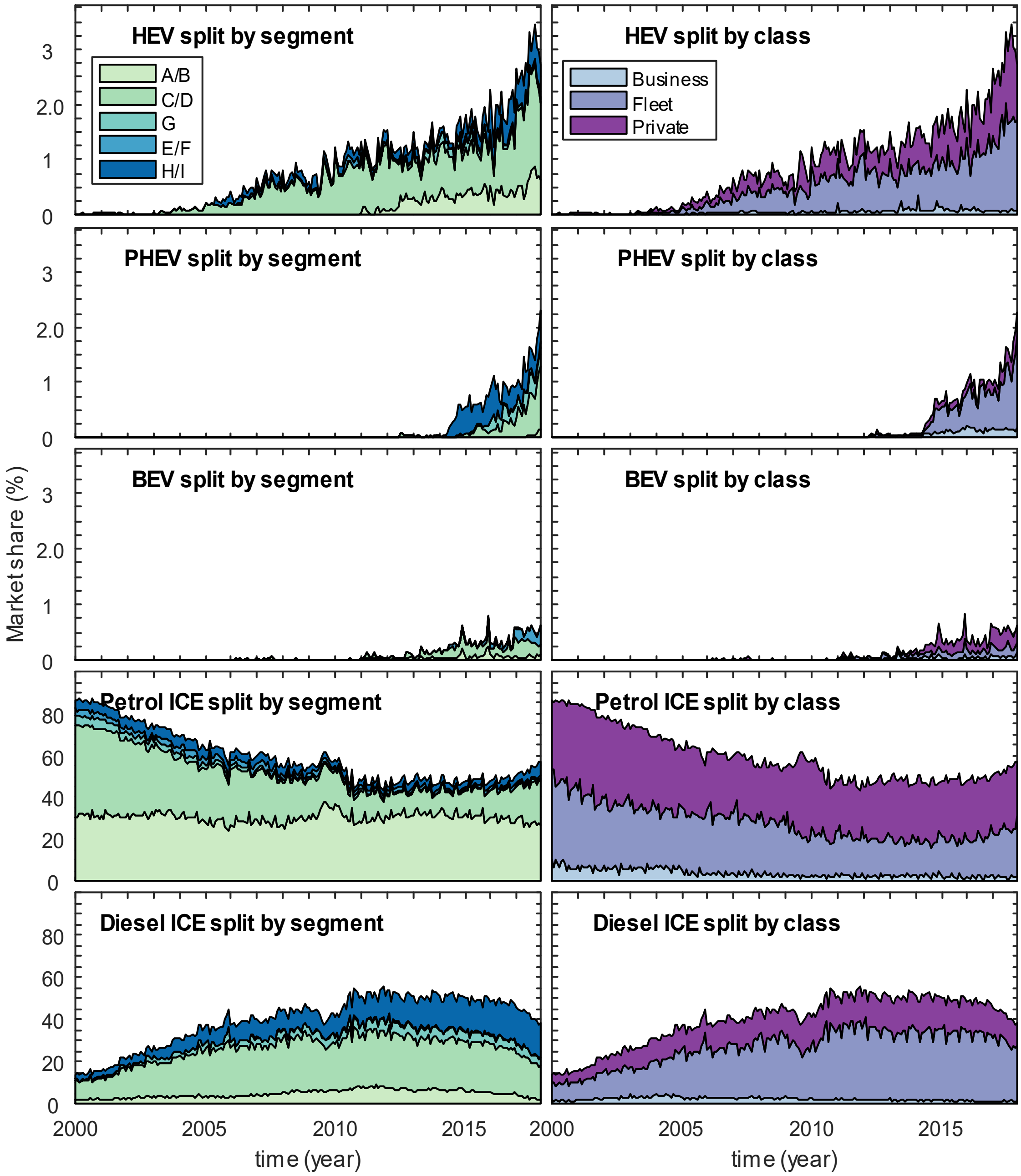

Figure 2-3: *UK market share of HEVs, PHEVs, and BEVs Jan 2000 - Dec 2017. (Data sourced from SMMT (Society of Motor Manufacturers and Traders, 2017)) Note that A/B (small), C/D (medium), E/F (large) and H/I (Multi/Dual Purpose Vehicle) vehicle segment size.*

The Multipurpose vehicle (H) segment accounted for 51% of PHEV sales in 2016 (mainly attributable to the Mitsubishi Outlander), but despite a late introduction in 2015 PHEV market share in the executive (E) segment car sales are rising fast resulting in 24% of total PHEV market share. At present PHEV models do not exist in the mini (A) or supermini (B) segments. This is mainly because the combination of the two drive trains with a large battery leads to increased vehicle weight and cost making it uneconomical to produce a 'small' PHEV.

Supermini (B) and medium (C) car segments are most popular for BEVs with these size segments representing 56% of BEV market share. BEV models have not been introduced in the executive (E) or luxury (F) car segments because of the expense due to the large battery size required. The Tesla models have been classed at sports vehicles, this segment (G) accounts for around 20% of BEV sales, but only accounts for 1.8% of total market share. It is worth noting that supermini (B), medium (C) and large (D) vehicle size segments together account for over 70% of total car market share.

Fleet and business car purchases account for approximately half of new vehicle sales in the UK (see Figure 2-3 for UK car market share split by purchase type and fuel type, see Appendix 2-B for definitions of business, fleet and private purchases). This figure is similar for other European countries such as Germany and France (PWC, 2015). Historically, 'fleet' purchases have accounted for a slightly higher proportion of HEV sales (around 57% in 2008) than the private market but private HEV purchases are now growing at a faster rate as a result of low taxes compared to petrol cars. Private purchases account for a small percentage of PHEV market share (14.9%).

PHEVs are very expensive due to their large battery but tend to have very low emissions for their size. Company car tax is graduated by vehicle CO_2 emissions therefore PHEVs are a favourable choice for fleet purchases – this cost comparison is explored in Chapter 4 of this thesis. Conversely, there is a higher proportion of BEVs in the private market (53.8% of BEV market share) than for PHEVs or HEVs. This is to be expected because smaller size segment vehicles are more popular with private purchasers than business purchasers. In other countries, such as The Netherlands and Germany business purchases account for between 90 to 95% of BEV and PHEV purchases (Rijksdienst voor Ondernemend Nederland, 2015).

In the UK, PHEV sales have grown much faster than HEV sales when they were first introduced; HEV sales took around a decade to reach 1% market share whereas PHEVs reached this within four years. This is partly as a result of availability of technology models across marques

(Department for Transport, 2015d). BEV sales have increased at a similar rate to HEVs, with BEV market share reaching 0.5% within 6 years.

2.4 DECARBONISATION OF THE TRANSPORT SECTOR: OTHER OPTIONS AND PERTINENT FUTURE FACTORS

2.4.1 Other Options for Transport Decarbonisation

With the growing problem of climate change, the continuing urban pollution issues and changing vehicle testing policies, there has been a shift towards electrification of the transport sector (IEA, 2018a). Cynics of electrification always quote that EVs are only as clean as the electricity they use. This is true, but EVs offer the opportunity to reduce pollution in cities – where 55% of the global population lives (United Nations, 2018), and utilise the increasing share of renewables on the grid. Many governments have chosen technology neutral policies – they do not 'pick winners', therefore other low carbon fuels including Liquid Petroleum Gas (LPG), Compressed Natural Gas (CNG), and Hydrogen Fuel Cells (HFCs) have been deployed to decarbonise the transport sector. In the future when there is excess renewable energy, these fuels could be manufactured synthetically as electrofuels.

LPG technology suits road vehicles of all sizes. LPG cars are usually retrofits and only constitute 1-2% of new registrations across Europe (ICCT, 2017b). It costs up to £2000 to retrofit a conventional petrol car to run on LPG, with an approximate fuel saving of £600 per year (based on annual mileage of 10 000 miles) due to the lower fuel price of LPG despite a decrease in fuel efficiency of around 15-20% due to lower energy density (RAC, 2018b). CNG is a technology for larger vehicles, such as buses and trucks, which can reduce CO_2 emissions but incurs a significant cost to install the technology (Alternative Fuel Systems Inc., 2015). However, Natural Gas is still a fossil fuel that contributes to climate change – even as an electrofuel, therefore these are only temporary measures in the future decarbonisation of road transport.

The development of HFC vehicles to power vehicles is still in an earlier stage of technological advancement than EVs (Xu et al., 2017). Most hydrogen is currently sourced from reforming natural gas (Nikolaidis and Poullikkas, 2017), however, there is the opportunity that hydrogen could be formed using excess electricity from the grid. Hydrogen powered vehicles face a similar chicken and egg problem with refuelling infrastructure. The electricity network is widespread, enabling a simple transition without the necessity of public charging infrastructure, whereas hydrogen fuel cell vehicles will have to have newly purpose-built refuelling stations. HFC vehicles have the advantage of only producing water vapour from the tailpipe. HFCs could be well suited to large vehicles that face electrification challenges.

Biofuels are often considered a low carbon alternative that could cut the carbon footprint of road transport without needing to change user behaviour. Biofuels encompass several different feedstocks, but advanced biofuels are being developed that will have a lower impact on agriculture, deforestation and climate change. Many countries are blending biofuels such as FAME (Fatty Acid Methyl Ester – biodiesel) and bio-ethanol with conventional petrol or diesel in small percentages. Brazil has the highest market share of bioethanol vehicles, with around 23 % of the energy for road transportation coming from biofuels (Cruz et al., 2014). The EU mandates that all petrol and diesel transport fuel is blended with a small percentage of biofuel by 2020 (10% bio-ethanol for petrol and 7% FAME for diesel fuel) (European Commission, 2018a). Historically, there have been problems with sourcing sustainable biofuels with early policy leading to deforestation, land grabbing and the destruction of peoples' and animals' livelihoods, therefore despite an initial push in this direction, EU policy has not favoured biofuels as it once did (Todts, 2017). In the near term, electric mobility is in the strongest position of any of the low carbon fuels to decarbonisation the road fleet.

2.4.2 Revolutions Affecting the Future of Transport

In the future, there are generally regarded to be three 'revolutions' that will change road transport: electrification, automation and Mobility as a Service (MaaS) (Sperling, 2017). Electrification of the road fleet is already happening with increasing adoption, falling battery prices and installation of public charging infrastructure, but automation and MaaS are considered long-term trends. Automation and MaaS will no doubt be introduced in large cities first, eventually reaching rural areas.

Autonomous vehicles are currently being built and tested on road by OEMs and start-ups such as Uber, FiveAI and BMW (UBER, 2018; BMW, 2018; Smale, 2018). These vehicles use a range of technologies such as GPS, radar, LiDAR, and optical sensors to continually assess vehicle position in relation to pedestrians, bikes and other vehicles; evaluate external information such as signage and traffic signals; and drive the vehicle amongst other vehicles in normal traffic conditions. To date, over ten million autonomous vehicle miles have been logged by companies such as Waymo, FiveAI and Uber, but the timescale for significant numbers of Autonomous Vehicles on road in cities is unclear (Hawkins, 2018). It is anticipated there will be a mix of vehicle types on the road in big cities by 2050 and the potential impact of these autonomous vehicles is uncertain (Bansal and Kockelman, 2017). Several different scenarios are considered where if Autonomous Vehicles were shared and electric, the transport system would be cheaper, more accessible, and with a lower environmental impact. However, if Autonomous Vehicle ownership follows historic private vehicle ownership trends then the problem of 'ghost' miles could create congestion, pollution and entrench societal issues (Sperling, 2017). There are many other anticipated consequences to vehicle automation, such as increased road safety, vehicle efficiency and accessibility (Milakis et al., 2017).

MaaS is the concept that transport will move away from conventional car ownership models to predominantly ride-sharing (Jittrapirom et al., 2017). Most vehicles spend on average 96% of the time unoccupied (Kempton and Tomić, 2005), therefore MaaS would reduce the vehicle fleet to smaller number of high mileage vehicles with a faster turnover. MaaS could provide benefits for both the supply and demand side; with lower cost, time reduction, and improved user experience (Kamargianni et al., 2015). Already, using a ride-hailing service such as Uber or Lyft, can in fact be cheaper than owning a car if the annual mileage is less than 9000 miles (Davidson, 2015). Trends of private vehicle ownership are already reversing, with young people less likely to have a driving licence and own a car than at any other point in the last twenty years (Morley, 2017a). Ride-sharing is gradually introduced in ride-hailing companies such as Uber and Lyft, but this is currently only in selected cities. Although many people are sceptical that there could be a shift to a mobility subscription service rather than an individual opting to have the freedom of their own car, even a decade ago it would have been unthinkable that people would switch from owning music to streaming services such as Spotify.

Modal split has stayed fairly constant over the past twenty years, but the introduction of electric bikes could increase the share of bike trips. Electric bikes have only been introduced into the mass market in the last couple of years, typically with a range of 50 miles, but research has already found that acceptance has been greater than conventional bikes (Guo, 2017). Subsidies are available in several countries, similar to electric cars, as battery price falls, the Manufacturer Suggested Retail Price of these bikes will fall and sales will grow.

2.5 SUMMARY AND CONCLUSIONS

This chapter finds that the adoption of hybrid and electric vehicles is still in the early stages, however, numbers are growing across vehicle markets indicating that electrification of the transport sector is happening, for this reason future scenarios of the vehicle fleet will be explored later in this thesis. Even if the share of these vehicle types is still low at present, governments across all habited continents have incentives in place to encourage adoption of low carbon vehicles, this is investigated in the next chapter of the thesis in the context of vehicle ownership costs. These measures range from financial subsidies (e.g. purchase rebates, free parking or reduced taxes) to non-financial incentives (information services, access to HOV lanes or bus lanes); all aimed at addressing the main barriers to adoption. In vehicle markets such as Norway and Japan there has been a significant rise in the number of hybrid and electric vehicles in the last five years and evidently there are lessons to be learnt from this trend. The increasing proportion of hybrid and electric vehicles will contribute to decarbonisation of the road fleet and reductions in urban air pollution, the extent of which will be modelled on a network level in Chapter 6 of this thesis.

The key barriers to adoption of hybrid and electric vehicles are upfront cost, range anxiety (for BEVs only) and uncertainty in new technology. Purchase choice is not purely rational or entirely based on cost; often purchase decision is motivated by image or intrinsic environmentalism. The links between cost and adoption are however explored further in the next chapter of the thesis. The rise of companies such as Tesla showcasing desirable EVs has changed the public's perception of this vehicle type. Accessibility of charging infrastructure is growing, with the charging network expanding each year. Coverage is varied, and there will be challenges in deployment of EVs for longer journeys as well as in rural areas.

Since hybrid and electric vehicles were introduced onto the mass market, technology has advanced: battery prices are dropping as is the cost of the electric powertrain. New opportunities for battery second life and recycling are starting to emerge. Although these processes are still very much in immaturity, this is the time in which regulation and standardisation can encourage battery designs that are simple and cost effective to disassemble. The rise of Autonomous Vehicles and Mobility as a Service could change personal mobility within the next thirty years. At present, the impacts and timeframe are uncertain, although it is agreed that by 2050 there will be a mix of vehicle types on the road in major cities.

In the next chapter, the incentives for hybrid and electric vehicles across several key markets and different continents will be examined in the context of vehicle ownership costs. Although vehicle ownership cost is only one factor in purchase decision, upfront cost is the greatest barrier to the switch from a conventional petrol/diesel to a hybrid or electric vehicle. The chapter will examine what lessons we can learn from HEV adoption and can apply to EV adoption to stimulate sales in countries without a strong EV sales record.

CHAPTER 3: HISTORIC TOTAL COST OF OWNERSHIP FOR HYBRID AND ELECTRIC VEHICLES

3.1 INTRODUCTION

With a larger battery and features such as regenerative braking, engine stop-start and a novel transmission system (Hutchinson et al., 2014), hybrid and electric vehicles have a higher manufacturing cost than conventional vehicles (Wu et al., 2015). Conversely, running costs are often lower stemming from cheaper annual fuel costs, taxes and maintenance. Many countries have offered subsidies or reduced taxes for low emission vehicles to reduce this price premium and stimulate adoption: for example the plug-in vehicle grant in the UK (GOV.UK, 2018), the clean vehicle rebate project in California (California Air Resources Board, 2016), and the green vehicle purchasing promotion measures in Japan (Japan Automobile Manufacturers Association, 2016a).

The focus of this chapter is an investigation of the Total Cost of Ownership (TCO) of hybrid and electric vehicles. The vehicle TCO accounts for all consumer related vehicle costs and therefore this calculation can determine whether subsidies and lower running costs can offset the associated price premium. This section compares the TCO of hybrid and electric vehicles across different vehicle markets and for an extensive timespan. It builds on work from the first year of the PhD where the cost of the Toyota Prius was compared across different vehicle markets for each year that a new generation of Prius was released (e.g. 1997/2000, 2003/4, 2009/10). Initially the motivation for this work stemmed from an assessment of technological readiness of different low carbon vehicles. Without properly defined definitions of technological readiness when technology was beyond the traditional 'Technology Readiness Levels' used (for example see Sauser et al. (2006)), it soon transpired that this was an impossible task to undertake analytically and thus the comparison of vehicle TCO emerged.

The key aim of this chapter is to assess if higher hybrid and electric vehicle market share in vehicle markets such as Japan and California is primarily due to cheaper costs and therefore whether adoption of hybrid and electric vehicles in less developed markets such as the UK market can be stimulated on this basis. To address this aim, this chapter provides a more extensive TCO assessment of conventional petrol/diesel cars, HEVs, PHEVs and BEVs in three industrialized countries – the UK, USA (using California and Texas as case studies) and Japan - for the time period 1997 to 2015. Finally, the link between HEV TCO and market share is analysed with a panel regression model – the time frame for running this analysis for BEVs or PHEVs was deemed insufficient.

This section contributes to the literature in three key areas: investigating how TCO has changed historically, examining how TCO varies across different geographic regions and analytically assessing the relationship between hybrid vehicle TCO and adoption. To assess the robustness of the cost model a sensitivity analysis is conducted for variation in mileage, fuel price, depreciation rate, ownership period and discount rate.

The contents of this chapter has been published as a peer reviewed journal article in Applied Energy (Palmer et al., 2018), featuring as one of the most downloaded papers of the journal in 2018. This article has received significant media attention with coverage in the Guardian (Carrington, 2017), The Daily Telegraph (Davis, 2018), MIT Tech news (MIT Technology Review, 2017) and a number of other news outlets (Sputnik News, 2017; Cooke, 2017; Futura Tech, 2017; Arab Forum for Environment and Development, 2017; Boada, 2017; Livedoor News, 2017; The Marker, 2017; Joseph, 2017; Sanchez, 2017; Guess, 2017; European Commission, 2018c; Hull, 2018) , and as a result was the basis for winning the Piers Sellers Prize for exceptional PhD research (2018 PhD category[4]).

3.2 TOTAL COST OF OWNERSHIP LITERATURE

Many TCO calculations have been published to assess the cost effectiveness of new vehicle technologies such as electric commercial vehicles (e.g. Falcão et al. (2017)), electric buses (e.g. Li et al. (2017)), and plug-in hybrid trucks (e.g. Vora et al. (2017))). As early as 2001, Lipman & Delucchi (2001) compared the cost of different degrees of hybridisation across multiple vehicle size segments. Since then, many other publications (see Table 3-1 for review of key studies in TCO literature) have compared the ownership costs of battery and hybrid electric vehicles. Many of the studies focus on a full spectrum of PHEVs with different battery sizes; to assess whether the cheaper costs of running a PHEV with a higher battery storage capacity offsets the larger initial battery price (for example Al-Alawi and Bradley (2013b) and Hutchinson et al. (2014)). The studies in the literature largely conclude that without government support hybrid and electric vehicles are still more expensive than conventional petrol or diesel cars.

Previous published TCO calculations usually only consider vehicle ownership costs in one country or geographic region (e.g. Gilmore et al. (2016) considers passenger vehicle TCO in India, and Diao et al. (2016) consider private car TCO in China, Hagman et al. (2016) consider

[4] Details available at http://climate.leeds.ac.uk/opportunities/piers-sellers-prize/

passenger car BEV TCO in Sweden, and Fontainhas et al. (2016) consider a similar TCO for the Portuguese private car market). Hutchinson et al. (2014) is the only study which compares HEV TCO across more than one country, concluding that the relatively high fuel price in the UK leads to a shorter pay back of less than 2.6 years for HEVs compared to 6.7 years in California. HEV TCO can vary substantially over different countries and American states as a result of varying fuel price, availability of low-emission vehicle incentives and region dependent average mileage. Levay et al. (2017) compare BEV and PHEV TCO across several European markets concluding that at present subsidies allow vehicles in certain size segments to be cheaper. Fuel price, average annual mileage, annual taxes and insurance prices along with driving style and congestion levels are state/country dependent (e.g. Saxena et al. (2014)), therefore conclusions of studies from different geographic regions are not necessarily transferable.

As vehicle technology matures manufacturing costs decrease, therefore TCO calculations become outdated. For this reason, it is difficult to directly contrast and compare the findings of multiple publications with different base years. With over 15 years of HEV cost data, this raises questions over how vehicle ownership costs have changed as the market has developed.

TCO methodology has not been standardised in the literature (see Table 3-1 for details of components included in key published studies). Two different approaches exist: either top down or bottom up (usually utilising an incremental cost model). It is apparent that factors such as maintenance, tax costs and vehicle resale are often excluded despite there being variation between vehicle types. Over a long time period such as that of this study, policies and cost incentives that play a crucial role in adoption of new technologies, particularly during the initial stages of deployment can also change. In this chapter, we build a comprehensive model taking all significant vehicle ownership costs including financial incentives into account.

Regression analysis is a common approach to assessing the strength of the relationships between different variables. Relatively few studies have used regression analysis to explore the factors contributing to adoption of new powertrain technologies. Studies such as Diamond (2009) use panel regression, examining both fixed and random effects, to assess the impact of incentives on vehicle adoption across different American states concluding that fuel price affects vehicle adoption more than incentives. Gallagher and Muehlegger (2011) use a fixed effects model to consider the effect of incentives across different US states concluding that the type of incentive offered is as important as the size of it. Shewmake and Jarvis (2014) analysed the link between HEV adoption and High Occupancy Vehicle (HOV) lane access using a parametric regression model estimating Willingness-To-Pay figures for HOV lane access. However, studies from the TCO literature (see Table 3-1) have not used this approach to assess

Table 3-1: *Total Cost of Ownership literature summary.*

	Lipman & Delucchi (2006)	Al-Alawi & Bradley (2013b)	Hutchinson et al. (2014)	Wu et al. (2015)	Levay et al. (2017)	This study
Vehicle class	Compact or mid-sized large car, pickup, minivan, SUV	Compact car, Mid-sized car, Mid-sized SUV, Large SUV	Mid-sized car	Small, Medium and Large cars	Small, Medium and Large cars	Mid –sized car
Powertrain type	Five degrees of hybridization	HEV, PHEV 5-60	Mild, HSD, Two-Mode, Inline Full, Plug-in HSD, Plug-in Series	BEV, PHEV, HEV	BEV, PHEV, ICE	BEV, PHEV, HEV
Purchase year	2000	2010	2013	2015	2014	1997/2000-2015
Economic yr	2000$	2010$	2013$	2015€	2014€	2015£
Economic country	USA	USA	USA and UK	Germany	NO, NL, FR, HU, IT, DE, PL	UK, USA (California, Texas), Japan
Annual vehicle miles travelled	Not specified - decreasing with age	12 000 miles/yr for cars decreasing with age	130 000 miles over lifetime	Three cases: 7484 km, 15 184 km and 28 434 km	12 000 km	10 400, 11 071, 15 641, 6213 for UK, CA, TX and JP.

Table 3-1 continued…

	Lipman & Delucchi (2006)	Al-Alawi & Bradley (2013b)	Hutchinson et al. (2014)	Wu et al. (2015)	Levay et al. (2017)	This study
Vehicle life	15 years	5 and 13 years	130 000 miles	6 years	4 yrs	3 years (ownership period)
Fuel economy	EPA adjusted	EPA adjusted	Fuel saving tests for urban and highway	Literature.	Manufacturer reported figures	Spritmoniter
Gasoline price model	1.46 ($/gallon)	Forecasted over vehicle life	3.20, 7.70 for USA, UK ($/gallon)	Own forecast	2014 country prices	Forecast over vehicle lifetime
Incremental cost model	MSRP used	EPRI (2001); Kalhammer et al., (2007)	Brooker et al. (2010); Clearly et al. (2010)	Yes, derived.	MSRP used	MSRP used
Salvage	None	Vehicle resale	Vehicle resale	Yes	Vehicle resale	Vehicle resale
Maintenance	Yes	Yes	None	No	None	Yes
Insurance	Yes	Yes	None	Yes	None	Yes
Tax model	Yes	Yes	None	Yes	Tax	Yes
Discount rate	None	6%	None	4.1%	1%	3.5 % (UK, Japan) 4% (US states)

the effect of changing vehicle costs on sales, instead they have generally only focussed on costs at a single point in time.

3.3 COST CALCULATION METHODS AND DATA SOURCES

3.3.1 TCO Model Overview

A cost comparison of a representative HEV, PHEV, and BEV has been performed across four different geographic regions. The Toyota Prius was first introduced in Japan in 1997 with HEVs now accounting for over 30% of new vehicle purchases (Japan Automobile Manufacturers Association, 2016c), for this reason Japan is included in this comparison. Like Japan, California has a history of adopting low carbon policies years ahead of other states in the USA (Greene et al., 2014). Consequently, hybrid and electric vehicles have been more popular in California than anywhere else in America (Muller, 2013). The state of Texas has also been included to provide a contrast to the Californian state because hybrid and electric vehicle sales are lower but average income is similar (United States Census Bureau, 2016). In most other markets, EV market share has been lower. The UK has been included as a country where EVs still have low market share (below 2%) despite high fuel prices.

This study considers the Toyota Prius (HEV), the Toyota Prius plug-in model (PHEV), and the Nissan Leaf Electric model (BEV), and contrasts these with the Toyota Corolla (petrol only) for Japan, California and Texas, and the Ford Focus (petrol and diesel) for the UK. The conventional vehicles for comparison were chosen based on a combination of high market share, size and a vehicle power similar to the Toyota Prius (comparative vehicle specifications can be found in Appendix 3-A).

The TCO analysis in this Chapter will only consider private ownership. In Japan non-private car purchases account for less than 5% (International Fleet World, 2016). In the USA and UK this figure is approximately half of new vehicle registrations (Bureau of Transportation Statistics, 2016; Society of Motor Manufacturers and Traders, 2017). In the following chapter UK company car costs will be calculated across different vehicle size segments, but this analysis was deemed too difficult in light of data requirements for the US and Japanese market.

The three year vehicle ownership length was chosen in line with average new vehicle ownership length in the UK (Leibling, 2008). This assumption is explored in a sensitivity analysis. A Consumer Price Index based GDP deflator for each country is used to bring all costs in line with 2015 prices (United States Department of Agriculture Economic Research Service, 2015; Department for Transport, 2016c).

A discount rate is applied based on the social discount rates (see Section 2.2.2 for discussion of discount rates). The discount rates applied are taken as 3.5%, 4% and 3.5% for Japan, California/Texas and UK respectively (Zhuang et al., 2007; HM Treasury, 2015). The social discount was chosen for a number of reasons. The individuals' rates are not consistent between studies (see Table 3-1), this is an area, which needs improvement, and therefore we use social discounts as a proxy. The three countries considered all have post-industrial economies with growth rates in the range of 1-3%. In the climate of low interest rates with subdued economic growth, it is reasonable to assume a slightly lower discount rate than the 4-6% range used in previous TCO studies (see Table 3-1). The effect of the selected discount rate on TCO is also explored further in the sensitivity analysis; with the short TCO ownership period of three years assumed here it was found that changing the discount rate does not have a significant impact on the resultant TCO (the difference in TCO calculated is less than 1%). Note all calculations are kept in the original currency to mitigate changes in exchange rate causing false correlations in results. The payback period is defined as the time it takes for the lower operating costs of the EV to offset the higher initial costs, therefore when calculating this payback period the costs used are not discounted.

The Total Cost of Ownership was calculated using the following formula,

$$TCO_c = \sum_{t=1}^{3} \frac{(I_c - s_c) * d^t{}_c + f_{ct} \times m_c \times e + a_{ct} + n_{ct} + x_{ct}}{(1 + r_c)^t}$$

where I = Initial Price, d = depreciation rate, t = time (yr of ownership), f = annual fuel price, m = annual mileage (miles), e = vehicle fuel efficiency (litre/mile), a = annual maintenance inclusive of vehicle testing, n = annual insurance, x = annual tax, s = annual subsidy, r = discount rate for geographic region c. This formula was chosen in line with other key studies in the TCO literature such as Al-Alawi & Bradley (2013b), Wu et al. (2015) and Levay et al. (2017), such that the results of these calculations would be comparable.

Many other economically rational and irrational factors play a role in vehicle purchase decisions, such as brand loyalty, spatial effects and availability of refuelling infrastructure. Such factors are difficult to accurately quantify and track over time, therefore the modelling in this chapter does not include these factors but focuses on vehicle TCO.

3.3.2 Initial Vehicle Costs, Depreciation and Subsidies

With a larger battery and features such as regenerative braking, engine stop-start and a novel transmission system, hybrid and electric vehicles have historically been associated with a manufacturing price premium over conventional petrol and diesel cars (Lave and MacLean, 2002). As HEV powertrain technology has matured, the price premium of development and manufacture has reduced with a proportion of this cost reduction passed on to the consumer. For BEVs and PHEVs the battery is still associated with a significant proportion of this incremental cost, therefore future vehicle prices will be closely linked to falling battery prices.

A country specific Manufacturer Suggested Retail Price is taken as the initial vehicle cost (Edmunds, 2015; RAC, 2015; RAC and Yourfleet, 2015; Goo-net-exchange, 2015) with depreciation rates from Storchmann (2004). Storchmann compares depreciation rates of cars across different vehicle markets indicating that vehicles in the USA, UK and Japan depreciate at approximately the same rate (16.9% annually). Depreciation is defined as the percentage that the vehicle decreases in value each year. Therefore, the value of depreciation is greatest in the first year of ownership and decreases over time. The same depreciation rate is assumed across all vehicle types. As the HEV and EV markets mature, there is more data available to calculate how HEVs and EVs depreciate. Gilmore and Lave (2013) found that HEVs have comparable vehicle value retention rates in California when calculating Willingness To Pay for HOV lane access. Tal et al (2017) investigated the second hand EV market in California, taking state, federal, and local authorities' subsidies into consideration. This study found that different EV models held value differently in 2015, ranging from 43% (the short-range 2011 Nissan Leaf) to 99% (2014 Toyota Prius plug-in). Schoettle and Sivak (2018) investigated the resale value of PHEVs and BEVs in comparison with ICEVs using manufacturer's suggested retail price and resale values estimated by Kelly Blue Book for model years 2011-2015. They found that PHEVs retained resale value as well as their ICEV counterparts. Guo and Zhou (2019) investigated the residual value of EVs taking into account federal incentives and using true market value data from Edmunds.com. They found that long-range, high-performance Tesla BEV models hold value better than other classes of vehicle. In addition, PHEVs and HEVs have similar declines in residual value to each other, which are slightly greater than for ICEVs. Finally, they also found that short-range (< 125 miles) BEVs hold significantly less value compared with ICEVs, HEVs, and PHEVs but this gap is narrowing for newer models. Because of the uncertainty of the depreciation rate, the assumption that all vehicle types depreciate at the same rate is explored by a sensitivity analysis.

The number of consumers purchasing vehicles with finance in the UK over the past decade has grown from 45% of new registrations in 2006 to 86% in 2016 (Finance and Lease Association, 2017), however, the amount paid by the consumer over the three years is comparable to the vehicle depreciation assumed in this study. For example, for the Toyota Prius over the three year period £13 980 would be paid on finance whereas the vehicle depreciates by approximately £13 196. Liao et al. (2018) found that at an aggregate level vehicle leasing does not affect EV adoption.

Initial vehicle subsidies were applied before depreciation was calculated, as it is reasonable to assume that a proportion of the cost savings will be passed on when the vehicle is sold. Several countries have levied subsidies to increase market share of low emission vehicles (see Figure 3-1 for timeline and size of incentives over the regions considered). Japan brought in the Clean Energy Vehicle Subsidy in 1998; this consisted of a subsidy along with tax cuts for low emission vehicles. This was superseded by the Eco-Car subsidy available between April 2009 to September 2010 and December 2012 to September 2013, varying between ¥100 000 to ¥250 000 (approximately £700 to £1700) depending on whether the new vehicle replaces an existing vehicle or not (Alhulail and Takeuchi, 2014). For this analysis, it was assumed the new vehicle was a replacement. In 2013, a plug-in vehicle subsidy was introduced where two thirds of the incremental cost of the plug-in vehicle compared to a similar conventional petrol vehicle was funded (Nelson and Tanabe, 2013). In the USA, the Clean Fuel Vehicle deduction was introduced in 2001 providing a $2000 initial cost reduction for the first 60 000 vehicles sold by each manufacturer. This was replaced with a hybrid tax credit (part of the Energy Policy Act) in 2006, which was phased out by the end of 2007 (Sallee, 2011). The Car Allowance Rebate System (often referred to as Cash for Clunkers) ran in 2009 and provided a subsidy of between $3500 and $4500 towards fuel efficient vehicles such as HEVs (U.S. Department of Transportations Federal Highway Administration, 2015). In Texas the AirCheckTexas Drive a Clean Machine Program introduced in 2013 provides up to $3500 subsidy towards hybrid or electric vehicles providing certain replacement and income criteria are met (Texas Commission on Environmental Quality, 2016). For plug-in vehicles, a federal income tax credit was introduced based on battery capacity in 2010, but an additional smaller state incentive (Clean Vehicle Rebate Project) is available in California (California Air Resources Board, 2016). In addition to financial incentives, in California HOV lane access stickers were sold to HEV owners from 2005-2011, and PHEV and BEV owners 2005 to present (Shewmake and Jarvis, 2014). With consumers able to apply for stickers for retrospective HEV purchases e.g. pre-2005, the ability of this incentive to stimulate new HEV purchases was limited. However, Shewmake and Jarvis (2014) found by utilising historic vehicle resale value and market share data that this incentive corresponded with a Willingness-To-Pay (WTP) for HOV lane access at nearly $1000. In the UK, the plug-in places grant applies to BEVs and PHEVs with different subsidy amounts available depending on CO_2 tailpipe emissions, this does not extend to HEVs (GOV.UK, 2018). For more information on subsidies in different countries see studies by Jenn et al. (2013), Alhulail and Takehuchi (2014) and Zhang et al. (2014). In developed countries such as those considered in this study the new vehicle market is primarily a replacement market, therefore electric vehicle adoption will predominantly displace purchase of petrol or diesel vehicles (Millard-Ball and Schipper, 2011). From Figure 3-1, PHEV and BEV incentives have a higher financial value than HEV incentives in all countries. Japan, California and Texas all offer significant HEV subsidies and tax breaks of a similar magnitude, however, in the UK the financial incentives are much smaller.

3.3.3 Fuel Costs

Annual fuel cost is usually the largest operating cost, therefore it is important to use representative real driving fuel consumption figures (Mock et al., 2017). Real-world fuel consumption figures have been sourced from Spritmoniter (2018) with electric-only range efficiency figures from The Idaho National Laboratory (2014). Vehicle fuel efficiency is assumed to be the same across all regions. There is difficulty in obtaining real world fuel efficiency statistics for a large sample size across the different regions to evidence how driving styles change in different regions. Different driving styles can lead to variation in fuel efficiency of up to 25% (Mierlo et al., 2004), therefore the error margin for different drivers will most likely be greater than the variation in average fuel efficiency across different regions.

Electricity is taxed at a lower rate than motor fuel and combined with the increased efficiency of the electric drive powertrain during urban driving, annual fuel costs are usually cheaper for BEVs and PHEVs (depending on the percentage of driving in fully electric mode) than a conventional internal combustion engine (ICE) vehicle. The all-electric range of the Toyota Prius PHEV is 12.3 miles (Idaho National Laboratory, 2014). Despite 70% of trips in the USA being under 10 miles (U.S. Department of Transportations Federal Highway Administration, 2009), Tal et al. (2014) found that the average percentage of battery-only driving for PHEV vehicles was 26% of vehicle miles travelled. The average PHEV driver clearly does not fully utilise the electric-only drive capability for every trip. In the UK the number of trips under 10 miles is considerably lower than the USA at approximately 30% (Department for Transport, 2015c), but without evidence of the average percentage of electric mode driving for these other regions the same ratio of battery to internal combustion engine driving has been assumed for all the regions in this study.

A region specific average annual mileage is assumed in the TCO calculations. This varies from a minimum of 6213 miles/yr in Japan, 10 400 in the UK, 11 071 in California, to a maximum of 15 641 miles/yr for Texas

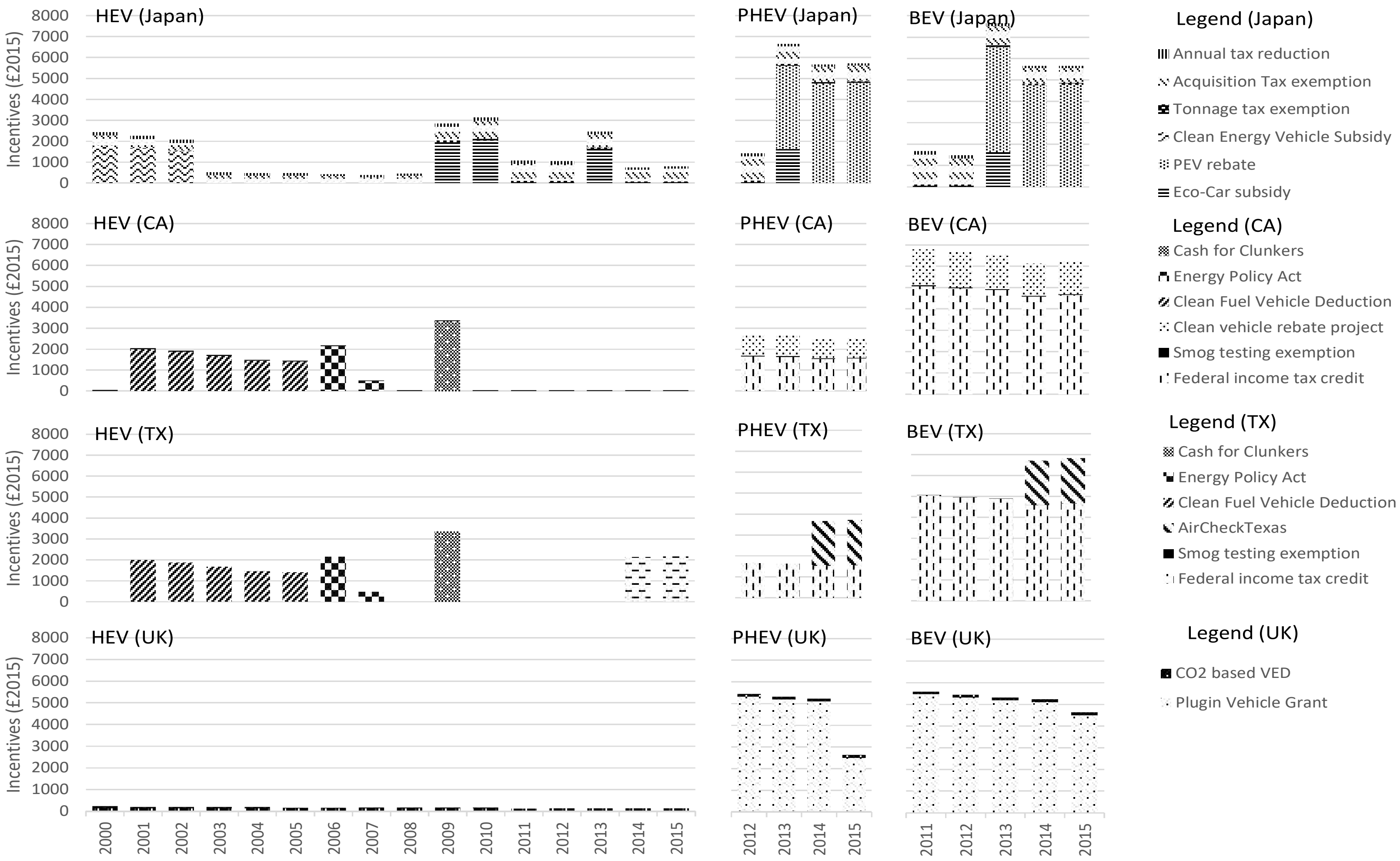

Figure 3-1: *Timeline of financial incentives available for HEVs and EVs. (Compiled from (Sallee, 2011; DMV.ORG, 2015; Texas Commission on Environmental Quality, 2016; Japan Automobile Manufacturers Association, 2016a; DMV.ORG, 2016; GOV.UK, 2017b; GOV.UK, 2018)).*

(Millard-Ball and Schipper, 2011; Department for Transport, 2013; U.S. Department of Transportations Federal Highway Administration, 2017) (see Table 3-1 for all regional mileage). The annual mileage used here is the average mileage over the first three years of ownership. Average annual vehicle mileage decreases with age therefore it is important to use figures that are representative of new vehicle purchases (Department for Transport, 2016a). With BEV range exceeding 100 miles, the restricted vehicle range does not necessarily pose an issue for the average car trip distance of 16 miles as found in the UK national travel survey (Department for Transport, 2016a) , therefore it is appropriate to assume the same annual mileage for all vehicle types.

Historic fuel prices were sourced from the International Energy Association (IEA, 2015) for Japan, the U.S. Energy Institute Administration (U.S. Energy Information Administration, 2017) for California and Texas, and the Department of Energy and Climate Change for the UK (Department for Business Energy and Industrial Strategy, 2017).

3.3.4 Maintenance and Insurance Costs

An average annual maintenance cost for each vehicle type is included. Costs are lower for electric vehicles due to less wear on the brakes and fewer moving parts. Vehicle model specific costs were sourced from CAPP automotive consulting (The Money Advice Service, 2015).

The Prius is classed as an average vehicle for insurance purposes (Carbuyer.co.uk, 2015). Therefore, the average comprehensive cover is considered to adequately represent insurance costs for all vehicle types. Estimates are used for Japan (Akita-ken, 2015) assuming that real costs have remained constant over the study timeframe. For the Californian model, the comprehensive average premium for California is used for years 2003-2012 (Consumer Watch Dog, 2007; Insurance Information Institute, 2009; Insurance Information Institute, 2013; National Association of Insurance Commissioners, 2014; Insurance Information Institute and The Public Policy Institute of New York State, 2015). Insurance costs for the Texas model are estimated as a proportion of Californian prices (Insure.com, 2017). For the UK model, the British Insurance Premium Index is used (The AA, 2015).

3.3.5 Vehicle Tax

Vehicle tax systems have changed over the time period of the TCO model in this study. In Japan, three different taxes are payable: an acquisition fee is dependent on the Manufacturer Suggested Retail Price of the vehicle, every two years a weight tax is owed, and an annual tax must also be paid (Alhulail and Takeuchi, 2014). In the USA, a state dependent registration and title fee is payable (GOV.UK, 2018). In the UK the only vehicle tax is the annual Vehicle Excise Duty (VED) payment. A new CO_2 emissions-based VED system was introduced in 2001 (GOV.UK, 2017c) and this has changed in April 2017 – as discussed in the next Chapter (GOV.UK, 2017b).

3.3.6 Regression Methods

To analytically assess the link between historic TCO and market share across the different geographical regions a fixed effects panel regression model was developed. The fixed effects specification was chosen instead of random effects to control for cross-sectional model variance and unobserved effects between the different geographic regions. The panel regression took a multivariate linear form with parameters fitted using the Ordinary Least Squares method. The regression was run primarily for HEVs because market share and TCO input data was available for 16-19 years whereas for BEVs and PHEVs there is insufficient data (<6 years of annual data) for reliable regression analysis.

Three forms of the general regression model were chosen for comparison to determine the relationship of best fit between the independent cost variables and the dependent market share variable. The initial model (Model 1) takes a linear specification between the TCO ratio defined as the total three-year TCO of the HEV to the total three year TCO of the conventional vehicle, such that:

$$S_{ct} = \propto_c + \beta_1 T_{ct} + \varepsilon_{ct}, \qquad (Model\ 1)$$

where S is vehicle market share, T is defined as the ratio of the TCO of the HEV to the TCO of the conventional petrol vehicle, β is the variable dependent coefficient, α is given as the geographic region-specific intercept, ε represents the residuals, c is a proxy for the geographic region and t represents the year.

The second model form (Model 2) compared the same variables but took a log-log specification in line with other studies (see Diamond (2009), Bajic (1988), and Gallagher and Muehlegger (2011)), such that:

$$\log S_{ct} = \propto_c + \beta_1 \log T_{ct} + \varepsilon_{ct}. \qquad (Model\ 2)$$

The final model specification (Model 3) split the TCO into initial cost and running cost components. This took the form:

$$\log S_{ct} = \propto_c + \beta_1 \log I_{ct} + \beta_2 \log R_{ct} + \varepsilon_{ct}, \qquad (Model\ 3)$$

where I is defined as the ratio of the initial cost of the HEV taking subsidies into account to the initial cost of the conventional vehicle and R is defined as the ratio of the running cost of the HEV vehicle over the three year ownership period to the conventional vehicle. This model specification is tested with and without inclusion of the Willingness to Pay for HOV lane access in California (in line with results from Shewmake and Jarvis (2014)) and for different TCO ownership periods. The HOV lane WTP is included in the regression model by including it in the TCO calculation for the appropriate years (see Section 3.3.2 for details of how the HOV lane permit scheme operated and the WTP figures).

The Engle ARCH and Durbin Watson tests were conducted on each model to check for heteroscedascity and autocorrelation respectively. Although evidence has shown that household income is a factor in low emission vehicle purchase decisions (Ozaki and Sevastyanova, 2011), it was not included in the model because it is difference stationary and therefore can cause spurious regression. The market share data was sourced from Japan Automobile Manufacturers Association for Japan (2016b), IHS Markit for the two US states (2017), and the Society of Motor Manufacturers for the UK (2017). This data was split annually for each region broken down by powertrain type.

3.4 RESULTS OF THE TCO MODEL

3.4.1 TCO Components

Cost components were found to vary over country, vehicle type and purchase year; however, the greatest cost to the consumer has always been vehicle depreciation (see Figure 3-2 for TCO

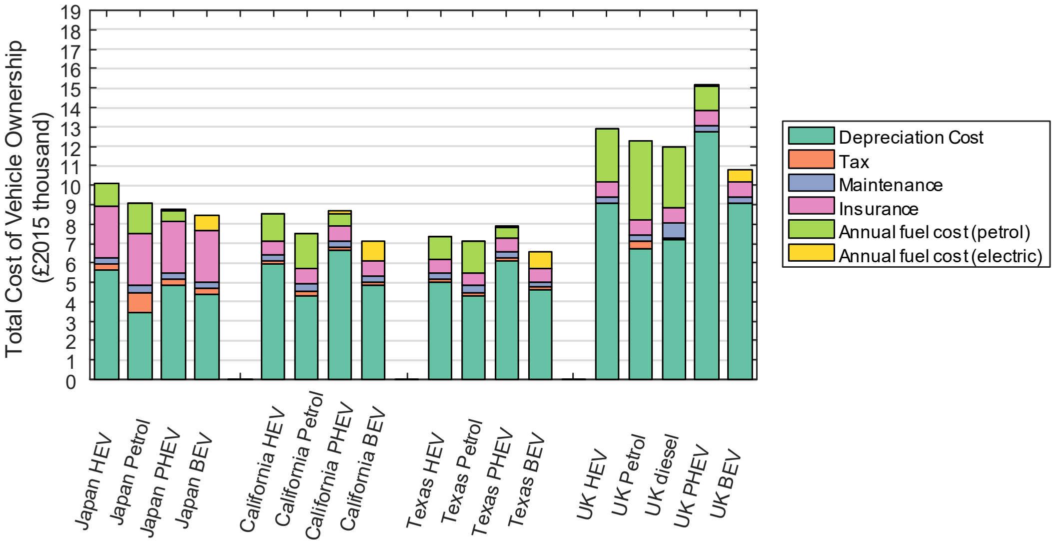

Figure 3-2: ***TCO component breakdown for 2015 across all regions.***

breakdown, costs table can be found in Appendix 3-B). This is most pronounced for BEVs and PHEVs due to the greater initial purchase cost coupled with low running costs. In Japan, insurance featured as the second greatest percentage cost, but for the UK, California and Texas annual fuel cost contributed a greater percentage of the vehicle TCO for petrol, diesel and hybrids.

3.4.1 Geographic TCO comparison

The HEV cost ratio (defined as HEV TCO divided by Petrol TCO) has reduced in all regions from introduction to 2015. This is most pronounced in Texas where the cost ratio has dropped by 0.23 in 15 years. Even in the UK where subsidies were absent, the cost ratio has fallen by 0.09. Between the years 2000 and 2015, the lowest average cost ratio for HEVs is in the UK at 1.03. The cost ratio for PHEVs is greater than for HEVs in all regions considered except Japan. Conversely, in California, Texas and the UK subsidies have enabled BEVs to reach cost parity. The lowest average cost ratio for BEVs across the regions considered is the UK (0.89). For PHEVs, the lowest average cost ratio is in Japan (0.97).

3.4.2 Region Specific TCO Trends Over Time

For Japan, the HEV cost ratio varied between 0.85 to 1.17 (see Figure 3-3 for Cost ratio and market share over time). Vehicle cost initially decreased from 1997 to 1999 leading to a lower cost ratio and increased market share. In 2009 greater tax cuts and an initial vehicle subsidy was introduced

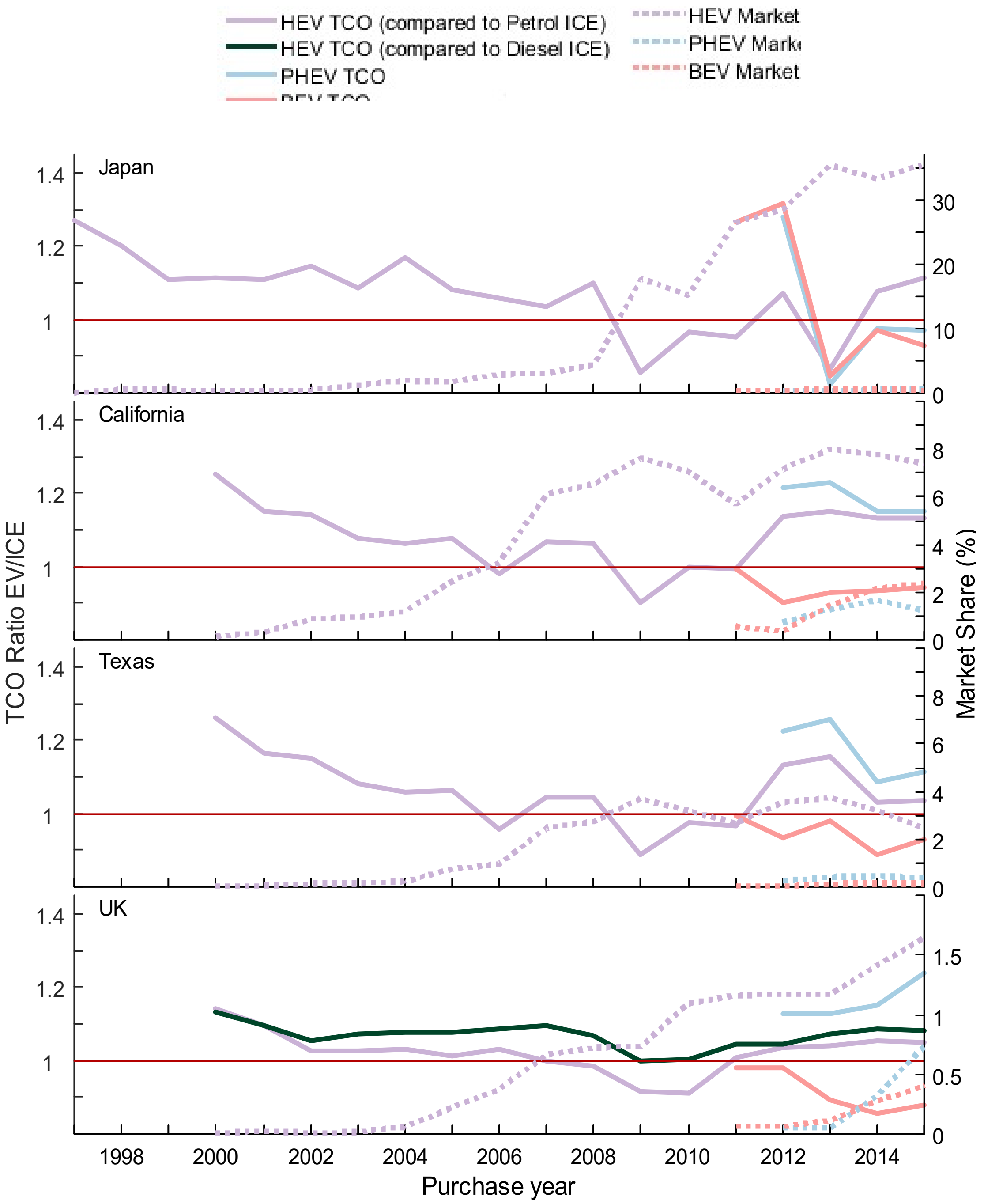

Figure 3-3: *TCO ratio and market share for the UK, California, Texas and Japan 1997-2015.*

such that HEVs were cheaper than conventional vehicles for the first time; this was met with a peak in HEV market share. With the Japanese tsunami in 2011, Toyota experienced manufacturing disruptions which propagated down the supply chain and caused shortages (Toyota, 2011). Despite this, market share in Japan still rose. In 2013, the cost ratio dropped due to a second wave of subsidies, which again corresponded to a peak in market share. With fuel price falling in 2014 and 2015, the cost ratio increased and HEV market share levelled out. The PHEV cost ratio varies between 0.82 and 1.28 whereas the BEV cost ratio varies between 0.84 and 1.32. This indicates that the large subsidies have brought PHEV and BEV TCO in line with conventional vehicles in Japan.

For California, the HEV cost ratio varied between 0.9 to 1.25. The cost ratio decreased from 2001 to 2005 as a result of rising petrol price despite the value of incentives falling. The Car Allowance Rebate System subsidy in 2009 (see Figure 3-1) results in a clear dip in HEV cost ratio and spike in market share. The supply disruption from the Japanese tsunami led to a dip in market share in 2011 and a return to 2009 market share levels by 2013. Larger subsidies for BEVs than PHEVs (e.g. approx. \$10 000 for BEV versus \$2500 for PHEV) led to a lower TCO ratio for BEVs of 0.94 compared to 1.14 for PHEVs. As a consequence, BEV market share is almost double that of PHEV market share.

For Texas, the HEV cost ratio varied between 1.02 to 1.14. The market share time series is similar in shape but roughly half the size of California. The cost ratio curve is also very similar to that of California, exhibiting the same dips and peaks for the same reasons (primarily fuel price and subsidy changes). Higher mileage (15 641 versus 11 071 miles per year) offsets the lower price of petrol in Texas compared to California leading to a similar annual fuel cost (approximately \$1353 and \$1191 respectively). The drop in cost ratio in 2014, attributed to the introduction of an initial vehicle subsidy incentive, has not stimulated HEV sales in 2014/15. In Texas a subsidy is available in equal value for all low emission vehicles (AirCheckTexas Drive a Clean Machine) therefore HEVs are cheaper than PHEVs and BEVs. The state financial subsidies available for BEVs in Texas are smaller than California (\$3500 versus \$10 000) leading to a lower cost ratio.

The HEV cost ratio varied between 0.91 to 1.14 in the UK. The initial fall in the cost ratio, comes as a result of the change in the vehicle excise duty tax in 2001. This new Vehicle Excise Duty system differentiated annual charges based on NEDC CO_2 emissions figures in contrast to the flat rate system it replaced (this was a two tier system based on engine power). The cost ratio remained fairly constant from 2002 to 2007 in line with stable fuel prices. With the fuel price increase in 2010, the cost ratio dropped, with a corresponding increase in market share.

Table 3-2: *Regression results.*

	Model 1	Model 2	Model 3	Model 3 + HOV lane WTP	Model 3
Ownership Period	3 yr	3 yr	3 yr	3 yr	1 yr
Indep. variable	Coeff. (Std. error)	Coeff. (Std. error)	Coeff. (Std. error)	Coeff. (Std. error)	Coeff. (Std. error)
(HEV TCO/ICE TCO)	-33.9 (10.0)***	-	-	-	-
Log (HEV TCO/ICE TCO)	-	-13.0 (2.22)***	-	-	-
Log (HEV IC Cost/ICE IC)	-	-	-10.0 (1.93)***	-3.56 (1.42)***	-8.01 (2.15)**
Log(HEV RC/IC RC)	-	-	-5.52 (2.13)**	-7.73 (2.37)***	-5.90 (1.90)***
N	67	67	67	67	67
R^2 (overall)	0.360	0.512	0.583	0.455	0.600
Adjusted R^2	0.319	0.481	0.549	0.411	0.567
Durbin Watson statistic[5]	0.359	1.07	1.30	1.30	1.31

*Note: **, and *** denote significance at 5% and 1% respectively. RC = Running Cost, IC = Initial Cost.*

Conversely, the fuel price slump in 2015 led to an increased cost ratio coupled with a surprising increase in market share. This surge in sales is most likely a result of the pending Vehicle Excise Duty changes in 2016. The new Vehicle Excise Duty system will involve a CO_2 emissions based initial charge of up to £2000 followed by a flat annual cost of £140 per year for all vehicles except those with zero emissions (GOV.UK, 2017b) – the effect of this new tax system on vehicle TCO will be analysed in Chapter 4. Diesel vehicles were found to have a lower TCO than petrol vehicles, to the point that the TCO model calculated that HEVs have never been cheaper than diesel vehicles over the time period considered. In the UK, the TCO ratio is lower for BEVs at 0.88 than PHEVs at 1.24. This is mainly a result of the plug-in vehicle grant that allocates a larger subsidy to BEVs (£4500) than PHEVs (£2500).

3.4.3 Panel Regression Analysis

The regression analysis evidences a historical link between HEV TCO and market share for the four geographic regions (see Table 3-2 for regression results for the three models specified in Section 3.3.6). The linear model form, which treats the independent variable as TCO and the dependent variable as market share, has a low value of R^2 (0.319) with large standard errors.

[5] The Durbin Watson statistic produces a value between 0 and 4, where 0 indicates very high negative autocorrelation, 4 indicates very high positive autocorrelation, and 2 indicates no autocorrelation.

The value of the Durbin Watson statistic shows that with this model specification there is very high negative autocorrelation. This indicates that the model is mis-specified because it does not sufficiently explain the variation of market share over the given time period.

Comparing the linear form (model 1) with the log-log specification (model 2) (see Section 3.3.6 for details of regression equations), the R^2 value increases in value from 0.319 to 0.481 indicating that model 2 is a better fit than model 1. The standard error reduces from 10.0 for the TCO component for model 1, to 2.22 for the TCO component for model 2. The coefficient also increases from -33.9 for the TCO component in model 1, to -13.0 for the TCO component for model 2. The value of the Durbin Watson statistic indicates that autocorrelation in model 2 is lower than in model 1, therefore this is a better model specification. Overall this model specification is significantly better ($p < 0.01$) than the initial model evidencing the link between vehicle cost and market share. A similar result stating that a link between TCO and market share exists was found by Levay et al. (2017).

By splitting the TCO into its constituent components: initial cost (including subsidy) and running cost, the R^2 value increases again from 0.481 to 0.549. The standard error reduces from 2.22 for the TCO component for model 2, to 1.93 for the initial cost component and 2.13 for the running cost component in model 3. The coefficient also increases from -13.0 for the TCO component in model 2, to -10.0 for the initial cost component and -5.52 for the running cost component in model 3. By accounting for the different cost components separately, the model is anticipated to improve. Toyota initially subsidised the Prius model to ensure it was cost-competitive on the market, and as initial prices increased government subsidies were introduced to encourage uptake. In this model the initial cost coefficient is more significant ($p < 0.01$) than running cost ($p < 0.05$). The initial cost coefficient indicates that a one percent reduction in the cost ratio leads to a 10% increase in market share, whereas a one percent reduction in running cost ratio leads to a 5.5% increase in market share. This directs us to the conclusion that at an aggregate level HEV purchases are more sensitive to changes in subsidies and vehicle price (e.g. the initial cost components) than fuel price change (e.g. the running cost component with most variation over time).

Changing the ownership period from three years to one year improves the fit of the model slightly (increasing R^2 from 0.549 to 0.567). The initial cost component coefficient increases from -10.0 to -8.0 with an increase in standard error from 1.93 to 2.15. The running cost component coefficient decreases slightly from -5.52 to -5.90 with a decrease in standard error from 2.13 to 1.90. The most marked effect of this model comparison is the increasing significance of the running cost component (from $p < 0.5$ to $p < 0.01$) with lower standard

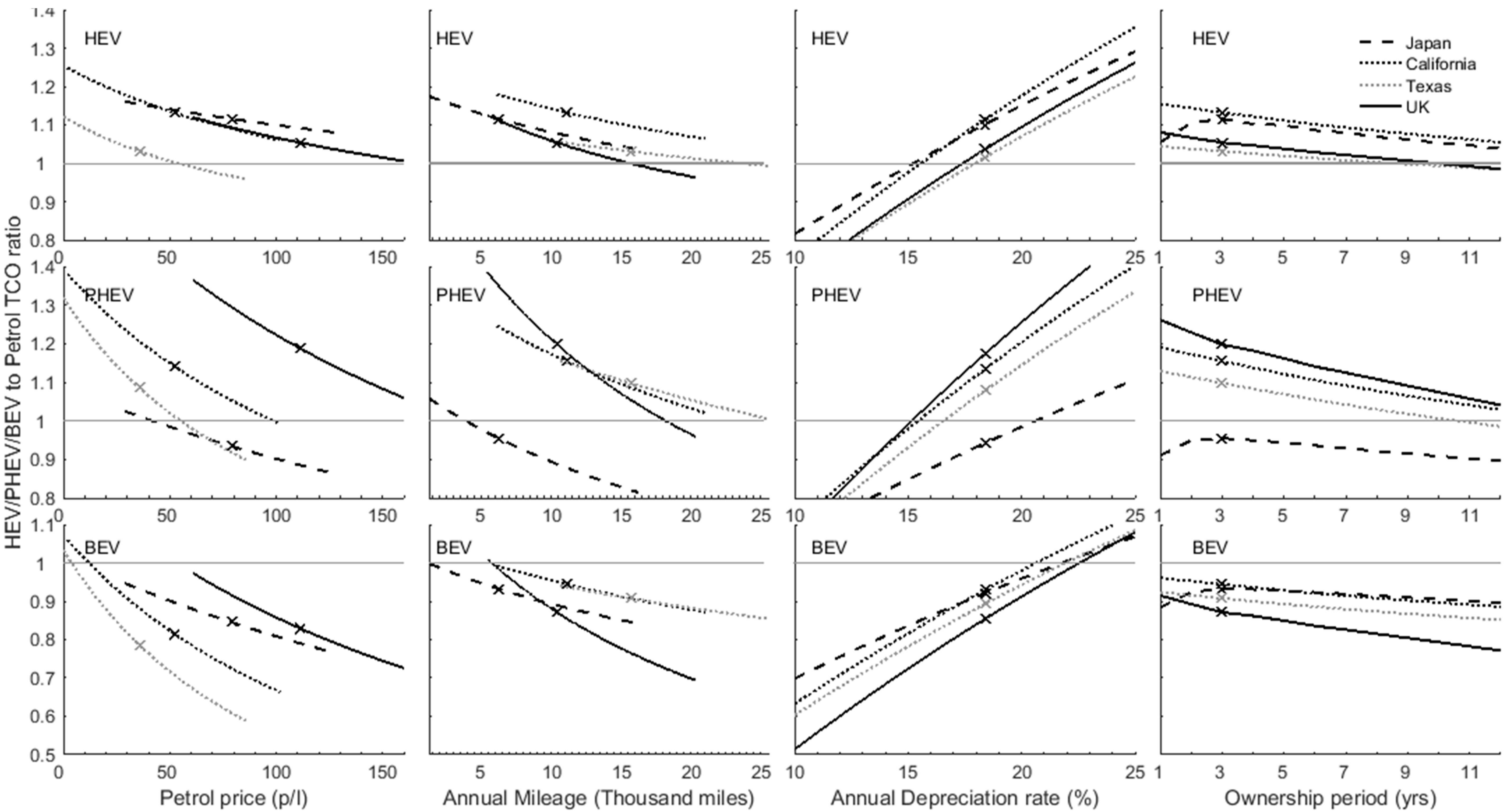

Figure 3-4: *TCO sensitivity analysis for base year 2015, cross (X) indicates baseline value.*

error; whereas the initial cost coefficient decreases in significance with larger standard error. The inclusion of Willingness-To-Pay for HOV lane access for California did not improve the model fit but increased the standard error for the running cost coefficient. Considering cost on an annual basis, model 4 does not have an adequate resolution (e.g. annual rather than monthly) to account for purchasers who adopt HEVs for HOV lane access.

3.4.1 Sensitivity Analysis of Cost Parameters

Several input variables were investigated to assess the model sensitivity to their variation. These variables include; fuel price, discount rate, annual mileage, vehicle depreciation rate, and TCO ownership length (see Figure 3-4 for Sensitivity Analysis Results).

The discount rate assesses a person's revealed time preferences, with a higher rate indicating that a person's opportunity costs are greater. Studies in the literature (see Table 3-1) use significantly different rates and because of this inconsistency, this variable has been investigated using a sensitivity analysis. Generally, the greater the discount rate the greater the variation in cost ratio over the time period considered. The effect of varying the discount rate was negligible over the three-year ownership period. For example, increasing the discount rate from 2 to 11% caused the cost ratio to only increase by approximately 0.2%. For a longer ownership period, it is anticipated that varying the discount would have a greater effect on the TCO ratio.

Fuel price is arguably the most important variable input to the model. Clearly historical changes in fuel price have had a significant impact on HEV cost ratio and vehicle market share (as discussed in Section 3.4.3). A higher fuel price creates more favourable conditions for HEV/PHEV/BEV adoption. The fuel price sensitivity in this study examines the 2015 fuel price for each region $\pm £0.50$, whilst maintaining a fixed electricity price. From Figure 3-4 it is clear that the regions with higher average mileage such as Texas are more sensitive to changes in fuel price. BEVs and PHEVs are more sensitive to changing prices than HEVs. For example, a 10p increase in fuel leads to a 0.2 drop in cost ratio for HEVs, but 0.4 for BEVs.

In the standard TCO calculation, annual mileage has been assumed to be constant for the geographic region. However, this is highly variable among different drivers and therefore this sensitivity analysis demonstrates different use cases. For example, higher mileage cars such as taxis or business travellers may find hybrid and electric vehicles (note range limitations) more cost effective because of fuel cost savings. For HEVs, the UK has the lowest break-even mileage at approximately 15 000 miles. This figure exceeds 20 000 miles in the other regions considered. The break-even mileage of PHEVS is greater than HEVs in all regions except Japan where annual mileage of around 4000 miles equates to cost parity. BEV subsidies mean that BEVs break-even at a lower average mileage of around 7000 miles for the UK, California and Texas, but are always the lower cost option in Japan.

Depreciation is the greatest component of TCO across all geographic regions. Varying the annual depreciation rate from 15% to 20% leads to an increase of cost ratio of approximately 0.17 across all regions (see Figure 3-4). This figure is greater for PHEVs at 0.2 because the initial purchase cost constitutes a greater percentage of TCO than HEVs. However, this figure is slightly lower for BEVs at 0.15 due to subsidies bringing the initial cost in line with HEVs (see Figure 3-3).

As previously discussed, low emission vehicles are associated with a price premium that can be offset by lower running costs over a certain time period. In this study, the baseline TCO was taken as three years in line with average length of UK and Japan new vehicle ownership. Generally, this ownership period is longer in the USA therefore the impact of a longer ownership period has also been investigated. The longer the ownership period the lower the TCO ratio (see Figure 3-4). Because this study took vehicle salvage value into account when calculating TCO for different ownership lengths, the TCO ratio was not found to be particularly sensitive to changing ownership period with a drop in TCO ratio of approximately 0.01-0.02 with each additional year of ownership.

3.5 DISCUSSION OF OTHER FACTORS AND COMPARISON TO THE TCO LITERATURE

3.5.1 Factors Affecting Adoption Rates

This chapter aims to compare historical TCO of BEVs, PHEVs and HEVs across countries with different levels of hybrid and electric vehicle uptake. As previously discussed in Section 3.4.4, regression analysis reveals that there is a clear link between changing HEV TCO and market share. First, these results are significant because they can inform the setting of policies to stimulate HEV adoption in regions where market share is lacking. Second, the approach and results may be applicable to future BEV and PHEV vehicle adoption. These vehicle types have been available on the market for a shorter amount of time and currently represent very low fleet share in most vehicle markets.

This analysis has focused on assessing the link between HEV TCO and market share. This enquiry has isolated ownership costs as the most pertinent time-dependent variable affecting adoption rates for HEVs. There is considered to be no underlying drivers that have caused a false correlation. However, several variables which could affect HEV adoption, such as HEV depreciation rates, income and HOV lane access, have changed in the time period considered and will be discussed in more detail in this section.

With depreciation as the largest cost to the consumer, sensitivity analysis found that vehicle TCO was highly sensitive to changing depreciation rates (see Section 3.4.5). Depreciation rates of low-emission vehicles are uncertain even for HEVs, which have been available on the second-hand vehicle market for over a decade. HEVs in California historically have had an inflated vehicle retention value due to supply issues and HOV lane access (Gilmore and Lave, 2013; Shewmake and Jarvis, 2014). However, results from Lebeau et al. (2013) found that BEVs, PHEVs and HEVs depreciated quicker than conventional vehicles in the Belgian vehicle market. The newest Tesla EV battery degrades by less than 10% over 160 000 miles (Lambert, 2018c). Along with uncertainty over diesel ICEV depreciation rates with the introduction of Clean air zones and Ultra-low emission zones, this evidence indicates that in future HEVs, PHEVs and BEVs will not depreciate at a faster rate than ICEVs.

A key factor in the high adoption rates of low emission vehicles in California compared to other states is the comparative wealth. The median income in California is $64 500 (the 10th richest state) whereas in Texas this figure is $55 653 (23rd richest state) compared to the US average of $55 775 (United States Census Bureau, 2016). As a result of this wealth, many more residents can afford the additional incremental cost of a low emission vehicle. Average income has increased over time, but this variable has not been included in the regression analysis as it is a non-stationary variable that results in spurious regression.

In California, low-emission vehicles have access to HOV lanes (Shewmake and Jarvis, 2014). Such incentives are difficult to financially quantify (although Willingness-to-Pay figures were estimated by Shewmake et al (2014)). Vehicle owners who had already purchased HEVs could apply for HOV lane access stickers, although these were only available for a limited number of vehicles.

With the highest count of Green Party registered voters (both as total number and as a percent of total registered voters) (Green Party US, 2017), Californians are evidently more environmentally aware than voters from other states. Kahn et al. (2007) found a link in California between green party voting and HEV adoption, therefore it reasonable to assume that high HEV market share in California can partly be attributed to environmentally-friendly attitudes.

Other factors have also contributed to high HEV market share in Japan. Japan has a history of innovation in this field, and represents the domestic Prius market where the vehicle model was first developed and tested (Toyota, 2012). The majority of vehicles purchased in Japan are domestic brands, with only a small percentage imported from the USA and Europe (Lee, 2011). With small roads and low annual mileage, the Japanese tend to favour smaller cars. Evidence for this can be found in the high market share of the Prius compact which is now one of the best selling cars in Japan (Lee, 2011).

The availability and accessibility of charging infrastructure is a barrier to BEV adoption. Although most BEV and PHEV owners have access to a home charging point (evidenced in the Nordic countries (IEA, 2018b)), public charging points are important for visibility as well as practical use for both short and longer trips (Bakker and Jacob Trip, 2013). In California the number of public charging stations has increased to 3820 whereas in Texas this number is lagging behind at 885 (US Department of Energy, 2016). Japan has chosen to invest heavily in charging infrastructure, aiming to stimulate uptake (Smith, 2013). In the UK, EV charging infrastructure has been installed strategically in dozens of cities (see Section 2.2.4 for more details).

Since Toyota introduced the Prius to the global market in 2000, many vehicle manufacturers have developed hybrid models. Toyota still maintains market dominance with over 50% of HEV market share, having diversified their hybrid range to include vehicles across most size segments. As the number of hybrid models across different size segments and brands diversifies and capacity to supply vehicles grows, it is anticipated that HEV market share will continue expand. The PHEV market is dominated by vehicles from larger size segments (such as SUVs) (Society of Motor Manufacturers and Traders, 2017), such that the Toyota Prius is one of the smallest PHEV available. It is anticipated that as the number of PHEV models expands its market share will also grow. It is also worth noting that in the UK additional competition exists from diesel vehicles which are more cost efficient than petrol vehicles at high mileages.

Many of these additional factors discussed in this section are difficult to quantify for all geographic regions and across the time period considered. The variables discussed are not deemed to be variable or significant enough to have caused a false correlation in the HEV TCO/market share regression analysis.

3.5.2 Payback Periods Compared to Other TCO Studies

The studies in the literature largely reached the same conclusions as this chapter; that the TCO of HEVs, PHEVs and BEVs without subsidies is still greater than that of conventional vehicles. The historical analysis in this chapter shows that incremental vehicle cost varies depending on the vehicle purchase year (see Figure 3-3), this is echoed by the conclusions of other papers in the TCO literature. The payback period of a new technology compared to its conventional counterpart is a common metric in the cost analysis literature. When comparing electric vehicle payback periods, unless a vehicle depreciation or loan model is used to represent initial vehicle costs, the calculated payback periods will be unrepresentative of the true payback period.

Al-Alawi and Bradley (2013b) estimated a HEV payback period of approximately 8 years when considering the vehicle salvage value in the TCO model. For a base year 2010, the payback time in this study is shorter at approx. 3 years for Texas and 4 years for California. Al-Alawi and Bradley (2013b) find a PHEV with a 10 mile electric range (similar to the Toyota Prius which has an all-electric range of 12.3 miles) has a shorter payback period of approx. 7 years. The discrepancy in these results stems from differences in the sourcing of initial vehicle cost data: Al-Alawi and Bradley have used an incremental cost model rather than the Manufacturer Suggested Retail Price.

Thiel et al (2010) estimated that in 2010 the payback period for HEVs, PHEVs and BEVs was 20, 22 and 23 years respectively, much greater than the 10,14 and 1 years calculated in this study. As Thiel et al (2010) used an initial cost model that did not consider the important subsidies or vehicle salvage it is perhaps unsurprising that the conclusions do not align with the findings for the UK in this chapter.

Hutchinson et al. (2014) found that the incremental cost of a HEV or PHEV depends largely on the style of driving. Hutchinson et al (2014) conclude that in 2013 HEVs and PHEVs have a payback period of 6.7 and 10.1 years respectively for city driving, but do not reach cost parity for highway driving. The greater fuel efficiency of HEVs and PHEVs in urban driving explains the shorter payback time calculated in Hutchinson et al (2014) compared to this chapter which estimates this to be greater than the vehicle lifetime in California. The conclusions from Hutchinson et al (2014) are echoed in this chapter such that in the UK HEV and PHEV TCO is closer to cost parity with conventional vehicles than in the USA.

Wu et al. (2015) find that in 2015 TCO depends on annual mileage driven which is mirrored in our sensitivity analysis. Wu et al. (2015) use Germany as their geographical focus, which has different relative fuel prices compared to the UK, limiting the comparisons between the conclusions from Wu et al. (2015) and this study. Levay et al (2017) conclude that in Norway, the TCO for BEVs was lowest due to incentives. In the Netherlands, France and the UK, the TCO of EVs and ICEVs is similar. In other countries, such as Hungary, Poland, Germany and Italy, the TCO of EVs is significantly greater than their ICE comparison vehicles. Although neither Wu et al. (2015) or Levay et al (2017) explicitly mention payback periods, the key conclusions from their studies are pertinent to this section.

3.6 SUMMARY AND CONCLUSIONS

This chapter concludes that in all regions the incremental TCO of hybrids and electric vehicles compared to conventional vehicles has reduced between the year of introduction and 2015 subject to the assumptions made in this analysis, confirming the original research hypothesis. Year on year hybrid electric vehicle TCO was found to vary least in the UK due to the absence of subsidies. Financial subsidies have enabled BEVs to reach cost parity in the UK, California and Texas, but this is not the case for PHEVs, which have not received as much financial backing. The value of this regional analysis highlights the variation of monetary incentives available across different regions and the effect on the comparative vehicle TCO. The cost ratio of EVs to ICEVs varies across the different regions more than anticipated.

The sensitivity of TCO to changes in the discount rate was found to be insignificant, whereas variation of fuel price and depreciation had a much greater effect. Insurance was found to be a surprisingly large percentage of TCO especially in Japan, whereas tax is a comparatively small proportion of TCO. This chapter establishes a clear connection between historic HEV TCO and market share; with evidence from regions such as Japan and California that long-term government support plays a role in higher adoption rates.

The results of this chapter are subject to the large number of assumptions made regarding the inclusion of the constituent parts in the TCO calculation and the values assumed for these components. The sensitivity analysis aimed to investigate how the variation in these components affects the results, but coupling this with the evidence in the literature that the TCO framework and the values of the constituent parts are not standard, leads us to conclude that it is necessary to recognise that these findings are clearly dependent on the assumptions made. The focus of this chapter was historic HEV and EV TCO; after discussing this subject in depth, several further questions arise on this subject that will be considered in the later chapters. HEV and EV TCO was calculated here using historic input data, but there is great uncertainty about the effect of changing prices on vehicle costs moving into the future. For example, how will oil prices vary over the coming decades, what will happen to financial incentives as EV numbers grow and how will battery prices change? Clearly, values for these variables cannot be accurately predicted and future scenarios cannot be tested exhaustively, but the effect of plausible changes of key variables on HEV and EV TCO needs to be assessed. For these reasons, the following chapter will analyse these questions, illustrating cost projections under three contrasting scenarios with different underlying assumptions for both the private and company car owner.

Because of geographical data limitations, the analysis in this chapter focused on the mid-sized car segment. This size segment accounts for approximately 40% of market share in the UK and is therefore the most popular vehicle size segment. However, a key question is how similar the cost ratios are between the different vehicle size segments. The following chapter (4) investigates this for the UK market, assessing vehicle TCO between small, medium, large and large+ size segments for several different future scenarios.

Finally, with a clear connexion established between HEV TCO and adoption in this chapter, as costs change (as investigated in Chapter 4), how will this affect the vehicle fleet composition and therefore network traffic emissions in the future? In Chapter 5 cost will be accounted for in scenarios in a vehicle adoption model and in Chapter 6 the effects of a changing fleet on network emissions will be assessed.

CHAPTER 4: A UK CASE STUDY OF HISTORICAL AND FUTURE UK VEHICLE TCO ACROSS DIFFERENT SIZE SEGMENTS AND OWNERSHIP TYPES

4.1 INTRODUCTION

Historically, hybrid and electric vehicles have had a greater Total Cost of Ownership (TCO) compared to conventional petrol and diesel ICEVs. The previous chapter considered how costs have changed since introduction of hybrid and electric vehicles to the present for the 'average' car, indicating that fuel price, depreciation rates and annual mileage are all significant inputs in vehicle TCO calculations.

In the previous chapter, the link between ownership costs and adoption was established. This adds further empirical evidence to the results of numerous surveys that have reported cost to be an important factor in hybrid and electric vehicle adoption (see Brownstone et al. (2000), Hidrue et al. (2011), and Sierzchula et al. (2014)). By projecting future vehicle TCO, conclusions can be drawn about how the electric vehicle market may evolve under different circumstances; enabling policy makers to adequately plan for electric vehicle charging infrastructure, air pollution limits, supply of raw materials, and budgets for financial subsidies. For these reasons, there is value in producing up to date future vehicle TCO projections and updating these when new data becomes available.

The inputs into the TCO model are inherently uncertain moving into the future. Consequently, the best approach to calculating future vehicle TCO is to account for several different possible futures in the form of contrasting scenarios. Financial policies are a big driver for future changes in cost: initial subsidies and tax exemptions contribute to a cheaper TCO and can abruptly change depending on a government's commitment to incentivising electric vehicle deployment. Cost projections of hybrid and electric vehicles have been extensively published: however, as this technology is still relatively new to the mainstream market (less than 2% market share in the UK and most other vehicle markets) and vehicle TCO changes rapidly (see Chapter 3) such cost projections quickly date. BEVs were introduced to the mainstream market around 2011, and the purchase price of these vehicle types has changed significantly since then (evidenced by chapter 3). In the future, there are external factors that could significantly change vehicle TCO, such as step changes in battery technology, the rise of Mobility as a Service (e.g. ridesharing) and automation (as discussed in Chapter 2). At present there is little agreement about the timescale of the impact of these developments, but many experts in the field agree that changing battery prices will play a pivotal role in changing EV TCO and the rise of electrification.

The focus of this chapter is an investigation of UK historic and future TCO of hybrid and electric vehicles. The TCO calculations in this chapter consider different size segments for different ownership types. The content of this chapter builds on work from the previous chapter where historic vehicle costs were compared across different regions but focused on the mid-sized vehicle segment and the private vehicle owner. Many aspects of vehicle costs such as fuel prices and taxes vary over geographic region. In the previous chapter, costs were estimated as accurately as possible for historic TCO, however, with the difficulty of obtaining data for foreign markets, and the uncertainties of future costs, the UK is the primary focus of the analysis in this chapter.

The key aim of this chapter is to assess when hybrid and electric vehicles will be cheaper than conventional petrol and diesel vehicles in the UK. To address this aim, this chapter considers the TCO of conventional, hybrid, plug-in hybrid and battery electric vehicles in the UK for the time period 2000 to 2040 across the four main vehicle size segments (small, medium, large and large+) for private car ownership. Private vehicle TCO is projected under three scenarios: Business-As-Usual, Battery Bonanza and Diesel Persists. These scenarios anticipate three different potential futures, illustrating how vehicle prices could change under a number of external factors such as financial policy, battery price, and fuel price. The conclusions drawn from this analysis are not forecasts but realistic possible futures depending on economic externalities.

Additionally, historic company car costs are analysed in this chapter. Company car costs primarily stem from governmental taxes: these change over time depending on the average rated CO_2 of company cars. Company car costs are more sensitive to changes in these tax rates than changes in the initial vehicle price. Furthermore, rated CO_2 will experience a step change with the introduction of the new test cycle legislation in 2020 (see Chapter 2). For these reasons, with the CO_2 rated emissions tax bands as the key cost determinant, the uncertainty of future company car cost is so great that there is little value in trying to create scenarios of tax bands to 2040.

This chapter contributes to the literature in three key areas: investigating how vehicle TCO has changed historically across different size segments, analysing vehicle TCO for both the private and company car owner, and analysing how vehicle TCO varies under several scenarios. The results of this chapter will feed into the next chapter where several adoption paths are constructed from these cost scenarios.

4.2 VEHICLE COST PROJECTION LITERATURE

With uncertainty about future costs of hybrid and electric vehicles, TCO projections have been published that forecast when these new vehicle types may reach cost parity with conventional petrol or diesel vehicles (see Table 4-1 for TCO projection literature). In this section, mainly the newest and most relevant cost projection literature is discussed. With changing oil prices, battery prices, and tax systems, vehicle cost projections quickly date; therefore, it is imperative that studies are continually updated to reflect the latest price changes. Despite this, there are TCO projections which are well researched and have use even if they are not up to date (e.g. Douglas and Stewart (2011)).

The literature falls into two categories: either top down or bottom up (usually utilising an incremental cost model). Douglas and Stewart (2011) published a key piece of literature when BEVs and PHEVs had only just been released onto the mainstream market. Douglas and Stewart (2011) concluded that petrol and diesel ICEV TCO will only increase slightly to 2030, and EVs will remain at a cost premium. Since then, many other publications (see Table 4-1 for review of key studies in TCO literature) have compared the ownership costs of hybrid and electric vehicles for different time frames.

It is difficult to directly contrast and compare the findings of multiple publications with different base years, study scope and geographic area. Many of the studies focus on a full spectrum of vehicle types with different cost scenarios; to assess whether the cheaper costs of running a BEV/PHEV/HEV offsets the larger initial battery price (for example Thiel et al. (2010), Douglas and Stewart (2011) and Wu et al. (2015)). Many studies consider different size segments (e.g. Contestabile et al. (2011), Douglas and Stewart (2011), and McKinsey (2012)). The studies in the literature largely conclude that hybrid and electric vehicles will reach cost parity without incentives between 2030 and 2040. Wu et al. (2015) is arguably the most detailed of the future projections, considering vehicle costs in 2015, 2020 and 2025 with a substantial Monte Carlo (probability) analysis of model sensitivities. From the literature, the key driver of future EV cost reduction is the battery technology, and therefore this will be a key focus of the projections in this chapter.

TCO methodology has not been standardised in the literature (see Table 4-1 for details of key published studies). It is apparent that factors such as maintenance, tax costs and vehicle resale

Table 4-1: *Total Cost of Ownership future projections literature summary.*

	Thiel et al. (2010)	Contestabile et al. (2011)	Douglas and Stewart (2011)	McKinsey (2012)	Hill et al. (2012)	Wu et al. (2015)	Lee et al. (2016)	Schmidt et al. (2017)	This study
Model type	Mainly economic (Bottom up)	Techno-economic (Bottom up)	Techno-economic (Bottom up)	Mainly economic (Top down)	Techno-economic (Bottom up)	Mainly economic (Bottom up)	Input to future adoption model (Top down)	Economic (Bottom up)	Economic (Top down)
Powertrain focus	ICEV-SI, ICEV-CI, HEV, PHEV, BEV	ICEV-CI, HEV, PHEV, BEV, FCEV	ICEV-SI, HEV, REEV, BEV	ICEV-SI, ICEV-CI, PHEV, BEV, FCEV	ICEV-SI, ICEV-CI, HEV, REEV, BEV	ICEV-SI, ICEV-CI, HEV, PHEV, BEV	HEV	BEV	ICEV-SI, ICEV-CI, HEV, PHEV, BEV
Vehicle classes covered	Mid-size vehicle	Supermini, Lower-medium, multipurpose luxury	A/B, C/D, E/H	A/B, C/D, SUV	C/D, van	A/B, C/D, J	Mid-sized car	Only considers fuel tank gasoline/ battery plus elt only not TCO	A/B, C/D, E/F, H/I

Table 4-1 continued…

	Thiel et al. (2010)	Contestabile et al. (2011)	Douglas and Stewart (2011)	McKinsey (2012)	Hill et al. (2012)	Wu et al. (2015)	Lee et al. (2016)	Schmidt et al. (2017)	This study
Sensitivity/ uncertainty analysis	Yes	Yes	Yes	Yes	No	Yes	4 scenarios, retirement subsidies	Battery Learning rates	Yes
Reference country	EU-27	UK	UK	EU27 + CH + NO	UK	DE	Korea	USA (UK?)	UK
Projection period	2010-2030	2010-2030	2030	2010-2050	2010-2050	2014, 2020, 2025	2020	2015-2040	2000-2040
Battery cost modelling	10%	Projections from DfT 2008	Projected costs	Own projections of battery costs	Not used, interpolated DfT projections	8.4% (2014 to 2020), 4.9% (2020 to 2025)	N/A	16 % +- 4%	11%

Note that DfT stands for Department for Transport.

are often excluded despite there being variation between vehicle types and sizes. Over a long time period such as that of this study, policies and cost incentives that play a crucial role in adoption of new technologies, particularly during the initial stages of deployment, can also change. In this chapter we build a comprehensive model taking all significant vehicle ownership costs including financial incentives into account. An important aspect of our analysis is that we used real-life car prices, utilising a top-down approach. Many of the studies do not consider resale value – a similar problem to the previous chapter.

Although fleet adoption motivations have been studied in the literature (as discussed in Section 2.2.2), to the author's knowledge, historic company car TCO have not been calculated, compared and analysed. In the UK, business and fleet purchases (see Appendix 2-B for definition of purchase types) account for around half of new car purchases with costs depending on the rated CO_2 of the vehicle.

Although this analysis uses the UK as a case study, the conclusions are likely to be similar for other European countries, but it is unlikely that this extends to the US vehicle market (see Appendix 2-A for comparison of vehicle size segment definitions for the UK, US and EU). The spread of market share across different vehicle size segments is similar for the UK and the rest of the EU (Thiel et al., 2015), with the majority of the same models of HEV, PHEV and BEV available. For the US, larger vehicle size segments such as SUV and Minivan dominate vehicle sales (The Wall Street Journal, 2017). This vehicle mix presents challenges for widespread adoption of EVs in the USA, because of the large incremental vehicle cost associated with the higher capacity battery required.

4.3 COST METHODS AND DATA SOURCES

4.3.1 Study Scope

The cost model calculates the TCO for each vehicle type and size segment on an annual basis following the same calculation framework as the previous chapter (the details of the inputs and their sources are given in Table 4-2 with details of the different scenarios modelled in Section 4.3.3). Representative vehicles have been chosen and grouped into four main size segments: small (mini/A and supermini/B), medium (medium/C and large/D), large (executive/E and luxury/F) and large+ (dual-purpose/H and multi-purpose/I), which together account for over 98% market share (Society of Motor Manufacturers and Traders, 2017). The main vehicle types BEVs, PHEVs, HEVs, Petrol ICEVs and Diesel ICEVs are represented, these account for 99.99% of car market share (Society of Motor Manufacturers and Traders, 2017).

Table 4-2: *Vehicle ownership cost summary (the components detailed here are assumed to be the same across each scenario detailed in 4.3.3, any assumptions that differ between scenarios are detailed in Table 4-5).*

Component	Details	Source
Past Initial Vehicle price	Minimum vehicle model Manufacturer Suggested Retail Price	Parkers (2017)
Projected Initial vehicle Price	Petrol and Diesel ICEV price assumed to increase to account for more stringent emissions legislation	Hill et al. (2012)
	BEV/PHEV/HEV vehicle learning rate of 6%	Safari (2018)
	Battery learning rate of 11% (base case)	Nykvist and Nilsson (2015); Schmidt et al. (2017)
Past Fuel Price:	Annual historic	BEIS* (2017)
Projected Fuel Price	Annual projected	BEIS* (2017)
Annual Mileage	Assumed as 10 400 miles (private car), 19 400 for company car, 7600 (pool car) (tested with Sensitivity Analysis)	Department for Transport (2012); Fleet News (2013)
Past Vehicle fuel efficiency	Real world fuel efficiency	Spritmoniter (2018)
Projected Vehicle fuel efficiency	Projected fuel efficiency for conventional petrol and diesel vehicles from 2016-2035	Department for Transport (2016b)
	HEV fuel efficiency trends extrapolated	
	Fuel efficiency increases from battery weight reductions calculated from first principles	

Table 4-2 continued…

Component	Details	Source
Past Maintenance	Lower for hybrid and electric vehicles due to less wear on the brakes and fewer moving parts	CAPP automotive consulting (The Money Advice Service, 2015)
Projected Maintenance	Assumed 2015 maintenance costs rise with inflation	
Past Tax	Vehicle Excise Duty: o Jan 2000 to Mar 2001: Annual rate based on Engine power o Apr 2001- Mar 2017: Annual rate based on NEDC rated CO_2 emissions o Apr 2017- : Annual flat rate for all vehicles (BEVs exempt) with an initial CO_2 dependent charge	Department for Transport (GOV.UK, 2017c; GOV.UK, 2017b)
	Benefit in Kind rates, Fuel Benefit charge, VAT fuel scale charge	Department for Transport (GOV.UK, 2017c; GOV.UK, 2017b)
Projected Tax	Assumed 2017 taxes rise with inflation	
Past Insurance	UK national insurance index	The AA (2015)
Projected Insurance	Assumed 2015 insurance costs rise with inflation	

******BEIS (Department for Business, Energy and Industrial Strategy) formerly DECC (Department for Energy and Climate Change) until 2016*

Table 4-3: *Representative vehicles for different vehicle types and classes (Data sourced from Parkers (2017) and Spritmoniter (2018)).*

	Small	Medium	Large	Large+
Petrol/Diesel ICEV	Ford Fiesta	Ford Focus	BMW 5 series	Kia Sportage
HEV	Toyota Yaris	Toyota Prius	Lexus GS 450h/300h	Lexus RX 400h/450h
PHEV	-	Toyota Prius Plug-in	Mercedes C350e	Mitsubishi Outlander PHEV
BEV	Renault Zoe	Nissan Leaf	-	Mercedes B class (electric)

Table 4-3 details the vehicles chosen for this TCO analysis. These vehicle models were chosen based on market share and model release date to ensure model continuity for the sales timeframe (see Appendix 4-A for details of vehicles attributes, time of model availability and details of market share in size segment).

For the case of the company car, the employee pays a Benefit-In-Kind (BIK) for the vehicle and fuel (only if the employer pays for fuel for private use). BIK is calculated by taking the product of the vehicle list price, the tax band of the employee (assumed to be 40% in this case) and the BIK percentage (dependent on vehicle rated CO_2). The Fuel benefit charge (e.g. the BIK paid on fuel) is calculated in the same way, except for simplicity a nominal amount determined by the government (approximately £20 000) is used instead of the vehicle list price (see Appendix 4-B i-ii for historic BIK percentages for petrol and diesel ICEV cars). For the employer, a lease fee is usually payable along with all the other components of the private car ownership (such as insurance, VED and maintenance). The employer can claim back the VAT on maintenance, the initial vehicle purchase and annual fuel cost. In addition, the fuel scale charge is only payable if the proportion of private mileage is unknown. Class 1A national insurance is payable by the employer, calculated as 13.8% of the annual BIK paid by the employee (for a summary of the costs to employee and employer for business cars see Table 4-4). If the company decides to purchase a car but does not allow any private mileage (including commuting), it is referred to as a pool car. In this case, BIK charges are not applicable to employer or employee.

4.3.2 Projected Cost Components

Table 4-4: *Tax summary for different vehicle ownership types.*

Vehicle Ownership	Tax type					
	Vehicle Excise Duty	BIK: Car	BIK: Fuel	National Insurance: Car BIK	National Insurance: Fuel BIK	Fuel surcharge
Private	✓					
Pool car	✓1					
Company car	✓1	✓2	✓2*	✓1	✓1*	✓1**

*Notes: 1 represents cost payable by employer; 2 represents cost payable by employee. Electricity is not counted as a fuel therefore fuel benefit charge is not payable even if employees charge at the workplace for private trips. * BIK Fuel is described as optional, as the employer can either pay for fuel and therefore pay National Insurance on the BIK payment or the employee can reimburse the employee for all fuel used for private mileage. ** Fuel surcharge is only payable if the company pays for all fuel (Private and business mileage) without keeping a record of the split, the employee can then reclaim all VAT from fuel but must pay this fuel surcharge.*

The key cost components for the vehicle TCO future scenarios are tax changes, battery prices, future petrol and diesel ICEV costs, and subsidies. The main developments in these areas are discussed in this section.

4.3.2.a Vehicle Excise Duty (VED) Tax

From the 1st April 2017, a new vehicle taxation system (referred to as VED) is applicable to all new vehicles registered in the UK. This was introduced to remedy the falling revenue from the previous VED legislation. In the previous system (applicable for new registrations April 2001 to March 2017), the tax bands were graduated based on test cycle CO_2 emissions (see Appendix 4-C for tax rates for the comparison vehicles considered in this study). Over this time frame, average vehicle test cycle emissions have gradually reduced as a result of better emissions technology coupled with optimisation of emissions for the NEDC test cycle, both of which have contributed equally (Transport&Environment, 2014). The difference between NEDC test cycle emissions and on road driving is now up to 40% (Mock et al., 2017). The new taxation system comprises of an initial payment (usually included in the 'on the road' price from the dealer), which is dependent on test cycle CO_2 emissions, thereafter there is a flat annual fee. BEVs are completely exempt from all vehicle taxation costs under both taxation schemes but under the new VED system all vehicles (including BEVs) with a list price above £40 000 must pay an additional annual charge of £310 in ownership years 2 to 5. In theory, this should discourage the purchase of large 'gas guzzlers', but this cost is only a small fraction of the MSRP of the vehicle.

4.3.2.b Battery Prices

For Battery price projections, a learning rate approach is used (see Section 2.2.3 for an explanation of learning rates and a comparison of battery cost projections). This approach is very common in the literature (see Table 4-1) and assumes a certain percentage reduction in price with every doubling in cumulative EV registrations. For the projected battery cost, a learning rate of 11% is applied in the baseline scenario in line with the lower bound learning rate found from historic Lithium Ion battery pack prices in Schmidt et al. (2017). For the Diesel Persists scenario a value of 6% is used in line with the learning rate found in Nyvist and Nilsson (2015). For the Battery Bonanza scenario a learning of 18% is used in line with the upper bound learning rate found from historic Lithium Ion battery pack prices in Schmidt et al. (2017). In this study it is assumed that future global EV deployment increases in line with IEA projections (IEA, 2018a). The IEA projections assume that there will be 130 million EVs by 2030 under their New Policy Scenario, on average this is a 34% growth of EVs in the vehicle stock year on year (IEA, 2018a). Several other EV projections exist in the literature, Bloomberg New Energy Finance (BNEF) estimates that by 2040 there will be 559 million EVs in the vehicle stock on average this is a 25% growth of EVs in the vehicle stock year on year (BNEF, 2018). Estimates by OPEC are lower at 235 million by 2040 on average this is a 20% growth of EVs in the vehicle stock year on year (OPEC, 2017), and BP estimate EV stock to be 350 million by 2040 on average this is a 23% growth of EVs in the vehicle stock year on year (BP, 2019). Unfortunately, none of these models are open source, therefore it is impossible to ascertain the assumptions behind these projections and the reasons why they are different.

At present, several different battery types are used in EVs such Lead Acid, Lithium-ion and Lithium Iron Phosphate. Lithium-ion batteries have the advantages of high volumetric and gravimetric energy density compared to other battery chemistries. Although new battery technologies are currently under development, expert opinion concludes that Lithium Ion batteries will be dominant in the medium term (Diouf and Pode, 2015). In fact, Toyota made the decision to change the battery technology in the 2016 Toyota Prius model from Lead-Acid to Lithium-Ion in line with the Prius plug-in model; all the BEV and PHEV models considered in this section utilise Li-ion battery packs.

Battery technology is improving every year; with batteries gradually becoming cheaper and lighter. This leads to BEVs with greater range and longer life spans, there are for example several cases of Nissan Leaf vehicles exceeding 100 000 miles without needing battery replacement (Kane, 2014). Over the lifetime of the battery, repeated charging and discharging leads to a fall in capacity; however, data from over 200 Tesla Model S drivers shows that this is less than 10% after 200 000 miles (Lambert, 2018b). Decreasing vehicle mileage with age most likely offsets any capacity drop. A recent study suggested that EVs are suitable to replace 87% of driving days in the US based on daily driving requirements (Needell et al., 2016); the UK National Travel Survey shows similar results (Department for Transport, 2013). However, as there is a range of trip distances for many drivers, this leads to the conclusion that several different battery sizes may be available for each vehicle model in the future.

In addition to cost reduction, as battery technology matures the weight-capacity ratio will also drop. This leads to lighter vehicle kerb side weight resulting in greater fuel efficiency. The effect of the lighter battery was calculated from first principles assuming 80% of the nominal battery capacity is utilised and the powertrain has an efficiency of 80% (Besselink et al., 2010). Regenerative braking was found to significantly reduce the efficiency gains from weight reduction of the battery. With lower battery prices in future, battery sizes are likely to be larger; however, comprehensive infrastructure deployment could contribute to solving range anxiety.

Similar to the battery learning rate characterising reductions in battery price due to ‘learning’ through increased manufacturing volumes (see section 2.2.3), the vehicle learning rate accounts for the lower prices of alternative powertrain components. The 6% value chosen here accounts for reductions in the cost of the electric motor system, on-board battery charger, and transmission system amongst other electrification costs (Safari, 2018). Profit margins are assumed to increase linearly from 0% on BEVs and PHEVs in 2020 to 24.3% in 2040; HEV profit margins assumed to stay constant at 24.3% (in-line with Wu et al. (2015)).

4.3.2.c Future ICEV Costs

New vehicles need to comply with more stringent CO_2, NO_x, and PM emission limits implemented by the EU (see Chapter 2 for an in-depth discussion of this point). For new vehicles to meet these new emission limits, more advanced emissions control technology must be fitted to the vehicle, which will likely lead to increased capital costs. Initial vehicle prices for petrol and diesel ICEVs are assumed to increase over the projected time period in line with figures from Hill et al. (2012). Hill et al. (2012) assumes that the capital cost of petrol and diesel ICEVs increases by approximately 15% between 2010 and 2050 with half of this cost realised by 2020. The report produced by Hill et al. (2012) is the outcome of an extensive literature review of all projections of vehicle capital costs and efficiency gains available at the time. The increase in capital cost in these projections stems from increasing powertrain costs as a result of higher powertrain efficiency. Other aspects of capital costs are assumed to remain static, such as the cost attributed to the glider. However, it is acknowledged that some aspects of the capital cost will reduce due to falling prices of new technology with learning (e.g. direct injection and variable valve actuation and lift). In addition, step changes in technology development cannot be predicted, but could result in step changes in cost.

4.3.2.d Subsidy

In the UK, the plug-in vehicle grant applies to BEVs and PHEVs with different subsidy amounts between £2500 and £4500 available depending on CO_2 tailpipe emissions (see Appendix 4-D for details of eligibility and details of how the grant has changed over time), but does not extend to HEVs (GOV.UK, 2018). The eligibility of EVs for the plug-in vehicle grant will be reassessed in 2020 (Morton, 2018). If the grant is reduced or phased out, this will affect the price and attractiveness of EVs.[6]

4.3.3 Scenarios

The TCO model will be used to model three policy scenarios: Business as Usual, Battery Bonanza and Diesel persists (summary of the differences between the assumptions in these scenarios are detailed in Table 4-5, the cost assumptions that remain the same across the different scenarios are given in Table 4-2). These scenarios are designed to illustrate contrasting futures with the types of policies that are pertinent to the current political climate. Scenario A – Business as Usual, follows a scenario such that hybrid and electric vehicle growth has minimal support. Scenario B – Battery Bonanza, considers longer governmental financial support for low-carbon vehicle purchase, extending vehicles and therefore the insecurity of stable resale values. The higher depreciation rate of 3% over the three year ownership period

[6] In September 2018 it was announced that contrary to previous government announcements earlier in the year that the grant would be unchanged until at least 2020, from November 2018 the maximum amount available for a BEV would be £3500 and PHEVs are no longer eligible. Unfortunately the results of this announcement could not be factored into this thesis as the results had been finalised and most of the thesis had already been written.

Table 4-5: *Underlying assumptions in policy TCO scenarios. This table details the differences between the scenarios, all other costs are the same across the scenarios as detailed in Table 4-2. Note that fuel prices follow the DECC scenarios (see Table 4-2).*

Scenario	Financial Policy	Battery Learning Rate	Fuel Price
A. Business as Usual	Plug-in vehicle grant (applied to BEV and PHEV): • 100% from 2017 to 2019 • 50% from 2020 to 2022 • 0% from 2023 Diesel ICEV depreciation rate equal to petrol ICEV depreciation rate.[7] Diesel ICEV efficiency assumed to rise at a lower rate than petrol ICEV (22% vs 33% by 2040).	11%	Low
B. Battery Bonanza	Plug-in vehicle grant (applied to BEV, PHEV and HEV - HEV grant available at 50% of PHEV rate): • 100% from 2017 to 2029 • 50% from 2030 to 2034 • 25% from 2035 to 2039 • 0% from 2040 Higher diesel depreciation rate (additional 3% over 3 year period). Diesel ICEV efficiency assumed to rise at a lower rate than petrol ICEV (22% vs 33% by 2040).	16%	High
C. Diesel Persists	Plug-in vehicle grant same as Scenario A. Diesel ICEV depreciation rate equal to petrol ICEV depreciation rate. Diesel vehicle efficiency assumed to rise at the same rate as petrol (33% by 2040).	6%	High

Note: 100% represents £4500 for BEVs, £2500 for PHEVs and £1500 for HEVs (when applicable).

[7] *Note that vehicle depreciation rates used in the scenarios are in line with the other chapters in this thesis (16.9% annually).*

was chosen from recent quantitative evidence collated by HPI (2017) that depreciation rates of diesel vehicles have risen. To compound this, stricter MOT tests have been introduced for DPFs, which are prohibitively expensive to repair. The higher battery learning rate illustrates that as EVs receive greater market share initial price falls (the reasons and references for the choices of battery learning rates are described in Section 4.3.2). Scenario C – Diesel Persists, sets out a scenario where diesel vehicles remain cost competitive as the UK government makes a U-turn on its previous assurances.

This analysis is based on vehicle TCO at a UK national level. Additional factors that maybe contribute to the decision to purchase an EV such as availability of public charging points, use additional support to hybrid vehicles. The greater depreciation rate for diesel ICEVs reflects consumer uncertainty surrounding the future of government policy towards high polluting of bus lanes and parking in city centre, are not considered. At present, adequate data is not available to evaluate and assess their impact independently. Additionally, these measures are not available in all regions. This may be solved in future TCO projections with more research into these areas as factors become more widespread across the UK and EV market share grows.

4.4 RESULTS OF UK HISTORIC AND FUTURE VEHICLE TCO

4.4.1 Historic TCO Comparison for Different Market Size Segments

Over the past decade, the TCO of different vehicle types over different market size segments has varied primarily with changes in initial vehicle price, fuel price and taxes (see Figure 4-1 for vehicle TCO for different size segments and ownership types). As expected, the larger vehicle size segments generally have greater TCOs with BEVs tending to become the cheaper option across all size segments moving towards 2017 (see Figure 4-2 for cost breakdown over different size segments). As in the previous chapter, depreciation is the largest cost across all size segments with fuel and insurance also featuring heavily (see Figure 4-2). In this section we compare changes in TCO with corresponding variation in market share. The correlation between these two variables is not necessarily a causation from changing cost, and the market may not be very responsive leading to lagged adoption.

In the private small-sized vehicle segment, the TCO for a hybrid powertrain is greater than that for other vehicle types in the small-sized vehicle segment as a result of the vehicle price premium. As a consequence, by the end of 2016 small hybrids only accounted for around 15% of hybrid market share (Society of Motor Manufacturers and Traders, 2017). The slow rise in

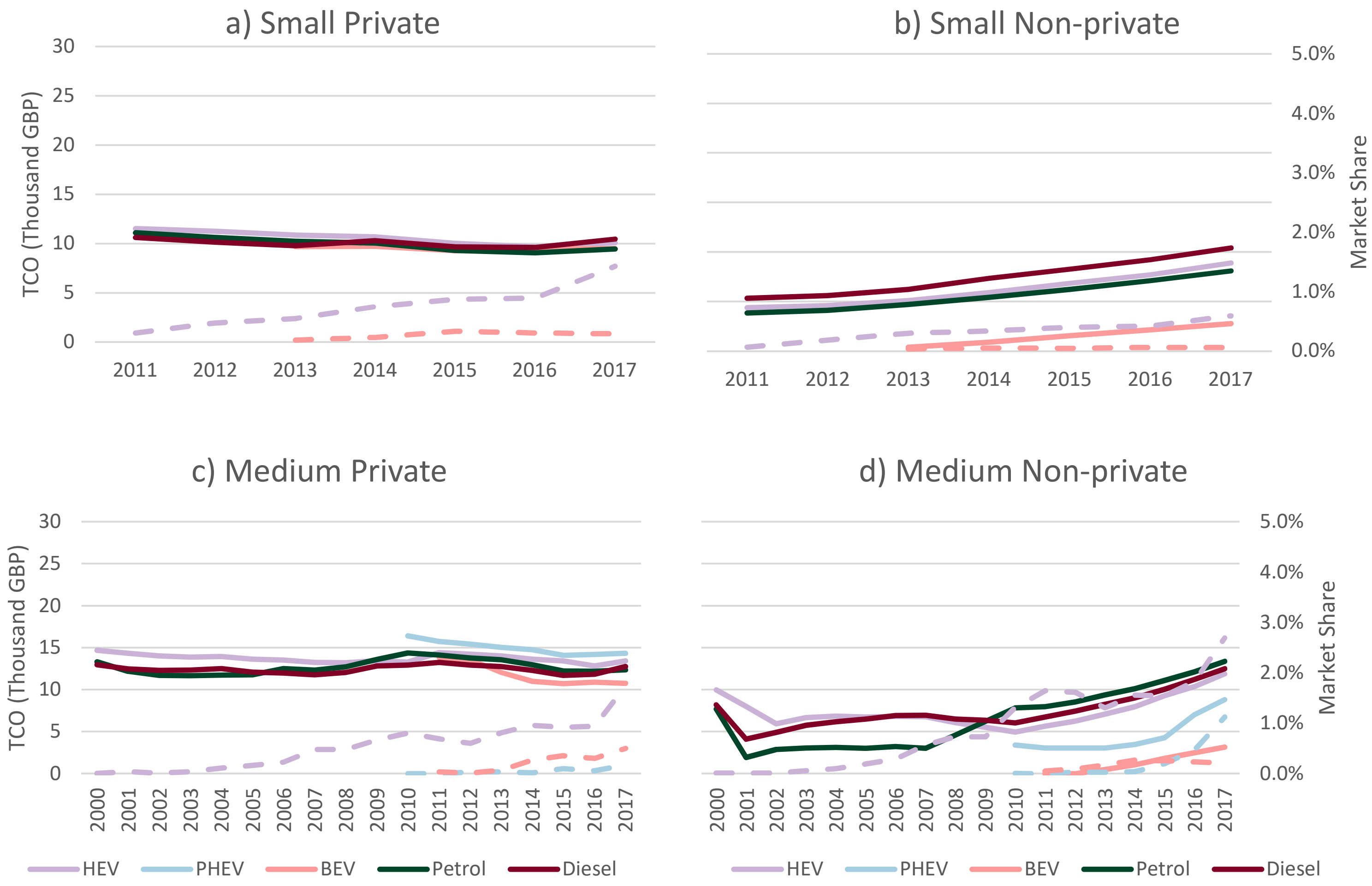

Figure 4-1 a-d: *Vehicle TCO (full line) and market share of segment (dashed line) for private and non-private (company) car across different vehicle segments.*

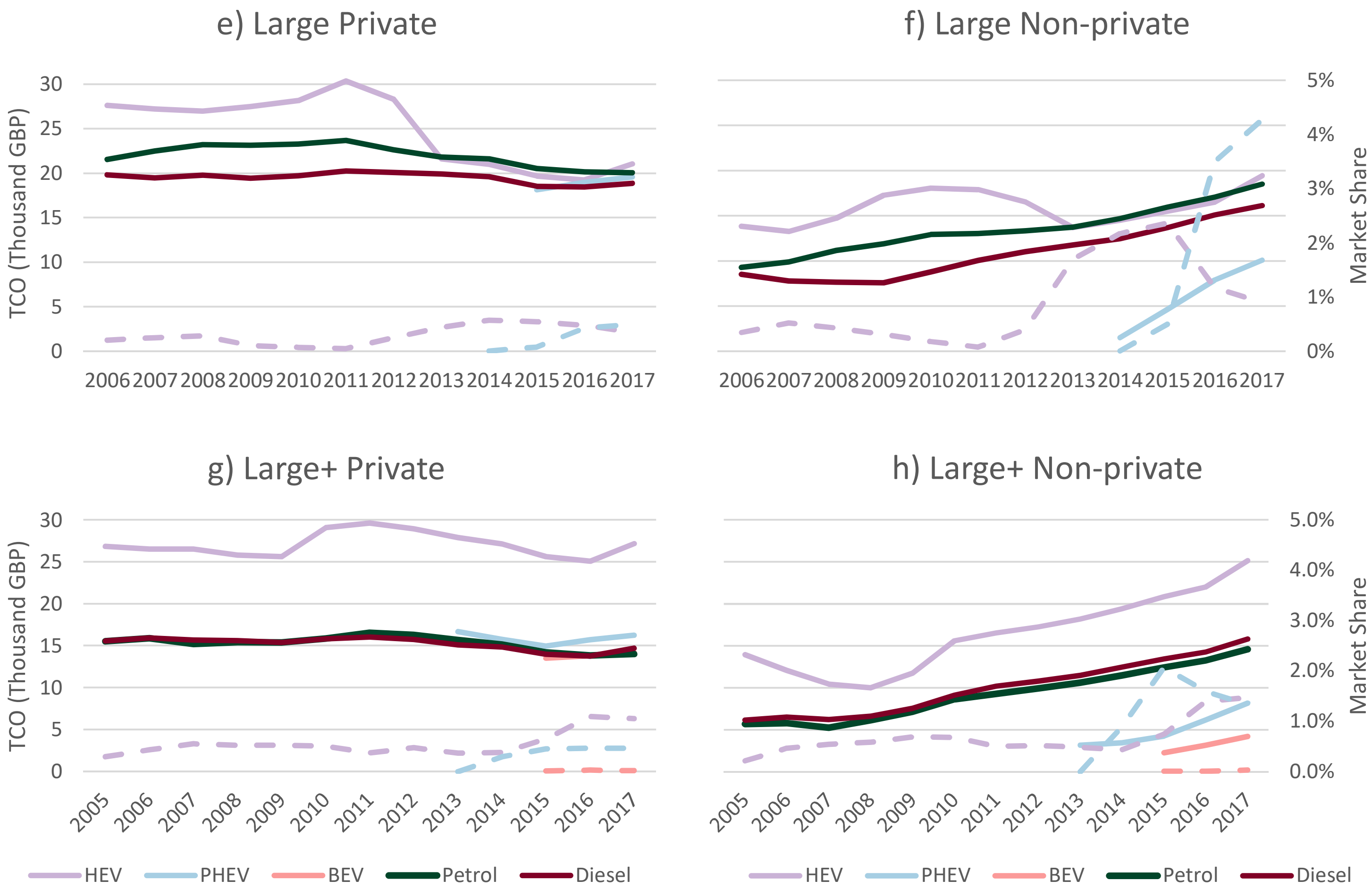

Figure 4-1 e-h: *Vehicle TCO (full line) and market share of segment (dashed line) for private and non-private (company) car across different vehicle segments.*

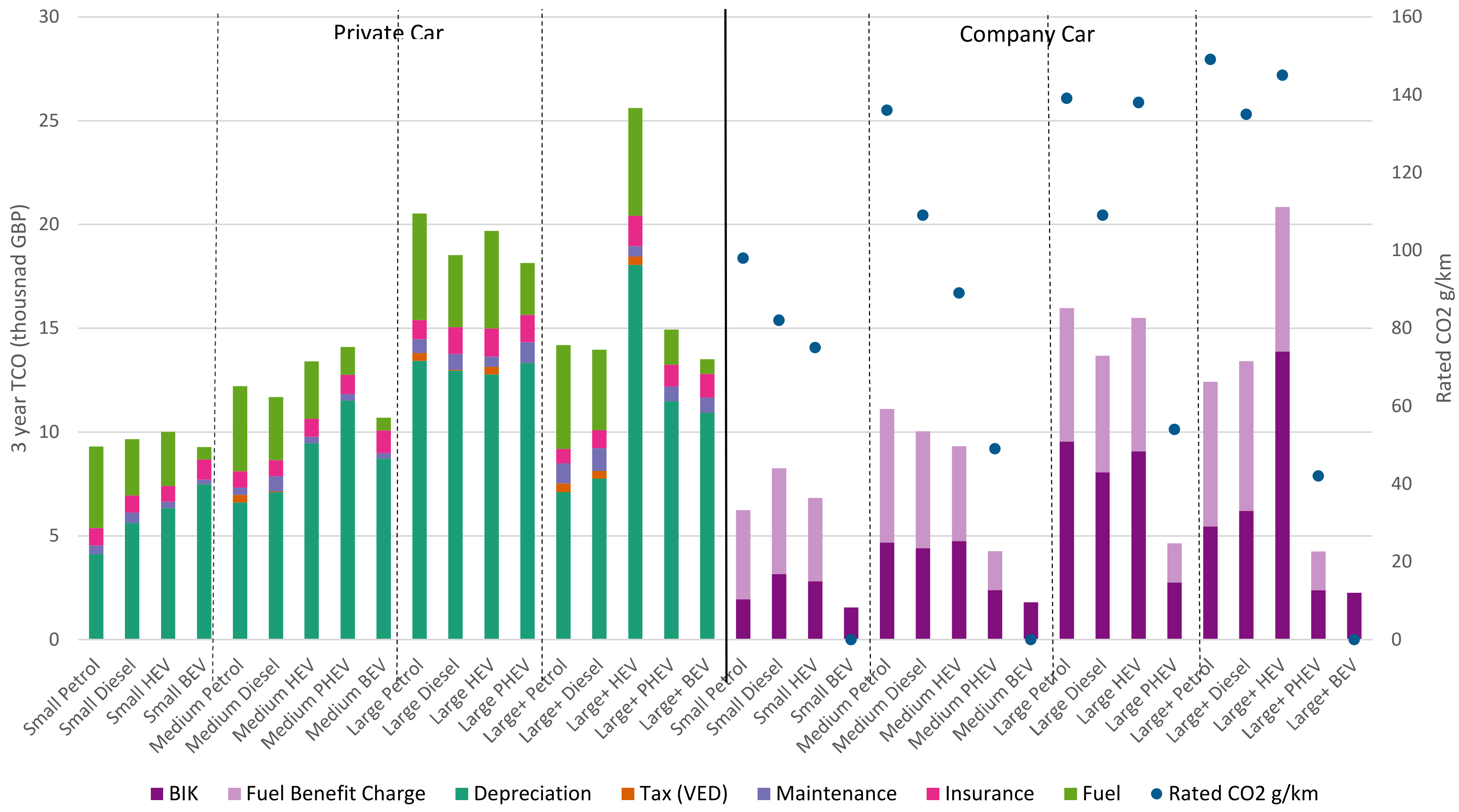

Figure 4-2: *TCO breakdown by segment and ownership type (£2015).*

HEV market share from introduction in 2011 to 1.28% corresponds to a gradual fall of HEV TCO by 15% from 2011-2015, this mainly stems from falling fuel price along with a small reduction in initial vehicle price. For BEVs the gradual fall in TCO 2011-2016 is approximately 7%, primarily because of falling vehicle price, corresponds to a gradual rise in market share from 2011 to 2016 to 0.19% market share. This is followed by an increase in BEV TCO in 2017 (around 1% from rising electricity prices), which corresponds to a fall in market share to 0.05%. Dieselisation in the small sized vehicle segment remains low at below 20%. From 2013, diesel ICEV TCO has been greater than petrol ICEV. It is expensive to equip small vehicles with emissions reduction technology; therefore, we anticipate a larger price increase for diesel ICEVs in the small sized vehicle segment than the larger sized segments.

In the private medium sized vehicle segment, the gradual fall in HEV TCO by 12% from 2010 to 2016, because of falling fuel prices, corresponds to a gradual rise in market share from 0.80% to 0.94%. There is a large increase in HEV market share in 2017 to 1.74% despite a 4% increase in TCO - as a result of changing tax rates. PHEV TCO decreases by 15% from 2012 to 2016 because of falling initial vehicle price that corresponds to a market share increase to 0.06%. There is a jump in market share in 2017 to 0.18% despite a 1% increase in TCO as a result of increasing VED rates for all vehicles. BEV TCO falls by 24% between 2011 and 2015, more than any other powertrain types because of falling initial vehicle price. Market share increases slowly over this period to 0.36%. The slight rise in BEV TCO in 2016 by 1% corresponds to a small fall in market share to 0.30%. The rise of dieselisation in the medium size segment is notable from 20% to 70% between 2000-2011 followed by a gradual fall to 45% market share by 2017. Diesel ICEV TCO has historically been cheaper than petrol ICEV, this was the case until 2017.

The 'typical' vehicles chosen in the large car segment have different attributes (see Appendix 4-A) therefore we cannot necessarily expect vehicle TCO to be entirely comparable. To illustrate this, the HEV model chosen is the bestselling of its powertrain type in this size segment but the vehicle price is significantly more expensive than the other vehicle types (£45 000 for the HEV in 2010 compared to £34 000 for the petrol ICEV). For the HEV choice of model for the private owner, the large drop in price in year 2013 is due to the introduction of a cheaper model (the Lexus GS 350h); this corresponds to a rise in market share by 0.24%. The PHEV TCO is closer to the diesel ICEV TCO than the petrol ICEV TCO. There has been a significant rise to 0.42% market share from 2014 to 2016, despite rising costs.

In the private large+ segment, the fall in HEV market share in 2010/2011 from 0.5% to 0.37% corresponds to a rise in TCO due to a spike in fuel price. Similarly, the rise in market share in

2015 corresponds to a 10% fall in TCO because of a dip in fuel prices. PHEV TCO falls by 6% from 2013 to 2015 due to reduced initial vehicle price with a corresponding market share rise of 1.03% to 2.53%, and a TCO rise of 4% from 2015-2016 due to an increase in initial vehicle price corresponding to a fall in market share to 1.67%. Rise of dieselisation in the large+ vehicle size segment is similar to the large car segment, from 35 to 85% market share between 2000 to 2011, then a decrease to 75% by 2017. The difference in TCO between diesel ICEVs and petrol ICEVs has historically only been between £500 and 1000, indicating that high mileage diesel vehicles may be the cheapest option. The rise of dieselisation in the large+ size segment is greater than any other size segment, from 20% to 85% from 2000 to 2013, then a small decrease to 75% by 2017. Historically diesel ICEVs are more than 5% cheaper than petrol ICEVs.

Company car costs have increased between 2010 and 2015 for all vehicle types and size segments as a result of the BIK rates increasing (see Appendix 4-B for details of BIK percentages over time). Despite rising costs, the market share of HEVs, PHEVs and BEVs has increased in all size segments. PHEVs have the highest market share of the three vehicle types, with nearly 4.5% market share in the large size segment and nearly 2% in the large+ size segment. Diesel vehicles have had an additional 3% BIK surcharge since 2010 to reflect their detrimental contribution to air quality. Despite this, diesel company cars are still approximately the same price as petrol ICEVs due to their lower rated CO_2. The larger car size segments have seen higher market share of company car PHEVs whereas the medium size segment has been the segment with highest market share for HEVs. The step change in costs in 2001 are due to a change in the way the BIK rates were calculated, whereas other step changes are due to introduction of an updated model with a different rated CO_2 (e.g. medium size HEV in 2010 from new Toyota Prius model release).

Evidence from the literature indicates that business purchases are more economically rational than in the private market (as discussed in section 2.2.2). The results of the analysis in this chapter find that it is clearer to attribute changes in cost to market share for the private market rather than the business market. The private market appears to be more responsive to changing external costs than the business market. This reduced sensitivity goes against the literature suggesting that fleet buyers are more sensitive to cost.

One of the key financial policies that has affected vehicle TCO is the change in VED. The new VED system was introduced to address the falling tax revenue as a result of the historic shift towards low carbon vehicles and artificially low CO_2 test ratings. If we assume all ownership costs remain the same apart from the VED change, Figure 4-3 shows that vehicle ownership

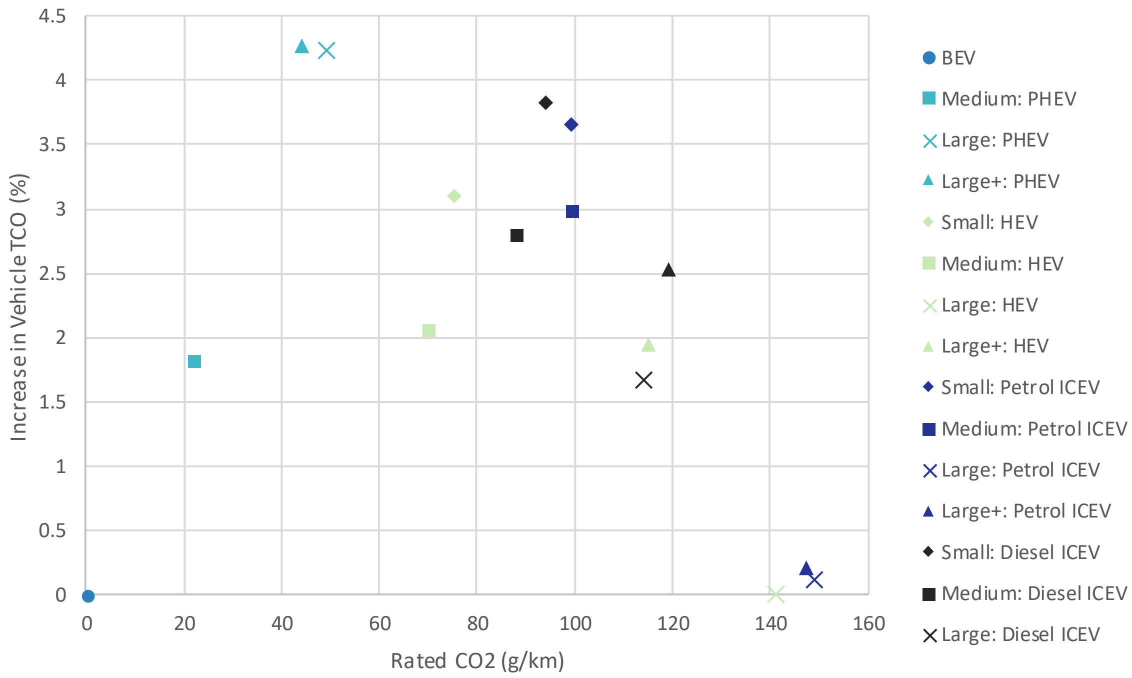

Figure 4-3: *Plot of each 'representative' vehicle's rated CO_2 (g/km) by the percentage increase in private vehicle TCO as calculated before and after the new VED tax system was introduced in April 2017. This calculation assumes all costs are the same for the vehicle TCO except for the change in VED. This figure shows that TCO has increased for all vehicles except BEVs. Vehicles in the small and medium size segments have seen a larger percentage ownership cost rise than those in the large and large+ size segments.*

costs have increased for all vehicles except BEVs. If we focus on HEVs, calculations show that across the HEVs of different sizes, HEVs in the small sized car segment are hit with the greatest percentage cost increase. Surprisingly, HEVs in the large sized vehicle segment have not experienced a tax increase because large HEVs have high test cycle CO_2 emissions, for example the Lexus GS 450h (141 g CO_2/km). Moderate cost increases are seen for HEVs in the medium and large+ sized vehicle segments. PHEV owners will see the highest rise in VED across all vehicle types (see Figure 4-3), with more than a 4% cost increase in ownership costs. Nearly 80% of PHEV market share is in the large/large+ vehicle size segments. These large vehicles are expensive with a list price of over £40 000 and are therefore liable for the additional £310 tax from year 2 to 5 of vehicle ownership. PHEVs already have a price premium resulting from their large battery and hybrid powertrain therefore an additional cost of around £1000 could affect whether consumers choose a PHEV or not. Over 80% of all PHEVs are bought as company cars, these vehicles are often sold on the general second-hand vehicle market at the three-year mark and therefore as the additional £310 is payable for ownership years 2 to 5 this will affect the next vehicle owner.

For BEV buyers there is no change in VED tax. In fact, with tax increasing for nearly every other vehicle, this makes zero emission vehicles even more attractive. In the small and medium vehicle size segments, BEVs have the cheapest ownership costs compared to other vehicles in the size segment.

As the new taxation system was designed to boost revenue, under this new scheme VED is either the same cost or is more expensive for all vehicles. For petrol and diesel vehicles, the small size segment vehicles experienced the biggest relative rise in cost. Small vehicles on average have lower CO_2 emissions than larger vehicles; therefore, historically they have been exempted from paying vehicle tax. Less fuel-efficient vehicles in the larger sized segments experience a much smaller relative tax increase.

Diesels in all size segments experience a VED tax increase. Historically, diesel cars have been favoured in the UK and across Europe because of higher fuel efficiency over conventional petrol vehicles (see Section 2.3.2 for more details). However, this vehicle type has been under high scrutiny recently as studies have found them to be the key cause of urban air pollution. Despite more stringent emissions legislation diesel cars still have poor air quality performance. Therefore, with air pollution exceeding legal limits in many cities across the UK, the government is trying to reverse fleet dieselisation. This new taxation system does not appear to discourage diesel purchases in the smaller size vehicle segments, however, in the larger size segments diesels vehicle tax rises much more than for petrol vehicles. Small diesels are the worst NO_x emitters, as larger vehicles often have better NO_x controls due to fewer budget constraints, for example the VW Passat 0.09 g/km NO_x versus the VW polo 1.2 g/km NO_x (Moody and Tate, 2017).

Large petrol and diesel cars have experienced the smallest tax increase across all size segments. These vehicles account for only around 5% of vehicle market share but are often high mileage business cars with low occupancy rates. With only a small tax increase it is unlikely that purchasing behaviour would change in the large size segment.

4.4.2 Historic TCO Comparison Between Different Ownership Types

Private car TCO and market share are more closely linked than company car cost and market share. This is evident from Figure 4-1, where private car market share is more reactive to changing cost than for the company car. The cost variation between different vehicle types is

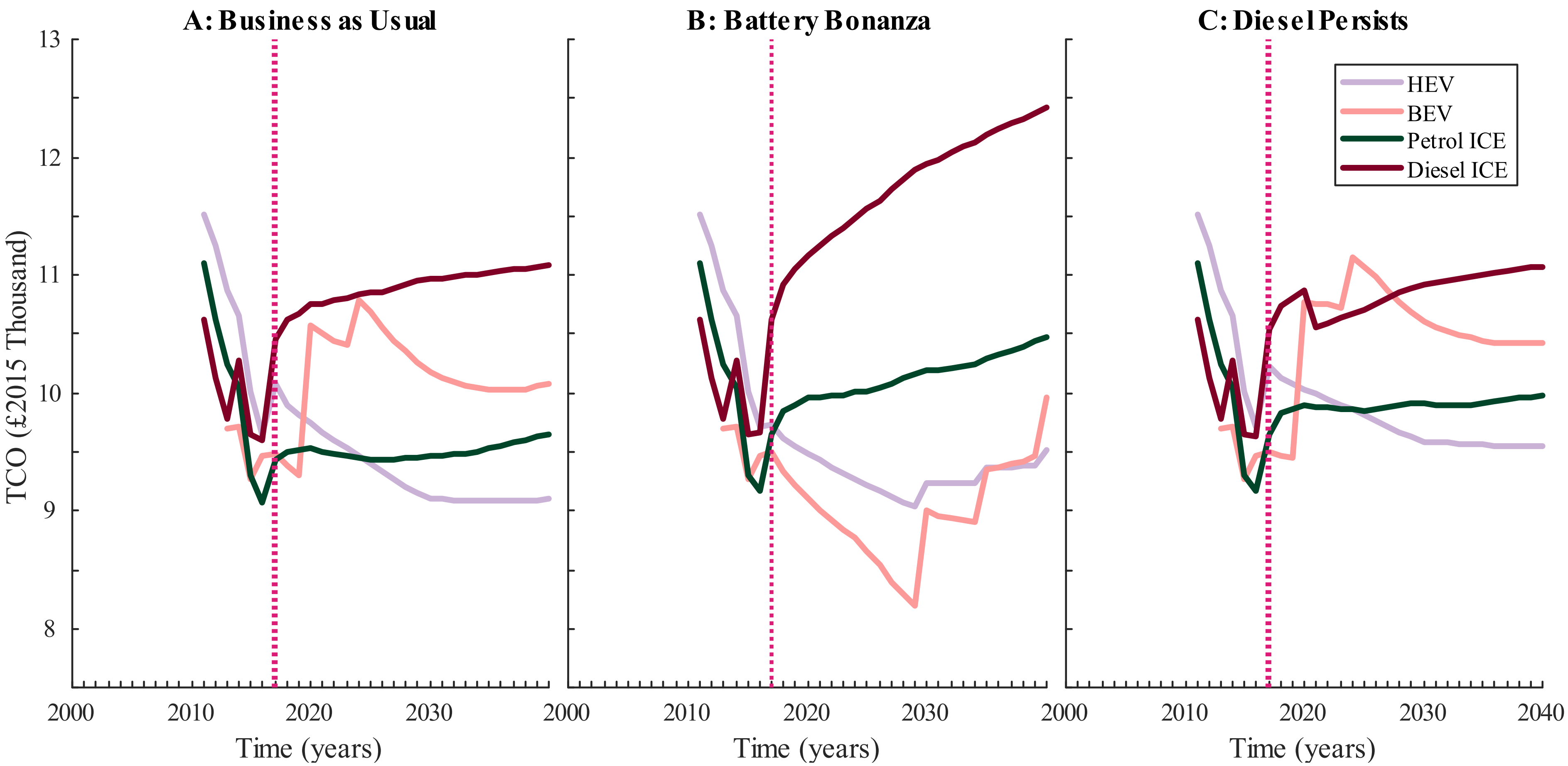

Figure 4-4a: *TCO scenarios – small size car segment.*

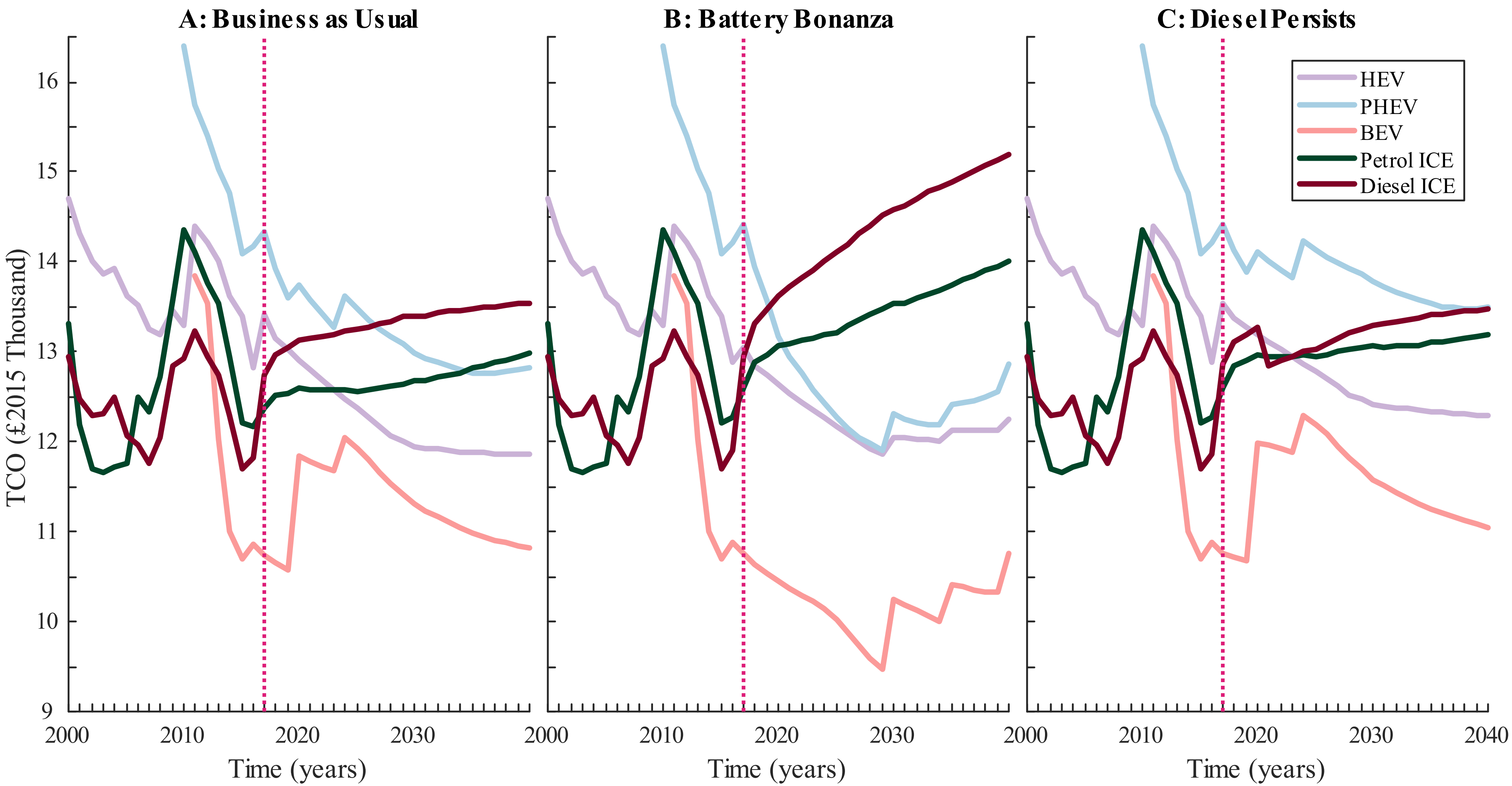

Figure 4-4b: *TCO scenarios – medium size car segment.*

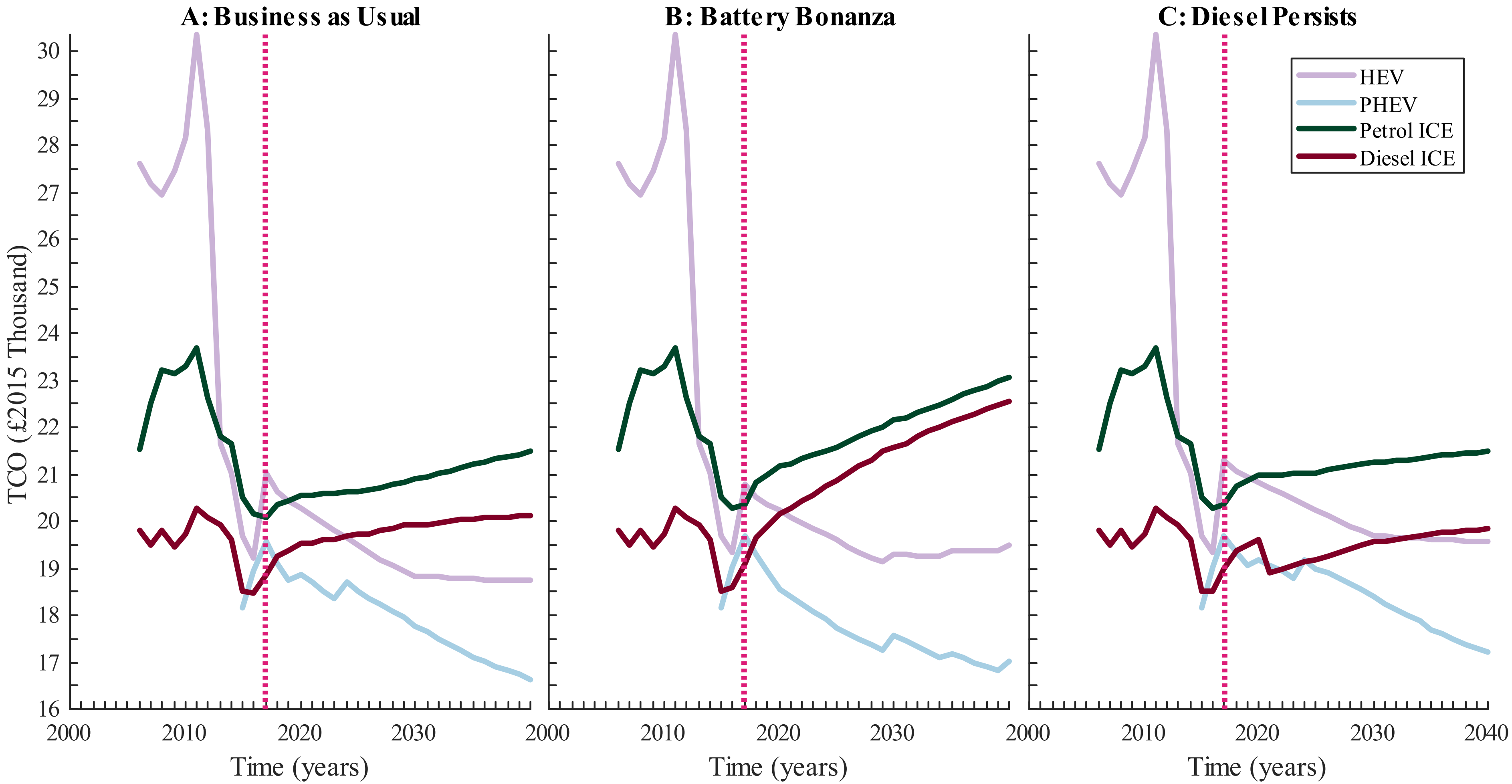

Figure 4-4c: *TCO scenarios – large size car segment.*

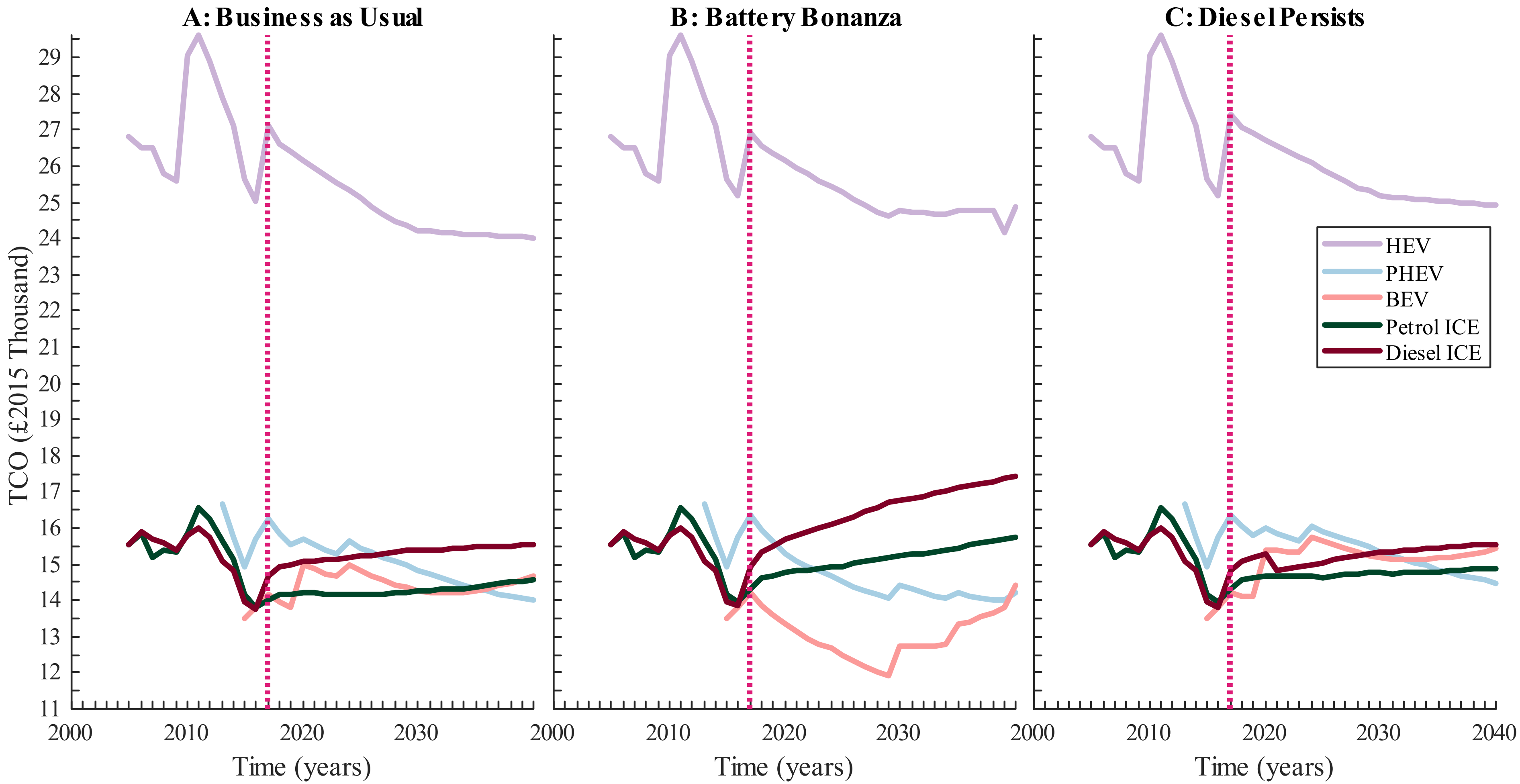

Figure 4-4d: *TCO scenarios – large+ size car segment.*

greater for company cars than for private cars. Low-emission vehicles such as BEVs and PHEVs have very low BIK rates and this offsets their high initial price. Generally, BEVs have higher market share in the private car market, whereas the majority of PHEVs were registered on the non-private vehicle market.

Across the different vehicle size segments, generally the larger the vehicle the greater the TCO (see Figure 4.1 a-h for details of historic vehicle TCO); this is true for both the private and company car costs. Company car purchases dominate large and large+ vehicle size segments (over 75% of new vehicle registrations). Company car taxes are graduated based on CO_2 with a surcharge for diesel (4% on the standard BIK rates - see Appendix 4 for full details), therefore company car purchases strongly favour vehicles with low rated CO_2. The differentiation is greater than for VED, for example the company car tax payable for 2018/2019 is £1824 for the BMW 5 series (petrol), £2100 for the diesel version and £903 for the Mitsubishi Outlander PHEV. Such a difference in costs can explain the high sales of Mitsubishi Outlander PHEVs in the non-private car market. Non-private vehicle purchases account for approximately 50% of new car registrations, therefore company car tax is a key policy tool for influencing EV purchases and deterring investment in diesel ICEVs.

4.4.3 Future TCO Comparison Between Different Market Size Segments

Based on this analysis, with falling costs, BEV uptake could be strong in the medium and large+ size segments (see Figure 4-1 a-h for HEV, PHEV and BEV market share across the different vehicle size segments) but financial subsidies and tax policy would have to support this. Cost components vary over market size segment, vehicle type and purchase year (see Figure 4-4 a-d for details of past and future vehicle TCO). Across the three scenarios, Battery Bonanza leads to the greatest divergence in vehicle TCO across powertrain types towards 2040. Towards 2030, EV TCO falls as a result of falling battery prices and lower manufacturing costs as global deployment grows. EV TCO increases towards 2040 as a result of increasing profit margins. The step changes in costs for BEVs and PHEVs (for example in 2020 and 2025 the baseline scenario) are a result of the assumed reduction in the Plug-in vehicle grant.

The small and medium size car segments account for over 70% of market share. Therefore, vehicle TCO in these markets are of key importance. In the small vehicle size segment, diesel ICEVs increase in cost faster than all other vehicle types in all three scenarios considered. This is most evident in the Battery Bonanza scenario as a result of the increased depreciation rate (see Table 4-5 for scenario details). In all the scenarios, HEVs are cheaper than ICEVs by 2025 at the national average annual mileage of 10 400. Long-term support of the Plug-in vehicle grant enables hybrid and EV TCO to fall further. It is likely in this scenario that OEMs would increase their profit margin to make up for losses as consumers switch away from petrol and diesel ICEVs (Wu et al., 2015). At present, there is no PHEV TCO for the small car size segment. With battery prices falling, it is anticipated that by 2040 battery and electrification costs would be low enough that PHEV models will be cheap enough to be introduced in the small size car segment.

In the medium size segment, BEVs are the cheapest vehicle type across all scenarios by 2040.[8] This is not the case in the small size segment because the battery in the Renault Zoe (the small BEV) is only 2 kWh smaller than that in the Nissan Leaf (the medium BEV) (22 kWh vs 24 kWh). By 2023, HEVs are cheaper than petrol and diesel ICEVs, this comes even sooner in the Battery Bonanza scenario with the Plug-in vehicle grant extended to support HEVs. PHEV vehicles in the medium size segment are very expensive because of their dual powertrain.

The large car size segment only accounts for 7% of the market share. Most vehicles (64%) in the large car size segment are bought as business or fleet purchases. In the large car size segment the purchase price of diesel ICEVs is less than petrol ICEVs, leading to a lower TCO for diesel vehicles (see Figure 4-2). For example, in 2015 petrol ICEV is £33 000, whereas diesel ICEV is £32 000. The large car size is the key segment where diesel vehicles could persist unless company car tax is sufficient to deter purchase of diesel vehicles. At present, PHEV TCO is greater than petrol and diesel vehicles. Battery prices need to fall dramatically for PHEVs to become cheaper than other vehicle types even in the Battery Bonanza scenario. PHEVs have only recently been introduced into the large size segment, in other size segments PHEVs have fallen in cost after introduction.

The large+ size segment accounts for 22% total car market share, approximately 65% of these are non-private registration and diesel ICEVs feature prominently in the large+ size segment. In this segment BEV TCO are projected to be significantly lower than other vehicle types by 2018 in all scenarios. The BEV chosen as the representative vehicle in this segment is not an SUV (unlike the other comparison vehicles) and therefore this may not be a truly comparable vehicle for consumers in this segment. PHEV TCO is greater than petrol and diesel ICEV TCO until around 2025. Note that the PHEV in the large+ size segment (Mitsubishi Outlander PHEV) is very popular in this company car market accounting for 75% of all PHEV purchases.

[8] In these cost scenarios the Nissan Leaf has a battery size of 24 kWh as was the case from release in 2010 to September 2018 when the new model of the Nissan Leaf was released with a slightly higher MSRP but a battery size of 40 kWh. At the time of this announcement the analysis in the thesis could not incorporate this information but the author is aware of this battery capacity step change.

4.5 DISCUSSION OF OTHER FACTORS AND COMPARISON TO THE TCO LITERATURE

4.5.1 Other Factors and Uncertainties Affecting TCO Projections

Historically there has existed variation in market share of different types of hybrid and electric vehicles across size and ownership segments (see Figure 4-1 for HEV, PHEV and BEV UK market share split by size segment and ownership type). The results and analysis in this chapter are dependent on the assumptions made regarding the cost components used in the TCO calculations. It is acknowledged that the assumptions made regarding the values chosen for the different parameters could have a significant effect on the conclusions drawn. Future vehicle costs are inherently uncertain but the scenarios in this chapter try to capture a proportion of this uncertainty.

Across the future scenarios considered in this chapter, hybrid and electric vehicles in the private market are likely to reach cost parity with petrol and diesel ICEVs at different points in time depending on the size segment – by segmenting the market there is greater insight into the cost projections. In this study it was found that BEVs could remain cost competitive across all size segments if there are favourable market conditions (as described in Scenario B in 4.3.3). Even under less favourable market conditions (as described in Scenario C in 4.3.3) BEVs could be cost competitive across all size segments without subsidies by 2030. PHEVs were found to take between 5 and 15 years longer to reach cost parity with ICEVs than BEVs. In most scenarios and size segments HEVs were found to have a higher TCO than BEVs in the long term.

At present the Manufacturer Suggested Retail Price of EVs may be artificially lower as OEMs are selling these vehicles with very small profit margin (Wu et al., 2015). OEMs need to meet EU mandated fleet average g CO_2/km targets by 2020, with each individual BEV counting for multiple vehicle sales (referred to as super-credits – see Section 2.3.1), therefore it has been found that these vehicles are being sold with a lower profit margin to stimulate sales (Wu et al., 2015). As the number of EVs manufactured rises over time, the cost of producing these vehicle types will most likely fall due to economies of scale, and the profit margin applied to these vehicles by OEMs will most likely increase to compensate for lost revenue from decreasing sales of petrol and diesel ICEVs (Wu et al., 2015).

The accessibility and price of charging infrastructure could affect adoption of EVs (Coffman et al., 2017). Experts consider fast charging infrastructure will most likely compliment the use of domestic charging points (IEA, 2018a). Access to fast charging infrastructure could enable EV drivers to travel further but primarily EV charging is anticipated to happen overnight. In the UK, publicly accessible charging points are often subsidised, but moving forward charging tariffs are likely to increase so that this can become a revenue stream for Local Authorities (Transport&Environment, 2018). Electricity prices may increase as the number of EVs grows, there are other policy options for potential falling revenue from petrol and diesel fuel sales such as road user charging. Although this option has been adopted in parts of cities such as Stockholm and Singapore, the political viability of implementing this option is challenging (Olszewski and Xie, 2005; Hensher and Puckett, 2005; Eliasson et al., 2009).

Market share of diesel ICEVs has fallen from 47% to 42% from 2016 to 2017 (Society of Motor Manufacturers and Traders, 2017). This is a result of a number of factors such as the public knowledge that diesel cars have contributed to urban air pollution (Schmitz et al., 2018); issues with compatibility of diesel ICEVs with LEZs (RAC, 2018a); the stricter MOT checks to detect failed DPFs (Evans, 2018); and the announcements of OEMs that diesel ICEV manufacturing will ramp down in the near future (IEA, 2018a). All these factors can contribute to uncertainty for consumers when considering vehicle purchase options. Such uncertainty is likely to lead to higher depreciation rates for diesel ICEVs towards 2040 (Morley, 2017b). In this thesis, all hybrids in this section are considered to be petrol rather than diesel. There are currently a small number of diesel HEV models available, but these only account for 1.2% of HEV market share. As market share of diesel cars has most probably peaked it is unlikely that diesels will expand significantly into the hybrid market.

As the VED tax system changed in 2017, it begs the question whether these increases are large enough to change vehicle purchase behaviour. As discussed in section 2.2.2, the actual value of financial incentives is not usually the same as the perceived value to the consumer. Therefore changing the tax system could be under or overvalued by consumers. PHEVs are seeing the biggest cost increase because of their large list price. On the other hand, the relative increase in tax on smaller vehicles is greater than other size segments because small vehicles tend to have lower CO_2 emissions and therefore historically have paid relatively little vehicle tax. The new VED tax system could lead to a shift away from smaller or low-carbon vehicles.

Other factors such as Mobility as a Service (MaaS) could affect vehicle ownership if adopted on a city scale (see Chapter 2 for more details). Similar to the current business market, ride-sharing companies would probably undertake a TCO assessment to ascertain which vehicle type could be cheapest. Such a TCO assessment would include the key TCO parameters from this chapter, certain component costs such as fuel and maintenance would most likely be greater than this study stemming from the high mileage of ride sharing vehicles.

4.5.2 Comparison to Other Studies

Other studies (described in Table 4-1) have projected future EV costs. Wu et al. (2015) forecasts that BEV TCO decreases to 2020 (these results agree with that of the analysis of this chapter) then increases after as a result of increasing profit margins. Petrol and diesel ICEV, and HEVs are projected to have stronger increase in TCO than PHEV or BEVs. For the short distance use case, the average TCO for PHEV and BEV is likely to remain higher than TCO of ICEV and HEV. Similar to the results of this chapter, PHEVs are predicted to have a greater TCO than BEVs. Wu et al. (2015) do not consider subsidies in their bottom up TCO model.

Hill et al. (2012) predict that the overall reduction in energy consumption between 2010 and 2050 ranges from 27%-50% depending on powertrain, this is a much greater energy efficiency gain than projected in this chapter. The difference in capital cost between powertrains are expected to narrow substantially by 2030 (similar to the results of this analysis), with many alternatives becoming cost-competitive if fuel savings are included. Similar to the results of this study, the battery cost reductions are important. Under low cost assumptions, BEV cars become comparable in price to ICEVs by 2050, a longer time scale than in the analysis in this chapter.

Contestabile et al (2011) identifies that market segmentation is key to future TCO studies, and the analysis of this chapter also find that powertrain TCO varies substantially across different vehicle classes. Douglas and Stewart (2011) produced a detailed TCO study that is quite dated now. They found that the TCO of the HEV, PHEV and BEV remains significantly greater than petrol and diesel ICEVs by 2025, contrary to the results of the analysis in this chapter especially for the small and medium vehicle classes. Thiel et al (2010) find that the high cost penalty that is linked to BEVs and PHEVs will remain a problem until 2030.

McKinsey (2012) find that PHEVs are more economic than BEVs in the short term but by 2030 PHEVs may be cost competitive with BEVs for small and medium cars, a similar result to that in this study. Fuel economy of ICEVs is expected to improve by an average of 30% by 2020, a more optimistic figure than used in this analysis. McKinsey (2012) finds that BEVs and PHEVs are viable alternatives to ICEVs by 2025, the analysis in this chapter agrees with this for most vehicle classes depending on the scenario. With tax incentives, BEVs could be cost-competitive with ICEVs as early as 2020.

4.6 SUMMARY AND CONCLUSIONS

This chapter examines how vehicle TCO changes across different vehicle size segments in the UK market. Investigating TCO by vehicle size segment and ownership type led to greater insight into how and why ownership costs have changed over time. It concludes that the difference between vehicle TCO amongst EVs and petrol/diesel cars varies over these size segments. Future vehicle costs will be affected by changes in several variables: primarily fuel price, battery price, and taxes. In fact, VED tax changes in 2017 affect PHEV purchasers greater than those who purchase other vehicle types. Based on this analysis, with falling battery costs, BEV uptake could be strong in the medium and large+ size segments but financial subsidies and tax policy would have to support this. Private car TCO and market share were found to be more closely linked than company car cost and market share; such that private car market share is more reactive to changing cost. The historic variation in company car cost was found to be more dependent on changing BIK tax rates than vehicle prices.

This chapter has built upon the TCO methodology from Chapter 3, extending the cost model to assess future vehicle cost scenarios. The cost scenarios in this chapter illustrate the uncertainty in future vehicle costs. Utilising the results of Chapter 3, that showed that vehicle TCO and market share were linked, along with the vehicle cost scenarios in this chapter, in the next chapter a vehicle adoption framework is introduced. The medium size segment is the most popular vehicle segment; therefore, this size segment is used as a case study. Although there is a difference in cost between different size segments, the general trends of falling hybrid/electric vehicle costs and rising petrol/diesel costs are similar across all vehicle size segments and using segmentation in this framework would give a false sense of accuracy. In addition, because the variation in company car cost was found to be more dependent on changing BIK tax rates than vehicle prices, and private car market share is more reactive to changing cost than company car market share, the market is not segmented by private and company car. In fact, the BIK rates for low emission vehicles have increased in recent years compared to petrol/diesel ICEV BIK rates, therefore market segmentation by purchase type is considered to add little value. Finally, in Chapter 6, the vehicle adoption scenarios from Chapter 5 are utilised to estimate the future on-road fleet mix under the three different scenarios outlined in this chapter leading to an assessment of network level vehicle emissions.

CHAPTER 5: MARKET DIFFUSION MODELLING OF THE FUTURE FLEET: LIMITATIONS AND EXTENSIONS

5.1 INTRODUCTION

In the coming decades, the vehicle sector is anticipated to transform as a result of changes in policy and public opinion. Diesel vehicles are largely held responsible for dangerous levels of urban air pollution , therefore the road transport sector is struggling to adapt with pressures to cut local air pollutants whilst reducing greenhouse gas emissions. With increasing news coverage publicising the high NO_x and particulate emissions from diesel vehicles, along with the VW dieselgate scandal, attitudes towards diesel vehicles are changing. Already in 2017 there is evidence that diesel vehicles are falling out of favour; market share has dropped by 10%, reversing recent trends.

Policymakers are considering policies to address the problems of urban air pollution such as the introduction of Clean Air Zones and Ultra Low Emission Zones. Hybrid and electric vehicles offer a low-pollutant alternative to conventional vehicles therefore sales could surge as consumers move away from traditional diesel cars. Hybrid and electric vehicle technology is advancing, with research and development in batteries leading to lighter, cheaper and more reliable models. As a result, hybrid and electric vehicle capital costs are falling, all-electric range is increasing, and consumer confidence is growing. Consequently, consumers are recognising the benefits of owning low-emission vehicles with record sales in 2017 (see Section 2.3.3). Taking the current challenges and opportunities facing the vehicle sector, up to date scenarios of vehicle adoption are interesting for policymakers who are trying to plan for the future.

This chapter considers future scenarios of electrification of the private vehicle sector in the UK from 2015 to 2040. Note that business cars are not modelled separately as it was found in the previous chapter that the link between cost and market share was primarily dependent on changing BIK tax rates. Therefore, the large uncertainties associated with estimating future tax costs based on the rated CO_2 emissions from the newly introduced WLTP test cycle combined with the changing BIK rates, leads to the conclusions that scenarios of company car costs would create a false sense of accuracy without providing any real insight. In Chapter 3 HEV TCO was found to be linked with market share, therefore the modelling in this chapter takes vehicle TCO projections (from Chapter 4) into account when modelling scenarios of the composition of future vehicle registrations.

The aim of this chapter is to assess the limitations of the standard market diffusion methodologies, evaluate how sensitive the standard market diffusion models are to different inputs, and assess when the standard market diffusion modelling method should and should not be applied to vehicle adoption. This chapter also considers a modelling framework that has a generalised form (e.g. generalised to include vehicle TCO) of the Bass model that is used to model different vehicle adoption scenarios. Without budget and time constraints, other approaches such as agent or choice models may be more insightful.

This chapter investigates the limitations of the three main standard market diffusion models – the Bass, Logistics and Gompertz models - also considering a simple generalised model. The generalised model estimates vehicle market share from 2015-2040. Other market diffusion scenarios have been published, but many only consider the standard market diffusion model without including a cost element. Often these use short data series or apply growth rates that have not been recalculated to adjust for the new market saturation level. The results of this chapter will feed into the next chapter (6) where the vehicle market share scenarios are used to estimate on-road fleet share then input into a coupled microsimulation traffic and instantaneous vehicle emissions model. For the purpose of this thesis, another set of pre-existing scenarios could have been used for input to Chapter 6. However, the author wished to fully explore the limitations of this modelling method, as well as using the vehicle TCO scenarios constructed in Chapter 4.

5.2 MARKET DIFFUSION MODELLING LITERATURE

Many studies have projected adoption of electric vehicles using a range of methods, such as agent-based models (e.g. Eppstein et al. (2011)) , consumer choice models (e.g. Brand et al. (2017) and Hackbarth and Madlener (2013)), systems dynamics (e.g. Struben and Sterman (2008)), and diffusion rate/time series models (e.g. Mcmanus and Senter (2009)). Agent-based models use computer simulated agents with individually assigned characteristics. These agents interact with each other, which in turn influences their purchase decisions. Consumer choice models are less complex than agent-based models as they use an aggregate level approach. Agent-based models and consumer choice models take into account complex interactions that are difficult to model accurately. Agent-based models and consumer choice models are usually reliant on large survey datasets, which can be challenging to deliver and expensive to attain (for a comprehensive review of papers using these methods see Al-Alawi & Bradley (2013a), Jochem et al. (2017) and Gnann et al. (2018)). Despite widespread acceptance of choice models, there are limitations stemming from the use of survey data that can rapidly become outdated. Opinions change with advancing technology and social exposure to new products. Additionally, surveys are often localised to a particular city and demographic, therefore they can be biased.

Market diffusion modelling has been applied to technology adoption in many different sectors including mobile phones (Michalakelis et al., 2008), electronics (Ford et al., 2006), renewable energy technologies (Rao and Kishore, 2010) and transportation (Mcmanus and Senter, 2009). It has the advantage over other modelling approaches, such as consumer choice or agent-based decision models, that it uses a simple design which accounts for social interactions and visibility of new technologies to model sales of consumer durable goods at an aggregate level (Bass, 1999). There is no need for expensive and time-consuming surveys, instead models are calibrated either using past data or assuming adoption will follow the same pathway as established technologies. However, there are systemic limitations to the market diffusion modelling methodology. Inaccuracies arise mainly from the need to specify the technology market potential, therefore if this method is used for future projections it can only be considered accurate if sales have reached the inflection point (the point at which the rate of new adoption has been reached) (Lindqvist and Puumalainen, 2001). This raises the question of how market diffusion models can be applied to gain a useful insight into future technological adoption pathways when the status of the technology adoption is pre-inflection point.

Several diffusion models are used in the literature but the Bass model features most prominently (Jochem et al., 2017). The Bass model accounts for two adoption factors: imitation – where adopters copy those that have already purchased the new technology, and innovation – where adopters chose to purchase the new technology despite lack of social exposure. This method builds mathematically on the notion of Roger's classical diffusion theory where cumulative adoption follows an S-shaped curve (see Figure 5-1). The first portion of adopters are labelled innovators, the later the individual adopts the greater they are said to imitate others following external factors rather than innovating according to internal attributes (Rogers, 2004). The Gompertz and Logistic models are a variant on the S-shaped growth curve, but are less common in the literature. Other similar market diffusion models exist (see Meade and Islam (2006) for full details of such models), but as these offer no advantage over the models discussed here therefore they are not included in this study.

The market diffusion literature is fairly limited compared to the wider vehicle adoption literature (Jochem et al., 2017). The studies that are available mainly examine the adoption pathways of hybrid or electric vehicles; investigating the potential for hybrids and electric

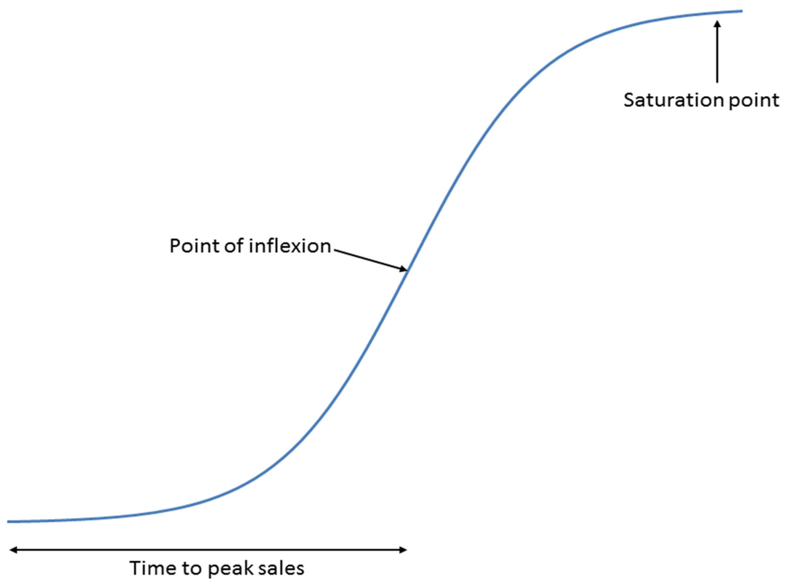

Figure 5-1: *Typical market diffusion adoption curve.*

vehicles in the road fleet (see Table 5-1 for review of vehicle adoption diffusion literature). The diffusion literature can be divided into two distinct groups: studies which project vehicle adoption by estimating diffusion parameters from historic data (e.g. Lamberson (2011), Cordill (2012) and Shoemaker (2012)) and those that use authoritative estimates (e.g. Won et al (2009), Davidson et al. (2013) and Park et al. (2011)). The Bass model is most commonly applied although several studies extend the basic model to include other pertinent factors such as vehicle cost or expanding the availability of charging infrastructure (e.g. Park et al. (2011)). Most studies specify the saturation point whereas others estimate this based on fitting the model to the historic data. Few of these papers have touched on the uncertainties associated with market diffusion modelling, such as Massiani et al. (2015) who explore the relationship between saturation level and parameters in the Bass model. Instead, most apply this method without taking model limitations or sensitivities into account. This is considered the first study to fully assess these sensitivities and to provide a framework for which to apply this relatively simple method within the context of fleet level vehicle adoption.

Many researchers have applied market diffusion modelling techniques (see Table 5-1 for market diffusion literature) but these studies have not illustrated how the method should be applied to minimise forecast error or do not have sufficient time-series data to make adequate projections. In light of the limitations of market diffusion modelling, this chapter explores how the diffusion methodology can be suitably adapted and applied to investigate the effect of different policy scenarios on vehicle adoption. Using hybrid vehicle adoption as a case study,

Table 5-1: *Market diffusion literature*.

Study	Time Window	Powertrain Type	Model Type	Location	Saturation Point	Model parameters
Davidson et al. (2013)	2013-2027	BEV	Bass	California's Santa Delano Valley	0.03, 0.25, 0.7 households	Authoritative Sources (Becker 2009)
Park et al. (2011)	2011-2050	Fuel cell	Generalised Bass	Korea, Japan and US	Total vehicle fleet	Japan HEV annual sales 1997-2006
Won et al (2009)	2009-2052	PHEV	Bass	Korea	Total vehicle fleet	HEV annual US sales 1999-2008
Lamberson (2011)	2011-2025	HEV	Bass and Gompertz	US	1.6 mln vehicles	Monthly US sales Feb 2001 – Oct 2007
Cordill (2012)	2012-2022	Prius, Civic, Ford Escape HEV	Bass	US	2.87, 3.68, 0.36 mln respectively	US sales 1999-10
Schoemaker (2012)	-	AFVs	Bass	US	435 000 vehicles	Monthly AFVs sales Dec 1995-Dec 2011
Massiani et al. (2015)	-	LPG, CNG, HEV, EV	Bass	Germany	Endogenous estimates based on different p values. Exogenous: 10 mln	Annual, AFV, 2005-2013, Monthly AFV Jan. 2009 to Sept. 2014

Table 5-1 continued…

Study	Time Window	Powertrain Type	Model Type	Location	Saturation Point	Model parameters
Jensen (2014)	2014-2020	BEV	Bass	Norway, The Netherlands and Denmark	Exo: discrete choice model	Jan 03-Jun 13
Cao (2004)	2003-2025	E85, CNG, HEV	Bass	US	245 971, 100 000, EIA scenario 19 mln vehicles	1993 – 2002 annual
McManus and Senter (2009)	2010-2050	PHEV	Bass, Generalised Bass, Logistic and Gompertz	US	1.9 mln vehicles	Annual data 1999-2008
Benvenutti and Reibero (2017)	1980-2030	AFVs and conventional vehicles	Generalised Bass	Brazil	Increasing based on cost	Annual data 1980-2016
This study	2000-2040	BEVs, PHEVs, HEVs, Diesel and petrol cars.	Generalised Bass (includes Bass, Gompertz and Logistic)	UK	Increasing based on cost	Monthly and Annual data 2000-2016

Note that AFV stands for Alternatively Fuelled Vehicles.

this chapter assesses the potential of the standard market diffusion models, as well as the market share adoption scenarios that can be achieved within a limited budget and under rigid time constraints. By applying this modelling framework, this study produces new up-to-date scenarios for the future vehicle registrations under different vehicle cost scenarios. These scenarios are not directly forecasts of the vehicle fleet, but are realistic futures that illustrate the difference cost plays in vehicle adoption. Disaggregate modelling approaches such as choice modelling are widely accepted as the optimum method of modelling vehicle adoption pathways. Many projects do not have the time or financial resources to utilise disaggregate modelling approaches, therefore in these situations the market diffusion methodology may be the best approach to gain the necessary level of understanding. Aggregate models such as diffusion models are easily updated as the market changes.

5.3 INVESTIGATION INTO STANDARD MARKET DIFFUSION MODELS

5.3.1 Standard Market Diffusion Model Methodology

The diffusion equations model adoption such that the number of hybrid/electric vehicles in the fleet follows an S-shaped growth curve (see Figure 5-1). The standard Bass and Logistic curves are symmetric around the inflection point (the point at which the rate of new adoption has peaked) whereas the Gompertz curve is asymmetric with the inflection point reached below half of the saturation level. In the standard model, the saturation level is specified by a constant in each model (exogenous) or can be estimated within the model (endogenous). However, this cannot be accurately approximated within the model unless the inflection point has been reached, which is not the case for hybrid or electric vehicles in any vehicle market across the world.

The Bass model builds on the notion of Roger's classical diffusion theory where consumers adopt depending on whether they innovate or imitate (Rogers, 2004). The equation governing the Bass model is given by:

$$A = M\frac{1-\mathrm{e}^{-(p+q)t}}{1-e^{-\frac{q}{p}(p+q)t}}$$

where *A* denotes cumulative adoption, *t* for time, *p* is the innovation diffusion constant, *q* is the imitation diffusion constant and *M* is the saturation level (the differential equation is given in Appendix 5-A).

The logistic model is another 'S-shaped' diffusion curve, originally used to study population growth in the 19th century. The equation governing the Logistic model is given by:

$$A = \frac{L_1}{1 + e^{-L_2(t-L_3)}}$$

where L_1 is the maximum saturation level, L_3 is the number of years to peak sales, finally L_2 is the slope parameter. L_1 is determined exogenously and the constants L_2 and L_3 is fitted using historic data (the differential equation is given in Appendix 5-A).

The equation governing the Gompertz model is given by:

$$A = G_1 \exp(-\exp(-G_2(t - G_3)))$$

where G_1 is the maximum saturation level, G_3 is the number of years to peak sales, finally G_2 is the slope parameter. G_1 is determined exogenously and the constants $G_2$and $G_3$are fitted using historic data (the differential equation is given in Appendix 5-A). The diffusion parameters in the models are fitted using non-linear least squares regression.

5.3.2 Sensitivity Analysis of Standard Bass, Logistic and Gompertz Models

5.3.2.a Bass, Logistic and Gompertz Projections

The Bass, Logistic and Gompertz models are the most common in the transportation literature (see Table 5-1). Analysing the model fit on UK hybrid historic data establishes that the error between the data and the model is similar for the three market diffusion models (on average less than 1%) the low error results from cumulative adoption of hybrid vehicles following the start of an S-shaped curve. Nevertheless, the prediction error is lowest for the Gompertz model compared to the other two models. The one-step-ahead error is significantly smaller for the Gompertz than Bass or Logistic (see Figure 5-2 for results of one-step-ahead error with explanation of how this metric is calculated), showing that UK HEV adoption is most suited to market diffusion modelling using the Gompertz model. With the same saturation point, the Bass and Logistic model projects steeper uptake than the Gompertz model towards 2040 (see Figure 5-4). In projecting future adoption to 2040, the variation in using the Gompertz method compared to the Logistic or Bass models using the same saturation level is greater than hypothesised. The Root Mean Squared Error (RMSE) was calculated as 7420 for the Bass model, 10 300 for the Logistic model, and 6010 for the Gompertz model. The much greater value of the RMSE for the Logistic model indicates that the Logistic model is less accurate in projecting HEV fleet share than the Bass or Gompertz models for this historic data set.

5.3.2.b Market Saturation Level

The market saturation level is the user input with the largest sensitivity. The greater the value of the saturation level, the greater the variability between projections using different methods. As the saturation level increases the value of the diffusion parameters falls (see Figure 5-3).

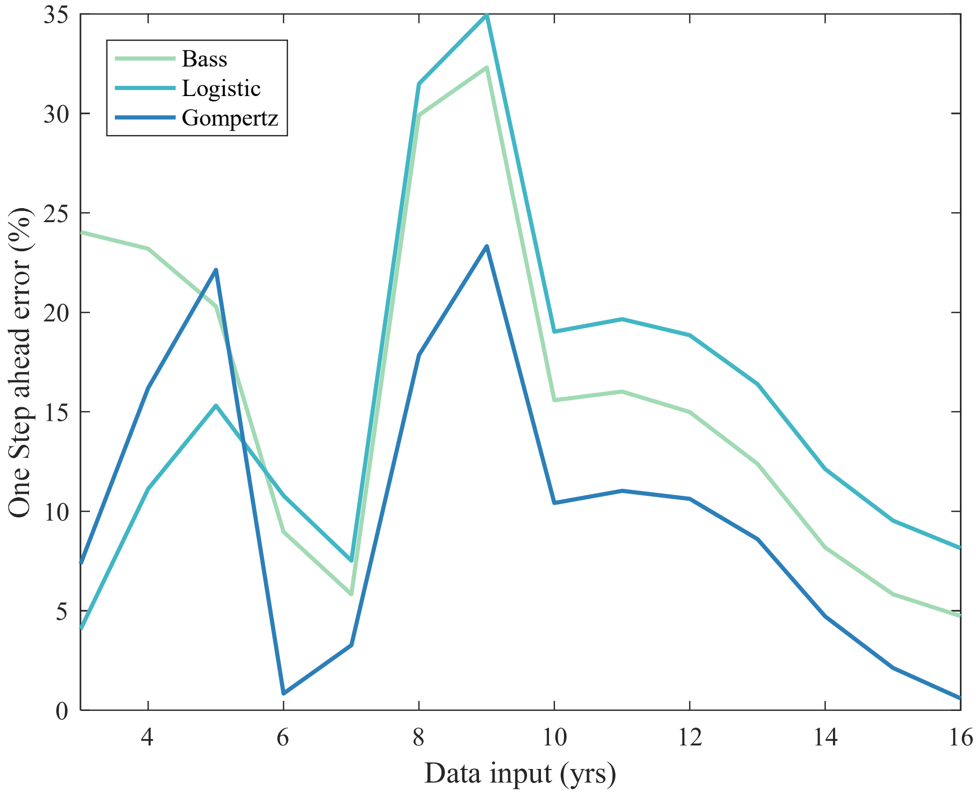

Figure 5-2: *One-step-ahead error for the standard market diffusion model calculated for HEV fleet share using data input years from the year 2000. The one-step-ahead error is defined as the percentage error between the predicted value compared to the actual value for the next value in the series (Montgomery et al., 2008). For example, 5 data input years indicates that the data used to build the model is HEV fleet share for the years 2000 to 2004, with the one-step-ahead error calculating the error between the predicted value for HEV fleet share for the year 2005 and the actual value of HEV fleet share in 2005. This figure shows that the error is significantly smaller for the Gompertz than Bass or Logistic, showing that UK HEV adoption is most suited to market diffusion modelling using the Gompertz model based on the historic data.*

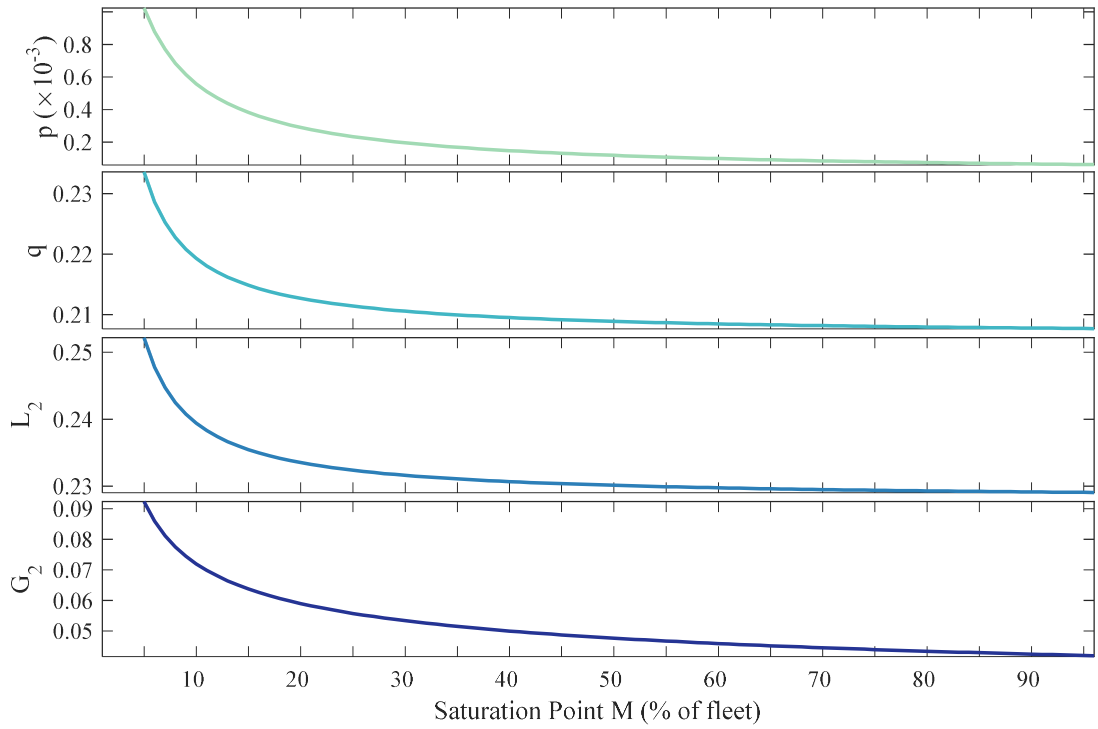

Figure 5-3: *Effect of different saturation level on diffusion parameters. The p and q parameters correspond to the Bass model,* L_2 *relates to the Logistic model and* G_2 *corresponds to the Gompertz model (see Section 5.3.1 for details of equations and their parameters).*

Analysis reveals that there is a non-linear relationship between parameters and the value of the saturation point (see Figure 5-3). Therefore, parameter estimates for the standard model are most sensitive to variation in the saturation level when it is small - in this case when saturation level is between 5%-20% of the total vehicle fleet (see Figure 5-3), which is the case in most EV markets. Massiani et al (2015) documented the relationship between the saturation level and the Bass parameters finding that "a doubling of [the saturation level] results in a bisection of the Bass *p* value". Analysis in this chapter corresponds to these findings. Because of the relationship between growth parameters and the chosen saturation level, unless the saturation level is similar to another study, the growth rate cannot be used from the study (see Table 5-1). Therefore, if a researcher chooses to use a growth rate from a pre-existing study the growth parameters must be adjusted to account for a different saturation level.

With this in mind, we ask the question: how should the saturation level be selected? If the modeller is unsure of the saturation point, there are two choices: a constant or a variable parameter. If a constant value is chosen, then the researcher needs to test several different scenarios and if a constant growth rate is taken from another study then this must be adjusted. Many studies use authoritative sources, and some models even include a choice model to determine saturation point (such as Jensen et al. (2014)), but this is often outside the

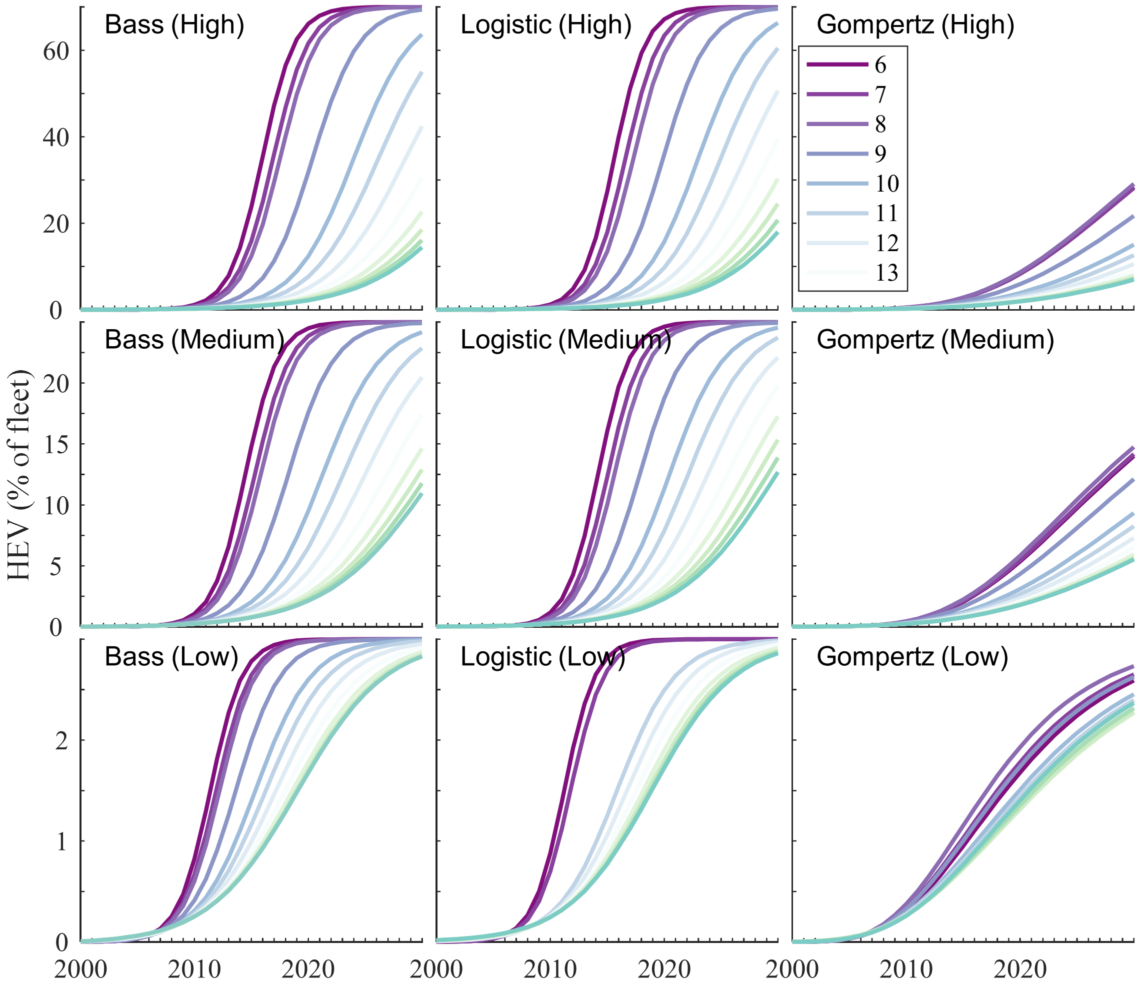

Figure 5-4: *Bass, Logistic and Gompertz projections using different numbers of time series input points for different saturation levels. For example, '8' represents the projection to 2040 when calibrating the projection based on time series data from 2000 to 2007. (High represents 75% of the fleet, Medium represents 25% of the fleet and Low represents 3% of the fleet).*

budget and time constraints of a project. If a variable saturation level is chosen then the main options include using a 'disadvantage curve' (see Pfahl et al. (2014)) or a price elasticity (see Benvenutti et al. (2017)). Both latter options lead to the saturation level increasing as hybrid/electric vehicle price falls compared to the conventional vehicle.

5.3.2.c Time period of calibration data

Many studies have fitted projections on limited time series data. The very nature of diffusion projections means they are needed while the available time series data is still very limited, and before the inflection point on the adoption curve has been reached. The issues with projection uncertainty with limited data series is illustrated in Figure 5-4. The more data points available in the data series the lower the fitted growth rate for the Bass, Logistic and Gompertz models. Predictions using different market diffusion models show that there is significantly less variation in the Gompertz predictions than the other models showing that the Gompertz model is more robust to the time period of calibration data when projecting HEV adoption.

With the Logistic and Bass model, using only 6 years of data (2000-2005) to calibrate the model, HEV sales are projected to reach their saturation point by 2017. When the observed fleet percentage of HEVs is still less than 2%, we can conclude that this projection is optimistic. Mass market PHEVs and BEVs have been available for approximately 7 years, therefore even if the saturation point is accurately estimated the growth parameters will most likely be too great, projecting the saturation level to be reached within a short time span. The average car scrappage age is 14 years (SMMT, 2015), therefore approximately 8% of the fleet is replaced annually. The timespan of the curve reaching saturation point would be deemed unrealistic if the adoption curves indicated more than an 8% increase in fleet share of HEVs in one year. Considering Figure 5-4, the 'high' saturation level with either 6 or 7 data points for the Bass and Logistic models produce forecasts that could not be realised with current fleet scrappage levels.

Market share of different types of hybrid and electric Vehicles has varied across different size segments due in part to tax, model availability and battery range limitations as discussed in Chapter 4. Due to the limited data available across different size segments, dividing projections by size segment gives a false sense of accuracy.

5.3.2.d Annual vs Monthly Calibration Data

Most studies in the literature use annual data, but some use quarterly sales data (such as Massiani et al. (2015), Shoemaker (2012) and Lamberson (2011)). In modelling, generally the greater the number of the data points, the lower the level of model bias (Van den Bulte and Lilien, 1997). Model bias is defined as the error between the expected (or average) prediction of the model and the correct value. Monthly sales data can be difficult and costly to obtain and therefore annual data is preferable. In the case of market diffusion modelling, the projection is fitted on cumulative adoption data therefore monthly data does not provide any additional information. This analysis finds that calibrating projections using monthly sales data, as opposed to annual data, does not reduce forecast error.

Parameter estimates are different for annual and monthly data. A multiplication factor of 12 is used to convert between annual and monthly data (as is convention in the literature), but due to the nonlinear nature of the model this factor may not be accurate. Nevertheless, when

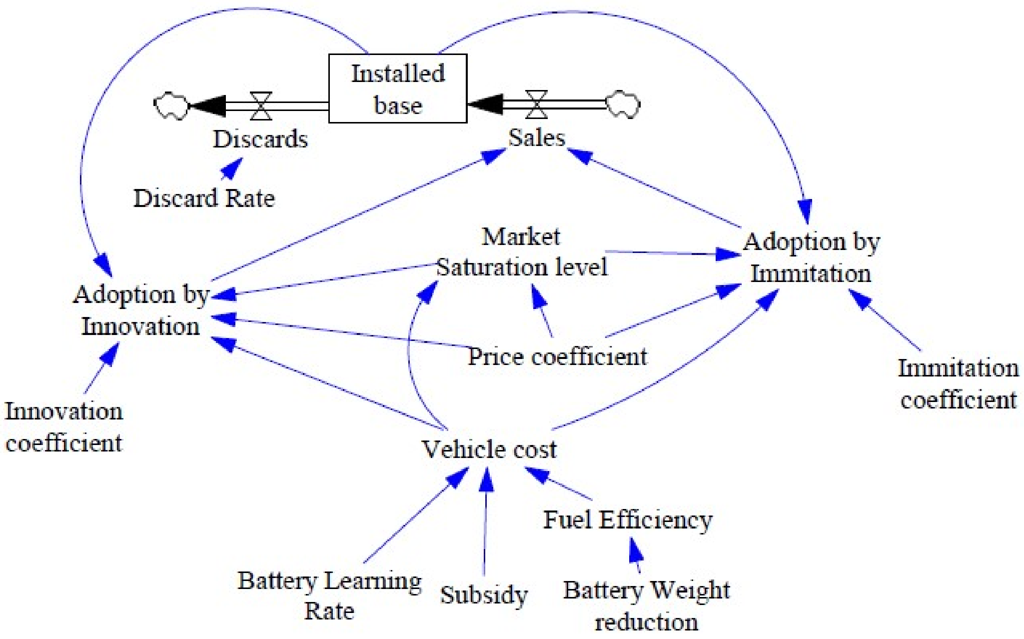

Figure 5-5: *Extended Bass modelling framework. (Note that the model was built within the MATLAB modelling environment, but a graphical interpretation was produced within Vensim).*

Table 5-2: *Description of model components accompanying Figure 5-5.*

Model component	**Description**
Installed base	Number of HEVs/PHEVs/BEVs in the fleet
Discard rate	Determined by scrappage curve (adapted from Leibling (2008) to reflect current average vehicle age).
Price coefficient	Coefficient to determine how much changing vehicle TCO affects future adoption.
Vehicle Cost	Vehicle TCO.
Battery Learning rate	Percentage reduction in battery cost for every doubling in manufacturing capacity.
Subsidy	Initial cost subsidy from the government.
Adoption by Innovation	Number of new adopters as a result of new adopters innovating determined by *p* value.
Adoption by Imitation	Number of new adopters as a result of new adopters imitating other adopters determined by *q* value.
Market saturation level	Function of vehicle cost.
Battery weight reduction	Annual weight reduction as energy density increases.

using this multiplication factor parameter estimates calibrating using monthly and annual data are within 1.5 % of one another. This uncertainty is negligible compared to other model uncertainties (such as saturation point) therefore annual data is adequate.

5.4 EXTENDED MODELLING FRAMEWORK

5.4.1 Extended Bass Model Methodology

The standard models can be generalised using a transformation to include other pertinent factors and policy drivers such as subsidies or increasing the availability of charging infrastructure. Costs of hybrid and electric vehicles are anticipated to change significantly in the next two decades (see results in Chapter 4). Panel regression analysis on historic adoption found that across different vehicle markets HEV ownership costs are correlated with market share (for more details see Chapter 3), therefore this is considered an appropriate basis for the model.

In the case of the Generalised modelling framework used in this analysis (see Figure 5-5 for model outline and Table 5-2 for an explanation of details of model parameters) the initial purchase cost and running cost per mile for the hybrid, plug-in hybrid, battery electric and diesel vehicle compared to its conventional petrol counterpart is included to account for changing costs over time.

The differential equation governing the generalised Bass model is given by,

$$\frac{dA}{dt} = \left(p + q\frac{A(t)}{M}\right)\left(M - A(t)\right)x(t)$$

with a cost transformation such that,

$$x(t) = 1 + \beta_1\left(\frac{P(t) - P(t-1)}{P(t)}\right) + \beta_2\left(\frac{G(t) - G(t-1)}{G(t)}\right)$$

where $P(t) = \frac{I_{EV}}{I_{ICE}}$ and $G(t) = \frac{R_{ICE}}{R_{EV}}$ and *I* and *R* indicate the initial vehicle cost and running cost per mile respectively, β_1 and β_2 are coefficients of initial and running cost respectively, (a summary table detailing the equations governing the generalised Bass, Logistic and Gompertz models is given in Appendix 5-A). The form of the model extension is supported by the regression analysis in Chapter 3 that found that the link between cost and adoption was strongest when initial cost and running costs were split. The values of the Bass model parameters (*p* and *q*) which are used in the generalised model are not directly comparable to the standard case because of the modelling extension. The *p* and *q* values for HEVs was fitted to the historic data, the same values were applied to BEVs (as evidenced by the similar adoption pathway from Section 2.3.3), and a factor of two was used for PHEVs (as evidenced by their quicker historic adoption pathway from Section 2.3.3).

Usually a market diffusion model is fitted on cumulative adoption of technology, whereas this form of the generalised model is fitted using market share data, therefore this model needs to be able to mimic behaviour where market share falls as well as rises. Market saturation level is variable with a price elasticity of 0.8 (following Benvenutti et al. (2017)) such that for each vehicle type as costs fall, the market saturation level rises (a similar approach is taken by Benvenutti et al. (2017)).

The generalised cost model will be used to model three policy scenarios: Business as Usual (where current support of electric vehicles phases out as expected), Battery Bonanza (where the 2040 target of 100% market share of hybrid and electric vehicles is met) and Diesel Persists (where support for diesel ICEVs continues) - as detailed in Chapter 4.3.3. The results of the cost model from chapter 4 are used as the input to the generalised market diffusion model. In the cost model the mid-sized vehicle segment (C/D) is used to represent the vehicle fleet with the Ford Focus, Toyota Prius, Toyota Prius Plug-in and Nissan Leaf assuming the role of the conventional petrol/diesel ICEV, HEV, PHEV and BEV vehicles respectively. Due to the limited data available across different size segments, dividing scenarios by size segment gives a false sense of accuracy in this modelling method, therefore this chapter gives vehicle adoption scenarios aggregated across vehicle powertrain type – note these scenarios are not necessarily forecasts but more an illustration of the difference between scenarios depending on external costs. Note that in the extended modelling framework consumers are assumed to switch from diesel ICEVs after 2017 when they replace their vehicle; whereas BEV, PHEV and HEV adopters are assumed to replace their vehicle with one of the same type (as evidenced in Hardman et al. (2016)).[9]

5.4.2 Results and Discussion

The uncertainties in the standard model illustrate that the standard market diffusion models should be used with great caution to directly project future technology adoption. Therefore, in this section using an extended Bass modelling framework, the effect of evolving vehicle costs

[9] Note that the extended modelling framework, can output either fleet share or market share. Because the author wished to be able to model vehicle emission Euro standards within the fleet for all petrol and diesel vehicles, it was simpler to output market share at this stage, then later model fleet and traffic composition by Euro standard in the following chapter using the 2015 Leeds ANPR survey as a baseline.

Table 5-3: *Parameter estimates for the Extended Bass Model (Note that there are not separate parameter estimates for petrol ICEVs as once market share of HEV, PHEV, BEV and diesel ICEVs has been projected, petrol ICEVs are assumed to be the remainder.)*

Vehicle Type	p *Innovation coeff.*	q *Imitation coeff.*	β_1 *Initial cost coeff.*	β_2 *Running cost coeff.*
HEV	0.0022	0.21	1.98	2.13
PHEV	0.0044	0.42	8.13	1.98
BEV	0.0022	0.21	8.38	2.00
Diesel ICEVs	0.0015	0.16	7.33	2.93

on adoption is investigated through different scenarios rather than forecasted projections. The model fit on historic data resulted in a model error on average less than 15% between modelled and historic values. In the standard model, only one 'projection' can be produced based on parameter assumptions and historic data, but with the generalised model the effect of financial externalities on vehicle adoption across the fleet can be quickly assessed, this adds a layer of value to the modelling and allows for more relevant insights.

The difference between the cost scenarios in Chapter 4 (see Figure 4-4 for vehicle cost scenarios) illustrates the effect of financial incentives on the TCO of hybrid and electric vehicles. These cost scenarios lead to different adoption pathways (see Figure 5-6 for market share adoption scenarios 2015-2040 for HEV, PHEV, BEV, petrol and diesel ICEV). Such an evaluation is useful and often necessary in the first stage of policy assessment and to plan for the infrastructure requirements for an increasingly electrified fleet.

Some of the limitations of the standard model do not apply to the extended Bass model, and therefore it is a better option for analysing vehicle adoption using different policy and cost scenarios rather than attempting to produce one single forecast. Although a longer time series is more desirable, meaningful results can still be gained using the extended method with only a short time series of 7 years. The cost basis of this model removes the unrealistic adoption curves that resulted from a short data series fed into the standard market diffusion model (see section 5.3.2). For the extended Bass model the parameter values of p and q for HEVs was found to be 0.0022 and 0.21, slightly lower than the values for the standard model. However, these parameter values are not directly comparable due to the model extension used. The parameter estimates for the extended Bass model (see Table 5-3) indicate that EV market share is more sensitive to changing initial cost than running cost because β_1 (coefficient for initial cost) is much greater β_2 (coefficient of running cost), this echoes the regression results in Chapter 3. EV market share is more sensitive to changing initial cost than for HEV market share as evidenced by the higher value of β_1 (coefficient for initial cost). The RMSE was calculated as 0.2 for HEVs, 0.52 for PHEVs and 0.1 for BEVs. This indicates that the results for BEVs and HEVs are a better fit on historic data than for PHEVs. Because the TCO underpinning the extended Bass model is based on the private purchaser and PHEVs are predominantly business purchases, this could partly explain the higher RMSE for PHEVs.

Utilising this modelling framework, market share of diesel vehicles is anticipated to fall between 2018 and 2040 (see Figure 5-6). Diesel car sales have already peaked and are starting to decrease as a result of changing public opinion regarding high vehicle pollutant emissions, increased tax rates, expected restrictions and uncertain depreciation rates. In light of this, hybrid and electric vehicle sales are expected to rise to fill the void. In addition, the UK government have legislated for a ban of conventional vehicles in 2040[10], therefore Scenario B (Battery Bonanza) illustrates adoption pathways that could achieve this target without a step change. Under Scenario A – Business as Usual, diesel vehicle market share declines to 14% in 2040 with a peak at 2020 (when the plug-in vehicle grant is removed). Scenario C (Diesel Persists) illustrates a worst-case scenario such that diesel vehicles remain a cost-effective option for high mileage cars and therefore market share only falls to 22% by 2040.

In Scenario A (Business as Usual) falling diesel market share leads to more consumers choosing to adopt HEVs – rising to 33% in 2040. HEVs require no change in behaviour as they do not have a plug-in capability, therefore this is an easy switch for consumers. Whereas, in Scenario B (Battery Bonanza) consumers move way from conventional vehicles choosing to purchase PHEVs and BEVs instead. In this scenario there is continual governmental support as the plug-in vehicle grant is gradually phased out to 2040. This keeps the price of PHEVs and BEVs low enabling market share to reach 37% and 32% respectively. In Scenario C (Diesel Persists), the higher market share of diesels impedes HEV adoption leading to a mere 13% market share by 2040.

The lack of smoothness in the adoption scenarios indicates the sensitivity of these scenarios to changes in cost. The changes in the plug-in vehicle grant are clear across all vehicle types, as the interconnected nature of the model illustrates that large changes in cost of one type of

[10] There is large uncertainty surrounding whether this ban will include HEVs or not, as there has been several contradictory announcements. The interpretation used in this research is that the ban will only include conventional petrol and diesel cars.

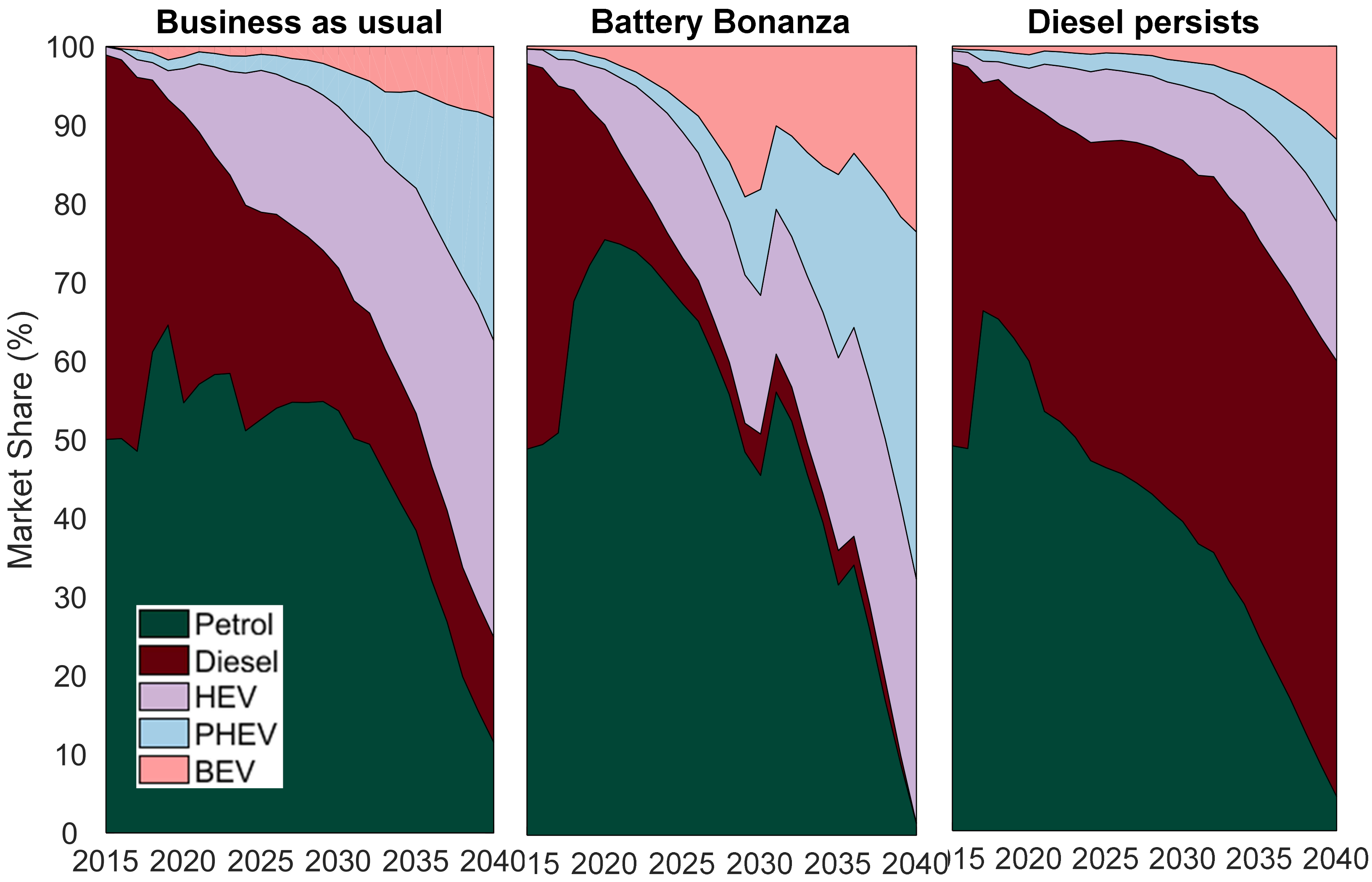

Figure 5-6: *HEV, PHEV, BEV, petrol and diesel market share scenarios using extended Bass model (see Appendix 5-B for results table).*

vehicle affect market share of them all. This modelling framework illustrates how the market diffusion methodology can be used as a basis to assess the effect of different cost scenarios on the adoption of hybrid, electric and diesel vehicles. Falling diesel market share could be the catalyst to rapidly increase hybrid and electric vehicle market share. If diesel costs increase significantly and incentives are used to persuade consumers to choose hybrid or electric vehicles over conventional vehicles, the 2040 ban on conventional vehicles could be achieved without a step change.

5.4.1 Comparison to Other Models

To put this work in context, the adoption scenarios are compared to other modelling studies. The projections from other studies (summarised in Figure 5-7) are generally complex models with dozens of sub-models and numerous hidden assumptions. Many of these models take years to build and are difficult to update. With market share of BEVs, PHEVs and HEVs increasing, many of these models cannot be updated or re-run to accommodate for changing conditions. The methodology detailed in this chapter has the advantage that it is relatively simple, inputting up-to-date market share data with clear model assumptions.

Unsurprisingly, different methods yield different forecasts (see Figure 5-7 for comparison to UK projections). Similar to the scenarios in this chapter, other projections forecast HEV market share will peak before BEV and PHEV market share. PHEVs are often considered as an intermediate technology as batteries improve and BEV range increases. Note that the projections included here are mainly those that forecast market share rather than fleet share. It is difficult to estimate market share from fleet share unless annual data is given therefore it was not deemed appropriate to try to include these other vehicle stock forecasts in this section. The forecasts compared in this section are primarily UK vehicle market forecasts.

In the UK, the projections from the National Emissions Inventory (NAEI) are the leading authoritative source on the future UK vehicle fleet (National Atmospherics Emissions Inventory, 2017), the most recent NAEI projections use 2016 as a base year and market share has been estimated from NAEI car stock projection figures. For HEVs, the NAEI projections are significantly lower than for the scenarios in this study reaching around 7% market share by 2035. However, for PHEVs the NAEI projections are slightly higher than even the most optimistic scenario in this study estimating around 27% market share by 2030. Finally, the NAEI BEV projections are well aligned with scenario C (Diesel Persists), the scenario with the lowest adoption of BEVs (see Figure 5-7) estimating around 4% market share by 2035. The methodology behind these projections is not publically available, therefore it is not possible to

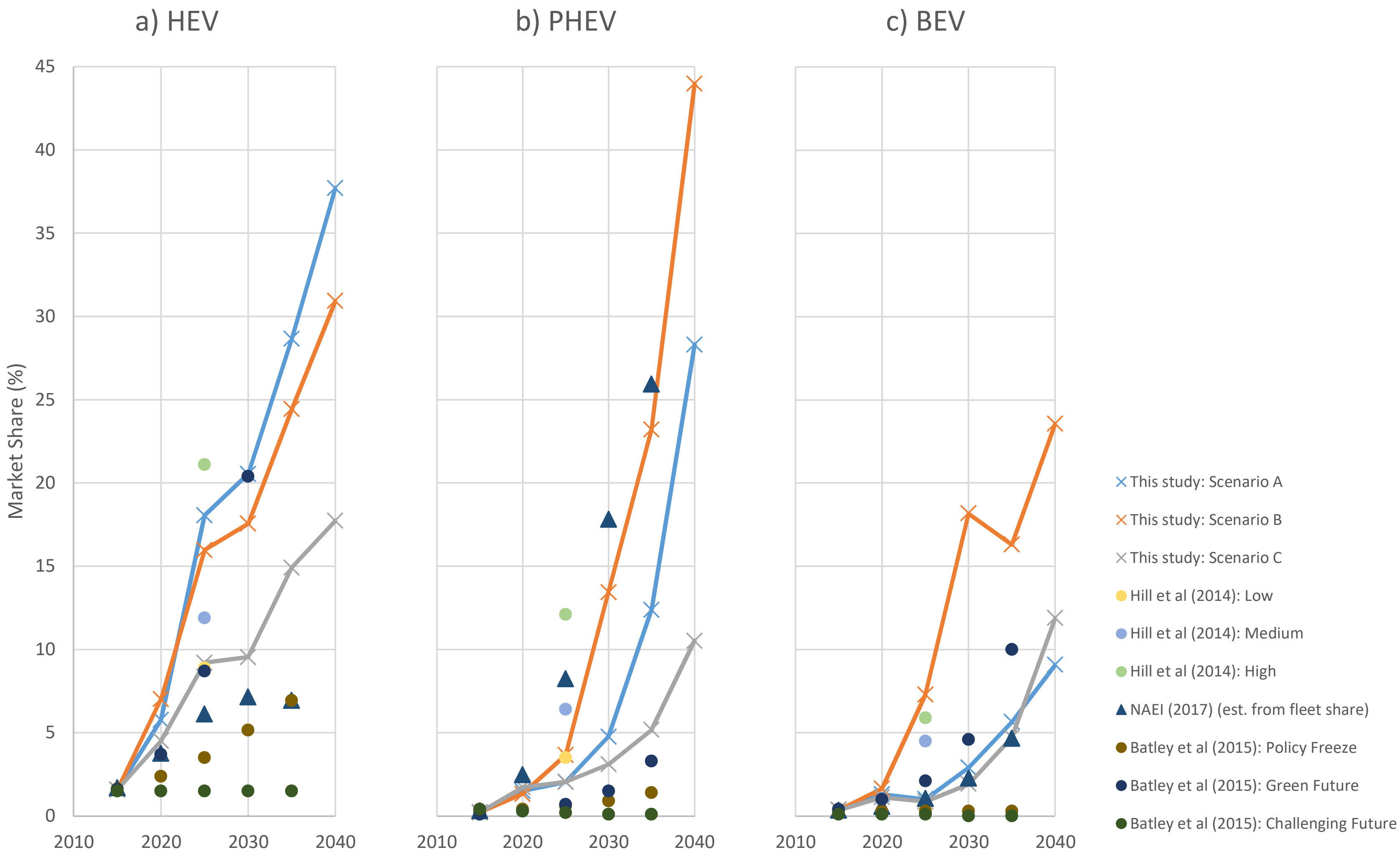

Figure 5-7 a-c: *Comparison of projections from other UK studies to the scenarios from the extended Bass model.*

analyse the assumptions behind these results.

Hill et al. (2014) uses the SULTAN (SUstainabLe TrANsport) model for its illustrative scenarios. The SULTAN model is a high-level model used to estimate the possible impact of policy on transport on a national scale. The SULTAN scenario model is based on the TREMOVE baseline model (version 2.7) updated to account for the recent recession. Many variables are sourced from TREMOVE including vehicle lifetimes, load factors, urban/rural/motorway split, NO_x and PM emission factors. In SULTAN, AFV market share is determined by a nested logic model. This is based on using cost and time matrices which are calculated on influencing factors such as infrastructure capacity and travel speeds both coming from the infrastructure module, structure of vehicle fleets, transport charges, fuel price or fuel tax changes. Hill et al. (2014) adopts three different scenarios to estimate CO_2 reduction from Low Emission Vehicle (LEV) adoption to 2025. The low scenario assumes a moderate rate of LEV uptake. The medium scenario has been developed as a more challenging evolution of the low scenario, presenting above average rates of introduction of electrified vehicles and more rapid uptake of a range of LEV technologies for heavy duty vehicles. The high scenario has been developed with extremely rapid deployment of the lowest emission LEVs necessary to achieve the 2025 GHG reduction target. The results of the scenarios show that HEV adoption could be almost double PHEV uptake by 2025 reaching 22% and 12% respectively, with BEV adoption much lower at around 7%.

Batley et al. (2015) designed a model ('EcoDriver') to illustrate future scenarios of uptake of ecodriving systems. The EcoDriver model is a comparatively simple excel based model with key inputs such as oil price and GDP to project the size of the vehicle fleet. AFV market share is determined as a result of focus groups consisting of experts from academia and industry. The market share represents the target penetration of the number of AFVs. The 'Green Future' scenario indicates that BEV adoption could be higher than PHEV adoption reaching 10% by 2035.

5.5 SUMMARY AND CONCLUSION

Estimating the effect of changing ownership cost on the potential number of Electric Vehicles can inform and direct low-carbon transport policy. Without budget and time constraints other more complex approaches such as agent or choice models are the optimal methodology to projecting future hybrid and electric vehicle adoption, but these methods still have limitations stemming from the use of survey data.

Market diffusion models can be used as a tool to test out policy when there are financial/time constraints in place such that we cannot use a more extensive model, in such situations often a model with a fine resolution is not necessarily needed. This chapter highlights the fact that the uncertainties associated with the standard model mean that the basic market diffusion model should not be used to project the fleet without sufficient data (i.e. technology adoption has reached its inflection point). However, adoption can be investigated if the saturation level is either variable or different scenarios are investigated e.g. low, medium and high, and if using a growth rate "off the shelf" it is adjusted for the saturation point used compared to the study it was taken from. The main value in this analysis is assessing how the parameter values change with different assumptions, and acknowledging the strengths and weaknesses in the standard market diffusion models. This extensive sensitivity analysis adds to the market diffusion literature showing the results of the three main market diffusion models and how they differ.

The results of the extended Bass model show how a generalised modelling framework can be applied to produce future adoption scenarios. The main value of this chapter is producing new up to date adoption scenarios with an easy updatable method. Going forward this means that with new data these models can be tracked and rerun to enable greater insight into the changing vehicle market. Scenario analysis illustrates how different ownership costs resulting from economic externalities affect adoption patterns for hybrid and electric vehicles. It is clear that by supporting the plug-in vehicle grant and ensuring diesel vehicle ownership costs are greater than conventional petrol cars, the dieselisation of the fleet can be slowly reversed.

In the next chapter the vehicle market share scenarios detailed here are translated into the on-road fleet composition of the Leeds road network. By utilising a coupled microsimulation traffic model with an instantaneous vehicle emissions model, the effect of the evolving fleet on network level vehicle emissions is assessed. Despite the uncertainties in the vehicle adoption scenarios in this chapter, the next chapter uses vehicle emissions models that are considered to be reliable, accurate and the state-of-art. The errors in the multistage modelling process compound with each stage, therefore there is little use in using aggregate level emissions estimates. Additionally, in this thesis we are interested in assessing how emissions vary in different levels of congestion, as there is a non-linear relationship between vehicle emissions and speed; for this assessment an accurate emissions model is required.

CHAPTER 6: THE EFFECT OF CHANGING VEHICLE FLEET COMPOSITION ON VEHICLE EMISSIONS: A LEEDS NETWORK CASE STUDY

6.1 INTRODUCTION

City level policy is incentivising and legislating for the purchase of hybrid and electric vehicles to improve air quality and meet greenhouse gas emissions targets. For example, the installation of EV charging points in city centres is a common method to encourage consumers to switch to electric. Incentivising and legislating for cleaner vehicle purchases is less politically sensitive than pedestrianizing city centres, creating Low Emission Zones/Clean Air Zones or installing bus lanes, with lower upfront costs than large public transport investment. In the coming decades, it is anticipated that more consumers and fleet managers will choose to purchase a low-emission vehicle (as investigated in Chapter 5), but the actual resultant change in vehicle emissions on a city scale has previously only been very roughly assessed.

This chapter uses a Leeds road corridor (A660) as a case study to examine the effect of the evolving traffic mix on network-level vehicle emissions. Leeds is a typical UK city with similar levels of congestion to other cities of the same size such as Birmingham and Manchester (GOV.UK, 2017a). It is therefore a representative case study area for the UK. London has important differences in not only the level of traffic demand but also fleet share due to policies such as the congestion charge, LEZ, and now ULEZ that have led to a lower average vehicle age than other UK cities.

The aim of this chapter is to assess how vehicle emissions change at a network level with a changing fleet mix. To do this, the vehicle market share scenarios are used from chapter 5 is combined with an Automated Number Plate Recognition (ANPR) traffic survey of the Leeds network from 2015, to estimate the expected trends in the road fleet composition (estimated in vkm) from 2015 to 2040. A microsimulation traffic model of Leeds is employed (built originally by Wyatt (2017) in the AIMSUN simulation environment and improved in this work to stimulate a 24-hour period amongst other advancements), to estimate realistic vehicle trajectories for all vehicle types. This input is collated into a second-by-second (instantaneous) vehicle emissions model. The 'Simulink H/EV Energy and Emissions Model' adapted from Richard Riley's doctoral thesis (2016) is used for hybrid and electric cars, and the PHEM model (developed by TU Graz) is used for all other vehicles. This multi-stage methodology allows for analysis temporally and spatially over the 24-hour modelling period with a breakdown of the contribution to emissions split by vehicle type and emissions Euro standard.

Several different methodologies could be used to estimate vehicle emissions from the future fleet scenarios. The microsimulation methodology in this chapter has been chosen because aggregate modelling methods do not have the resolution to estimate the effect of the changing fleet on a network level spatially and temporally. Research by Wyatt (2017) found that at a vehicle scale second-by-second vehicle emission models were significantly more accurate than aggregate models. Therefore, as model errors will multiply at a vehicle network level, this was concluded to be the most appropriate method to use. The advantages of using the microsimulation methodology are extensive, enabling in-depth analysis into spatial emission hotspots, the effect of the stochastic nature of traffic, and the variation of vehicle emissions throughout the day.

This chapter contributes to the literature in three key areas: incrementally improving the microsimulation traffic model to span a 24-hour period; studying bus vehicle dynamics from primary data collection; and assessing the effect on energy and emissions of different numbers of hybrid and electric vehicles in the on-road fleet mix using microscale models. Although there is great uncertainty surrounding the future fleet composition (as discussed in Chapter 5), it is important to attempt to accurately assess the effect on emissions of the changing fleet to understand the effect of evolving Euro standards and higher penetrations of hybrid and electric vehicles: small percentages of EVs may have significant non-linear effects on network level emissions, especially in congested windows. Errors in the multistage modelling process can potentially amplify; therefore, this is considered the most rigorous method to draw meaningful conclusions despite the inherent uncertainty in future fleet scenarios.

6.2 COUPLED TRAFFIC SIMULATION AND VEHICLE EMISSION MODELS LITERATURE

6.2.1 Traffic Models

Traffic simulation models have been used for several decades to model urban and highway networks. The applications of this analysis vary widely from analysing road layout designs, traffic signal timings, driver behaviour and the effect of new technologies such as intelligent transport systems. Traffic simulation models vary on scale and therefore detail. Macro-scale models encapsulate larger networks at a lower resolution, whereas micro-scale models deal with behaviour of individual vehicles on a 1 or 2 Hz frequency. In these situations, there is a trade-off between computing power/the time needed to run the model and the detail necessary for the modelling purpose.

Several different microsimulation traffic models have been designed to model vehicle flows such as VISSIM, PARAMICS, and MITSIM. AIMSUN is arguably one of the best microsimulation models for running network models for several key reasons, including fewer modelling parameters, better vehicle dynamics behaviour and ease of user interface (Olstam and Tapani, 2004; TSS, 2011). The AIMSUN software supports static and dynamic equilibrium traffic assignment, and dynamic simulations, amongst other important features. To model vehicle movements at a microscopic level, AIMSUN introduces sub-modules for the drivers' car-following and lane-changing behaviour (TSS, 2011). These sub models include car following, lane changing, gap acceptance for lane changing, gap acceptance for yielding, overtaking, on-ramp, off-ramp, and look-ahead distance. AIMSUN has several modelling parameters that can be manually altered which influence the internal behaviour models, these parameters fall under the categories of global, local and vehicle attributes[11]. FHWA (Federal Highway Administration) recommends selecting the least possible number of parameters for calibration; running calibrated simulations repeatedly for robust results. AIMSUN has fewer modelling parameters than popular microsimulation tools like VISSIM, PARAMICS, and MITSIM (Olstam and Tapani, 2004). This lower number of parameters leads to lower modelling error (Brockfeld et al., 2003), this is one of key reasons why AIMSUN is a better choice for this study.

Vehicle dynamics in the traffic simulation model are critical to the accuracy of modelling vehicle behaviour and are mainly determined by the car-following and lane-changing sub-models (Panwai and Dia, 2005). The Gipps model governing car-following behaviour in AIMSUN, has been shown to be superior to the psychophysical spacing models used by PARAMICS and VISSIM (Panwai and Dia, 2005).

Finally, AIMSUN has a graphical user interface, this is easier to use than other microsimulation traffic modelling interfaces such as VISSIM or PARAMICS. The simulation in AIMSUN can be run either graphically or as a 'batch' simulation, such that the modelled vehicle can be seen moving around the network in real time or the 'batch' simulation can be run quicker without this feature. These characteristics make the vehicle flow calibration process simpler for the user.

[11] A full explanation of the AIMSUN methodology is available in the AIMSUN User Guide (TSS, 2013b) and the Dynamic Simulators Users' Manual (TSS, 2013a).

Previous microsimulation traffic studies have focused mainly on a smaller geographic area for example a single junction or a small number of vehicles. By contrast, the work by Wyatt (2017) is a larger and more detailed network than modelled in the literature. The work in this thesis builds on the work from Wyatt (2017) incrementally enhancing the underlying network modelling before applying to the future vehicle fleet scenarios developed in this thesis and applying a microscale vehicle emissions model. Despite the time intensity of using the microsimulation traffic modelling approach, the use of this higher resolution methodology enables greater insight into the effect on network level emissions of different penetrations of hybrid and electric vehicles in the fleet temporally and spatially.

6.2.2 Vehicle Emission Models

Several key factors have been found to affect vehicle emissions. These include the vehicle specifications (e.g. vehicle and engine type), vehicle loading, traffic conditions and road gradient (Colberg et al., 2005; Xue et al., 2013; Wyatt et al., 2014; Elkafoury et al., 2015). A vehicle emissions model should take most of these into account to reduce error in the modelling process. A properly calibrated coupled traffic and vehicle emissions model (as defined in Appendix 6-E) can produce estimates of network level emissions of which the cost of undertaking primary data collection of vehicle emissions at that scale would be prohibitively expensive (Jackson and Aultman-Hall, 2010). There are several existing vehicle emissions models which are used for this purpose including DEFRA's (Department for Food, Rural and Agriculture affairs) Emissions Factors Toolkit (EFT v8.0.1) (DEFRA, 2018), The HandBook on Emission FActors for road transport (HBEFA v3.3), The United States (US) Environmental Protection Agency's MOtor Vehicle Emission Simulator (MOVES v2014b) (EPA, 2015) and The Technical University of Graz's (TU-Graz) Passenger car and Heavy duty Emission Model (PHEM v11.7.10) (Hausberger, 2017). Each of these models estimates vehicle emissions with a different methodology.

DEFRA's Emissions Factors Toolkit (EFT v8.0.1) (DEFRA, 2018) is an average speed model based on the COPERT (Computer Programme to calculate Emissions from Road Transport) emissions calculation tool. In this model, the vehicle emissions are calculated as a function of average speed over a link. The total vehicle emissions for that link can be estimated by entering in the average link speed, the vehicle fleet composition, the length of the link, and the total vehicle flow through the ink. This methodology is suboptimal as trips through the link with the same average speed may have different acceleration profiles therefore leading to different emissions (Barlow and Boulter, 2009; Vallamsunder and Lin, 2011). These types of models can be inaccurate at a microscale. In Wyatt (2017), the EFT model was found to significantly underestimate vehicle emissions because it does not account for congestion or road grade.

The HandBook on Emission FActors for road transport (HBEFA v3.3), is a 'traffic situation' model where several factors are used to estimate vehicle emissions including road type, traffic conditions and average link speed. Traffic situations include area (rural or urban), road types, speed limit and level of service (e.g. level of saturation). Each of the 276 traffic situations are represented by a real-world speed-time driving pattern for the vehicle type. The PHEM instantaneous emissions model is then used to estimate the emissions factors from these speed-time driving patterns. HBEFA was designed primarily to inform emission factors for city, regional and national scales (Schmied, 2014), however, this methodology has been applied to estimating emissions at a link level with generally poor results (Wyatt, 2017).

The United States Environmental Protection Agency's MOtor Vehicle Emission Simulator (MOVES v2014b) is a model which 'bins' a vehicle's Vehicle Specific Power (VSP) (see Appendix 6-A for definition and derivation of VSP) and speed. MOVES was designed to estimate emissions at a regional/national level but has the capacity for a microsimulation application. The key assumption in this model is that the vehicle emissions within the 'bin' are broadly similar for a particular vehicle type and age. Using VSP as a proxy for CO_2 emissions is becoming increasingly popular in vehicle emission models (Song and Yu, 2009; Coelho et al., 2009; Xu et al., 2010).

The Technical University of Graz's (TU-Graz) Passenger car and Heavy duty Emission Model (PHEM v11.7.10) (Hausberger, 2017) is a second by second instantaneous emission model. PHEM uses engine power output and simulated engine speed to interpolate from a high resolution engine emission map to estimate pollutant emissions (Luz and Hausberger, 2015). These engine maps details fuel consumption and exhaust emissions of Nitrogen Oxides (NO_x), Carbon Monoxide (CO), Hydrocarbons (HC), Particulate Mass (PM), and Nitrogen Monoxide (NO). TU Graz have used a large number of vehicles to build this model, and it is being constantly updated and improved to include new vehicle types. The narrow operating regions in PHEM over the engine power output and engine speed lead to a larger number of bins than is possible in the traditional binning methodology. For example, the most detailed engine maps in PHEM have more than 350 bins, as opposed to the 23 offered in MOVES. This approach should therefore reduce the error in estimating vehicle emissions. Wyatt (2017) found that when comparing measured and modelled vehicle emissions, PHEM was found to be the most accurate vehicle emissions model discussed in this chapter, for this reason PHEM is used for the vehicle emissions modelling in this thesis.

AIMSUN also has an inbuilt vehicle emissions module. This model assumes that vehicle operate within four modes: idling, cruising, acceleration or deceleration (Swidan, 2011). However, Anya et al. (2014) found that these estimates differ by more than 16% on arterial roads. Hence, the default AIMSUN emissions model was not considered accurate enough for this study and instead, fuel consumption and other pollutant emissions were calculated using the PHEM platform.

Research by Wyatt (2017) found that second by second vehicle emission modelling tools were significantly more accurate than using aggregate models. Wyatt (2017) found that the HBEFA and EFT models significantly underestimate the majority of micro-scale section real-world CO_2 emissions when compared to real world PEMs data, whereas, MOVES and PHEM only slightly underestimate the CO_2 emission factors. Through statistical analysis of the vehicle emission tools and the real world PEMs data, Wyatt (2017) found that MOVEs and PHEM provide a good approximation of the on-road emission of the test vehicle. Wyatt (2017) concluded that the "EFT 'average-speed' emission model and the HBEFA 'traffic situation' model were unable to replicate the CO_2 emission of a real world test lap with sufficient accuracy to make either of them a useful tool in estimating the real-world emission of the specific test vehicle." This leads us to the conclusion that on a network scale these modelling errors could multiply therefore necessitating the need for a second-by-second vehicle emission model such as PHEM in this research.

At present, the PHEM emissions model does not include a module for Hybrid or Electric Vehicles, emissions from these vehicle types are estimated using the 'Simulink H/EV Energy and Emissions Model' described in Section 6.3.7.

6.3 METHODOLOGY OF THE COUPLED TRAFFIC SIMULATION AND VEHICLE EMISSION MODELS

In this section, the steps in the modelling process linking the vehicle market share scenarios (see Chapter 5) through to calculating network level vehicle emissions are detailed. The focus of this modelling is the Leeds city road network. In terms of traffic and pollution problems, Leeds is a typical UK city similar to other UK non-capital cities such as Birmingham and Manchester. Vehicle emissions will be aggregated on an hourly basis over a 24-hour period for four different snapshots in time (2015, 2020, 2030 and 2040) under three different future scenarios (Business as Usual, Battery Bonanza and Diesel Persists) to reflect the effect of the evolving fleet on network level emissions.

The flow diagram in Figure 6-1 shows how the vehicle market share scenarios from Chapter 5 feed through to calculate network level vehicle emissions. The fleet for the base year (2015) was sourced from an Automated Number Plate Recognition (ANPR) traffic survey of the city (with duplicates removed) – this is discussed further in section 6.3.1. For subsequent years, the vehicle stock is aged, vehicles are scrapped according to scrappage curves and new vehicles are introduced based on the market share scenarios (Chapter 5) with their corresponding Euro standard attached. From the 2015 Leeds traffic survey, the age distribution and split of vehicle types is calculated for the fleet both in terms of number of total number of registrations and on-road vkm split. Conversion factors between total number of registrations and on-road vkm split were calculated based on this survey and used to estimate fleet split in terms of vkm for the future scenarios. The trajectories from the Leeds network traffic model, along with the fleet mix are fed into the TU-Graz PHEM emissions model for all vehicles except hybrid and electric vehicles that are fed through the Simulink H/EV Energy and Emissions Model. Finally, the results of these two models are aggregated for our analysis to calculate total network emissions of CO_2 and NO_x. Each step of the flow diagram will be discussed in detail in this section.

6.3.1 Leeds ANPR Survey

The 2015 base fleet is taken from the 2015 Leeds Automated Number Plate Registration (ANPR) survey. The Leeds ANPR survey was undertaken on Monday 9th February 2015 on the A660, by Nationwide Data Collection on behalf of Leeds City Council and the University of Leeds Institute for Transport Studies. The ANPR cameras were positioned on the A660 (Headingley Lane) at 53.816552N, 1.567555W (see Figure 6-2), capturing data from both northbound and southbound traffic flows. The survey lasted for a complete 24-hour period, starting and finishing at 00:00. On the date the survey was undertaken, the weather was dry and overcast. With no unusual events or roadworks in the vicinity, the traffic was considered representative of 'typical' traffic in the location.

The ANPR survey captured 16 930 number plates in total with a success rate of 94.86%. For cars 31% of the vehicles in the ANPR were found to be duplicates, by removing these duplicates we can also estimate the vehicle fleet composition. The average age of the cars in the ANPR survey was found to be 7.9 years; this is insignificantly greater than the national average of 7.8 years (Society of Motor Manufacturers and Traders, 2018). From Figure 6-3, it is

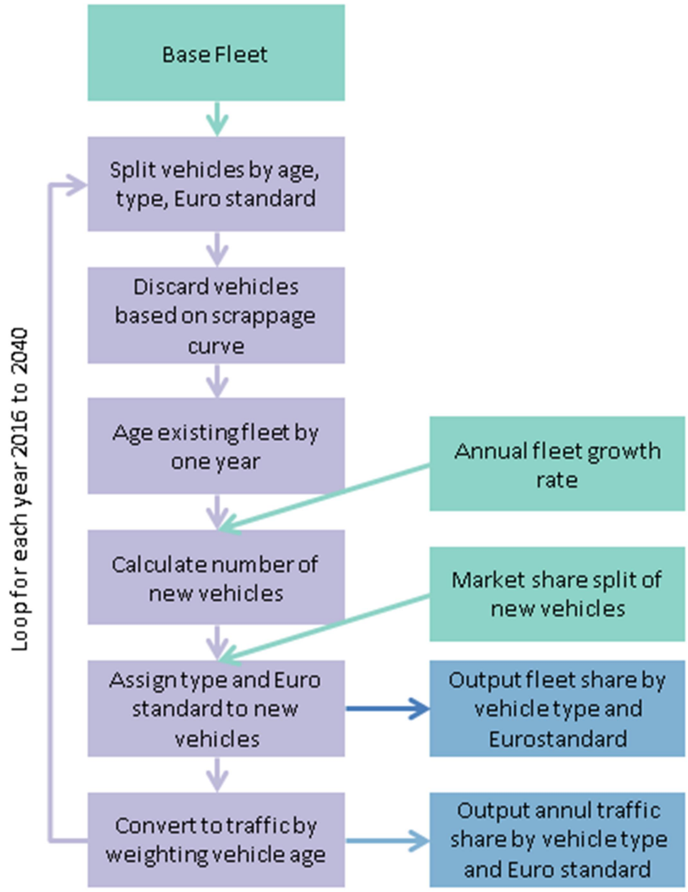

Figure 6-1: *Vehicle turnover model to convert Leeds base fleet (2015) to output Leeds vehicle fleet mix (vkm) 2016 to 2040.*

Figure 6-2: *Map of Headingley Leeds network displaying ANPR camera position (Wyatt, 2017) (©Copyright Google™ 2015).*

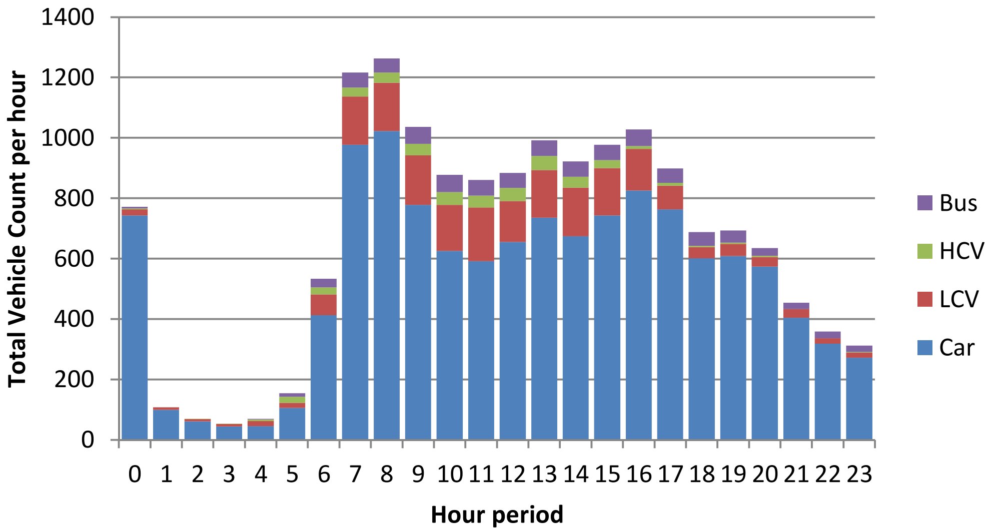

Figure 6-3: *ANPR vehicle count by hour and vehicle type.*

evident that cars dominate the traffic mix, with 79% of the number plates captured.[12]

6.3.1 Vehicle Scrappage and Replacement Model

For the years 2016 to 2040, the vehicle turnover model determines annually which vehicles to scrap and the number of new vehicles in the fleet. Vehicles are scrapped according to scrappage curves. This assigns a probability of scrappage depending on vehicle age (see Figure 6-4 for vehicle scrappage curves). All cars are scrapped by the time they reach 20 years of age, however, the average age is 13.5 years in line with current averages (Society of Motor Manufacturers and Traders, 2018). The focus of this analysis is the car fleet; however, the vehicle turnover model extends to buses, LCVs and HGVs, this is to ensure the split of Euro standards for different years is conceivable for these vehicle types. The scrappage curves are designed to be vehicle type specific designed to keep the age distribution of the fleet constant in line with the base year.

For the vehicle replacement model, assuming an increase of car fleet size of 1%, together with the number of scrapped cars calculated, the number of new cars to be added to the fleet is computed. These new vehicles are split by powertrain type according to the results of the scenarios from Chapter 5. New vehicles are assigned the appropriate emissions Euro standard

[12] For a highly detailed analysis of the Leeds ANPR survey see Wyatt (2017).

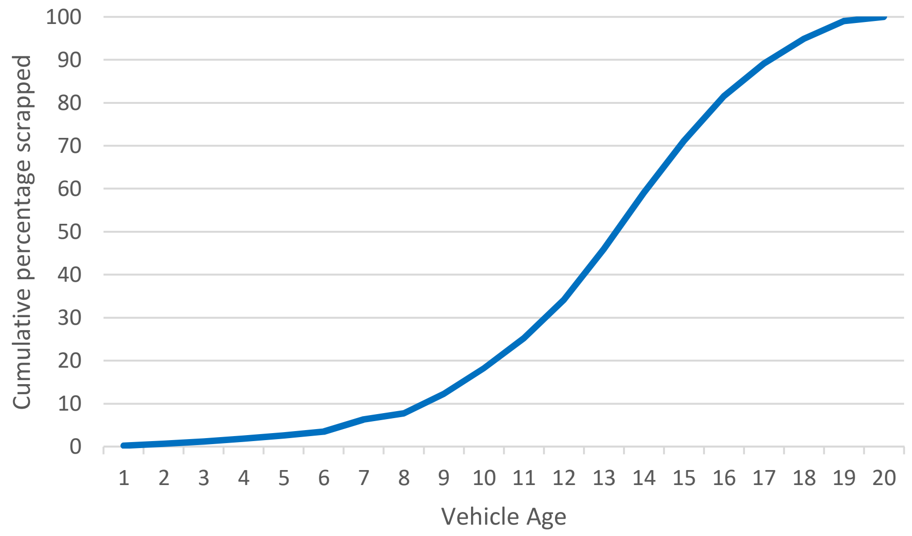

Figure 6-4: *Cumulative scrappage age for cars (Adapted from Leibling (2008)).*

according to current legislation for the introduction of new Euro standards (see Table 2-3 for details of Euro standard introductions for different vehicle types).

6.3.1 Converting the Total Number of Vehicle Registrations to the On-Road Fleet (vkm)

The composition of the traffic on the network is different to the composition of the vehicle fleet. Usually the age distribution of vehicles differs because newer vehicles are driven more (Department for Transport, 2013), and there are disparities between the split of powertrain types because diesel vehicles tend to have a higher annual mileage then conventional petrol (10 700 miles vs 6500 miles) (Department for Transport, 2016a). Therefore, in the model there is a conversion from the annual fleet output (in terms of total vehicle registrations) to the on-road fleet composition (vkm). To calculate this, a comparison was made for the base year from the ANPR survey data. Factors were calculated to convert between age distributions of fleet registrations and on-road fleet, and to account for higher mileage diesel vehicles (see Figure 6-5 and 6-6 for difference in scenarios for fleet percentage split of vehicle registrations versus vkm).

6.3.2 Development of the AIMSUN Leeds Traffic Model

The traffic model used in this analysis was developed in several stages through incremental improvement. The traffic model was developed in AIMSUN (Advanced Interactive Microscopic Simulator for Urban and non-urban Networks) with the most up to date version of the model

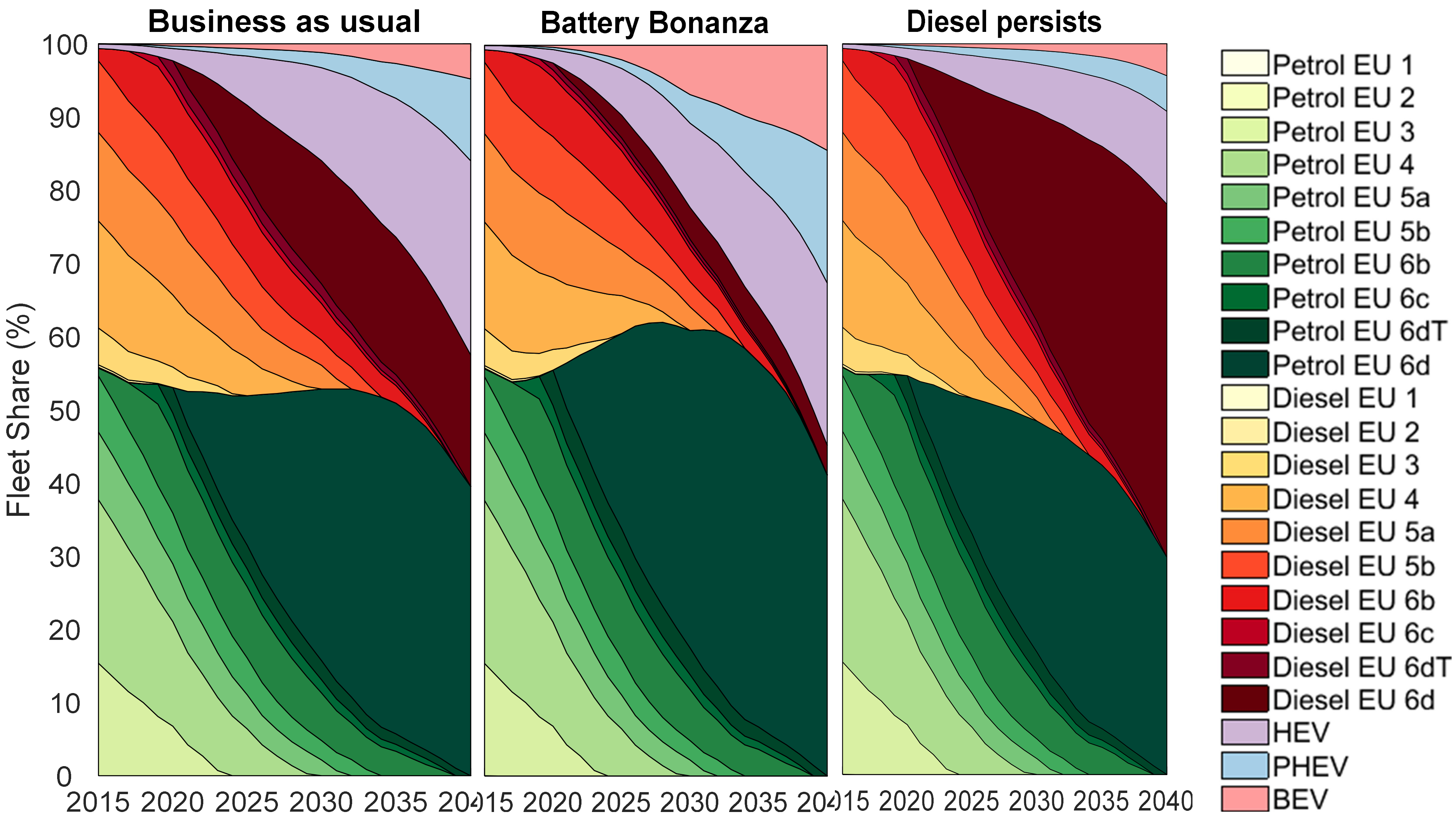

Figure 6-5: *HEV, PHEV, BEV, petrol and diesel fleet scenarios (vehicle stock - % of registrations) (see Appendix 6-B for results table).*

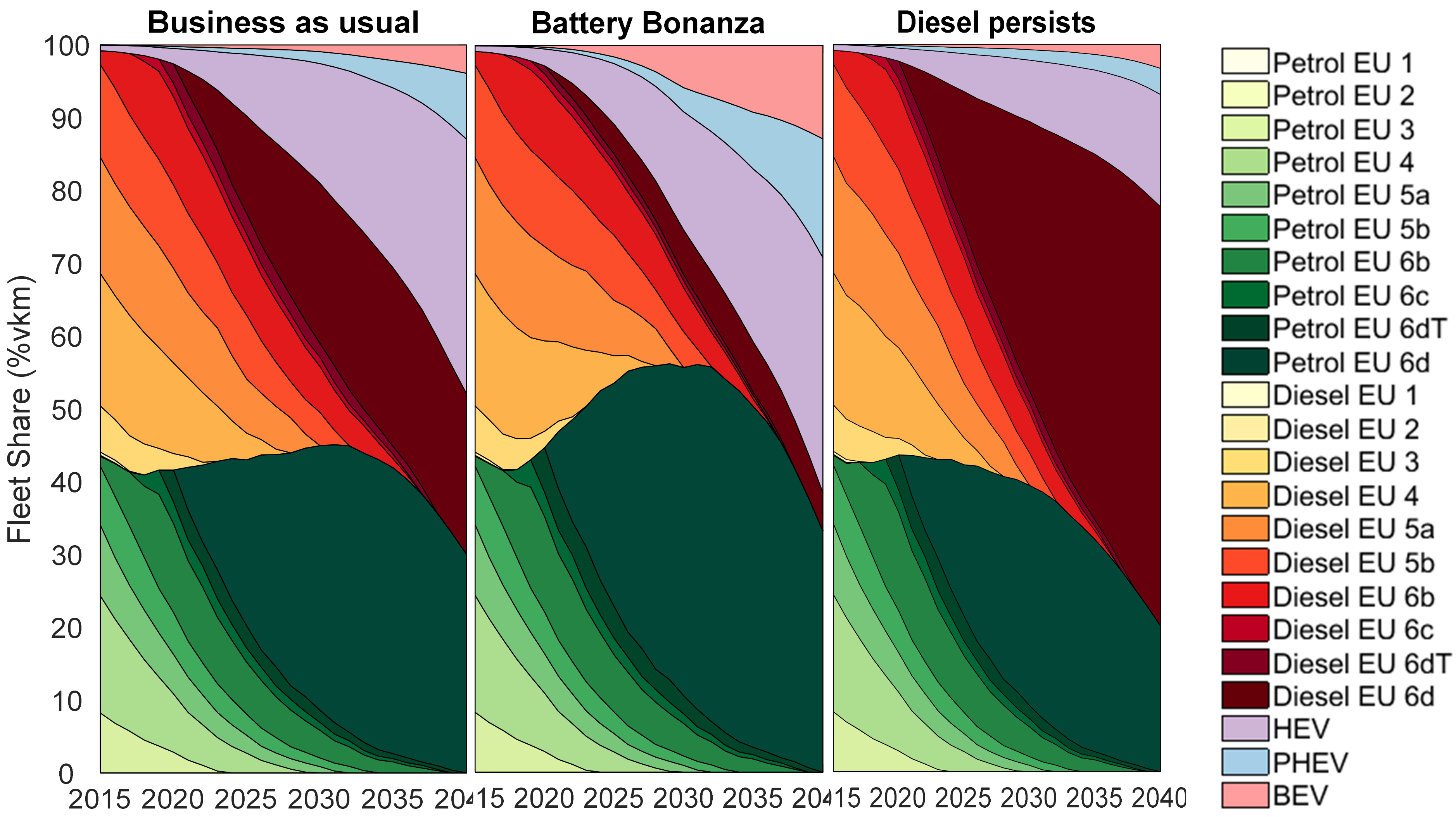

Figure 6-6: *HEV, PHEV, BEV, petrol and diesel fleet scenarios (vkm) (see Appendix 6-C for results table).*

run in AIMSUN 8.0.4.

The car-following model is the major internal behaviour model. The car-following model implemented in the AIMSUN simulation package is based on the safety distance model. This utilises the Gipps car-following model (as outlined in Gipps (1981))) and sets limits on the performance of the vehicle to calculate a safe speed with respect to the preceding vehicle. The vehicle dynamics parameters are imperative in determining second-by-second speed and spatial position of the vehicle in the simulation, this falls within the car-following sub-model. Maximum desired speed, maximum acceleration, and normal deceleration were the three parameters chosen for calibration process in this research study (as defined in more detail later in this section, see Table 6-4). This is principally because harshness of acceleration/deceleration can significantly affect vehicle tailpipe emissions.

Random seeds are a model input in traffic microsimulation modelling taking the form of a discrete number between 1 and 9999. Random seeds are used within the model to determine lane selection, traffic management actions, vehicle path selection and vehicle generation in the traffic model (TSS, 2013b). The model used in this analysis is run with 10 different random seeds. These random seeds are generated with the random number function in MATLAB.

The AIMSUN model simulates the Headingley network (see Figure 6-7) in North Leeds. The original 'Version 0' model was developed for a smaller area, including only the A660 through Headingley and its major junctions (Tate, 2011). This model only simulated two time periods "weekday morning" (8:00 – 9:00 hrs) and an "off-peak period" (11:00 – 12:00 hrs). Detailed fleet composition data was not available for Leeds therefore the Version 0 model utilised a recent Automatic Number Plate Recognition (ANPR) survey conducted in York (Tate, 2011).

The next stage of model development, 'Version 1' was undertaken by David Wyatt for his PhD thesis (Wyatt, 2017). This extended the original Version 0 model to include all roads in the Headingley network (see Figure 6-6 for details of network coverage), incorporating road gradient to each road section and updating traffic flow by way of Automatic Traffic Count (ATC) and Manual Classified Count (MCC) data (see Appendix 6-D for details of all sites of ATC and MCC data collection). To ensure the AIMSUN simulated traffic flows were characteristic of observed flows in the real-world, 26 calibration points were included in the Version 1 model, increased from only 4 calibration points in the Version 0 model. In the Version 1 model the two time periods were extended to five AIMSUN simulations. These represented five time periods with different traffic flow conditions observed during temporal analysis of the ANPR vehicle fleet data. These time periods included: the morning peak traffic (07:30 – 09:30); an

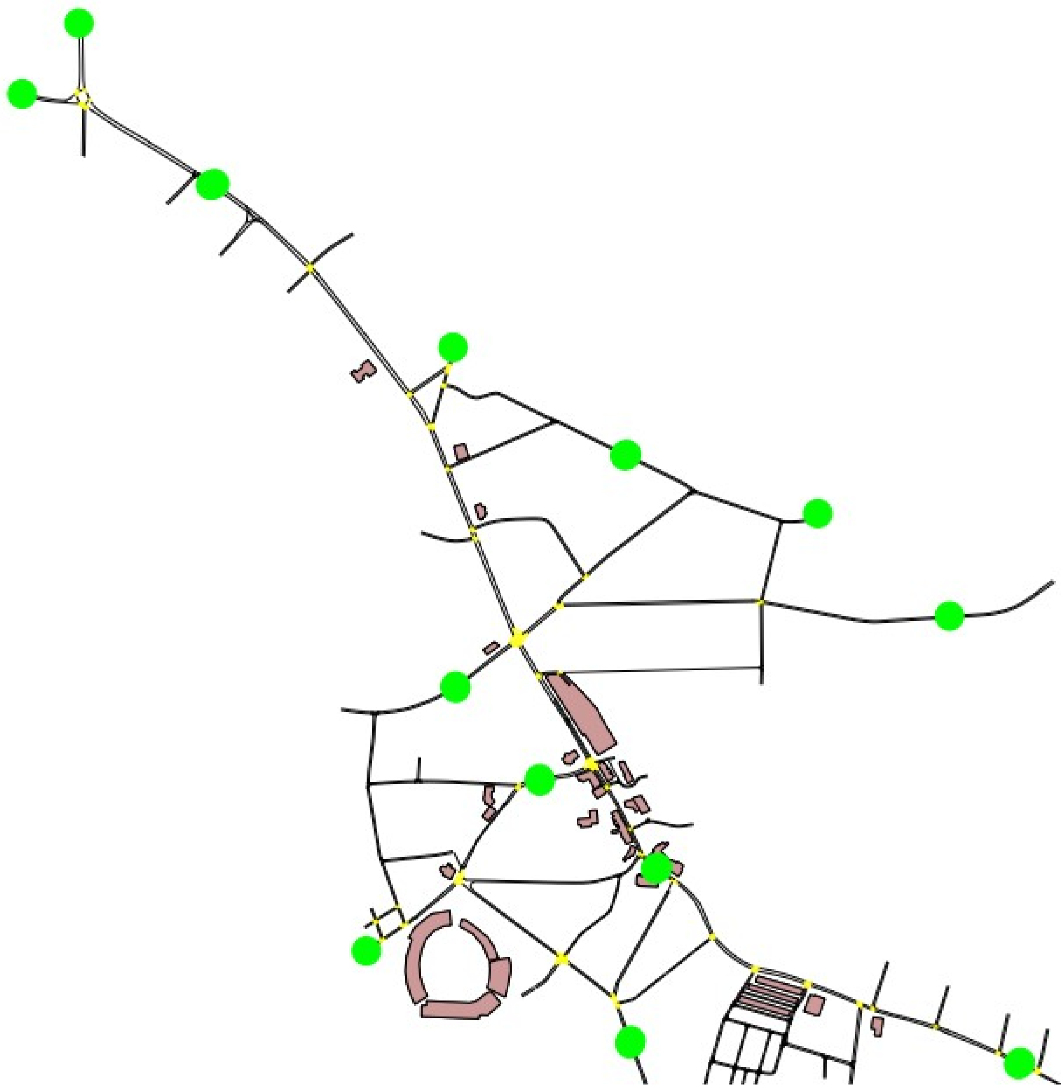

Figure 6-7: *Leeds network traffic model scope with validation points (Wyatt, 2017).*

calibration). An initial state is used (instead of a warmup period), so the model started running with the network populated by vehicles at 00:00.

inter-peak period (13:00 – 15:00); the afternoon peak traffic (16:00 – 18:00); the evening period and the night period (01:00 – 03:00). The ANPR survey discussed in Section 6.3.1 was used to provide an accurate description of the composition of the local vehicle fleet. The Version 1 model also incorporated traffic signal control timing data from four junctions in the Version 0 model.

For this analysis, the model was again incrementally improved to 'Version 2'. The model was extended to run for the full 24-hour period instead of the original 5 time periods in Version 1.

Table 6-1: *Input data sources.*

Input Data	Details
Vehicle flows	Manual Classified Count (MCC) and Automatic Traffic Count (ATC) data supplied by the Highways and Transportation Department of Leeds City Council (LCC). The Urban Traffic Management and Control team made available traffic control signal timing data for junctions.
Bus timetables	Timetables from the two main operators First bus and Tiger bus available from the West Yorkshire Metro website, timetables were sourced for with September 2015 to align with the model (West Yorkshire Metro, 2015)
Types of buses	Type of bus (e.g. single/double decker or articulated) checked by number plate from ANPR survey, then cross referenced with from the Sheffield Omnibus Enthusiast Society (SOES) fleet list (Sheffield Omnibus Enthusiasts Society, 2015).
Dwell times	Studied for the New Generation Transport proposal in Leeds, dwell times were investigated for the A660 within the Leeds ring road (Steer Davis Gleave, 2014)
Turn movements	Sourced from the Version 1 model with minor alternations during the calibration process.
Traffic fleet	For 2015 from the Automated Number Plate Recognition Survey taken on the A660 Otley Road, scenarios used for 2020, 2030 and 2040.
Vehicle dynamics data	Collected from PEMS (Portable Emission Measurement System) data carried out by Wyatt (2017) for cars and LCVs, own primary data collection and analysis undertaken for buses.

The same input sources were used (see Table 6-1) as the previous model Version 1 but this required significant time to rebuild and recalibrate the model (see Appendix 6-E for details of To extract the simulated vehicle data from the AIMSUN network model whilst the traffic simulation is running, an Advanced Programming Interface (API), written by the ITS, records vehicle ID, road section/junction number, vehicle type ID, vehicle speed, position and road gradient, for each vehicle in the network, at every 0.5 second simulation step. The data was then sampled at a 1 Hz frequency to produce the trajectories fed into the vehicle emissions model. The Version 2 model trajectories were used for all time periods of the model (e.g. 2015, 2020, 2030 and 2040). The Leeds city cordon vehicle count has shown that the number of vehicles entering and exiting the inner ring road has varied by around 5% in the past twenty years (Department for Transport, 2015a). This evidences the assumption that with the current road layout and policies in place, the vehicle flows are not expected to change significantly between now and 2040. This contradicts the DfT Road Traffic Forecasts 2018 (Department for Transport, 2018), which project urban traffic growth. However, with the high levels of congestion across most of the day, it is unlikely with the current policies in place this could materialise.

6.3.3 Bus Dynamics

The reliability of estimating vehicle tailpipe emissions is dependent on the quality of trajectory estimates from the microsimulation traffic model. To produce realistic vehicle trajectories, the parameters governing vehicle dynamics must be representative. Studies such as Wilmink et al. (2009) and Anya et al. (2014) have found that the default parameters values in micro-simulation programs such as VISSIM and AIMSUN do not produce realistic trajectories. The default values provided for these parameters are only applicable to rather specific circumstances, which are not detailed in the user manual. A plethora of research has examined how driving behaviour can change vehicle fuel efficiency by up to 40% (for example see De Vlieger et al. (2000), Ericsson (2001) and Rakha and Ding (2003)), therefore the calibration of these parameters is necessary for validity of the model outputs.

Studies have been published examining bus vehicle dynamics such as Carrese et al. (2013) and Ma et al. (2015), which conclude that driving behaviour, road gradient and vehicle load all affect fuel consumption significantly. For these reasons, primary data collection was carried out to calculate realistic vehicle dynamics parameters for buses. Data collection and analysis had already been completed for cars by Wyatt (2017) for the Version 1 of the traffic model, however, this analysis did not extend to buses. This vehicle type is heavier than cars, with lots of stop-start behaviour, therefore the vehicles dynamics are anticipated to be different. In Leeds it was found that buses account for 4.7% of traffic composition (according to the ANPR survey), although they are anticipated to have a higher contribution to network emissions.

The data for this study was collected on a single day (Wednesday 18th October 2017) using a VBOX kit. The information logged included latitude, longitude, altitude and velocity at a frequency of 20 Hz data, then sampled at a 1 Hz rate. Data was collected for a total of ten journeys were in different congested states, with an average journey length of 4.34 km and an average journey time of 15.22 minutes (see Table 6-3 for details). These trips were within the

Table 6-2: *Details of bus trips.*

TRIP #	Distance (km)	Time start	Trip time (minutes)
1	5.79	08:32	17.8
2	3.95	08:56	13.7
3	3.74	09:31	11.1
4	5.58	09:52	18.7
5	3.20	10:21	8.3
6	4.25	10:43	14.7
7	6.09	11:07	19.3
8	4.71	11:48	18.6
9	3.67	12:21	16.1
10	2.42	12:43	13.9

Table 6-3: *Definitions of vehicle dynamics parameters in AIMSUN. (Note that definitions are quoted from the AIMSUN User Manual (TSS, 2011)).*

Parameter	Definition	Interpretation
Maximum acceleration	"This is the maximum acceleration, in m/s2, that the vehicle can achieve under any circumstances. This acceleration is as used in the Gipps car-following model"	Calculated as 97.5th percentile of acceleration from each trip (then averaged over all trips)
Normal deceleration	"This is the maximum deceleration, in m/s2, that the vehicle can use under normal conditions. This deceleration is as used in the Gipps car-following model."	Calculated as the 90th percentile of deceleration from each trip (then averaged over all trips)
Maximum deceleration	"This is the most severe braking, in m/s^2, that a vehicle can apply under special circumstances, such as emergency braking for e.g. in front of a traffic light."	Calculated as the maximum deceleration of each trip (then averaged over all trips)

Table 6-4a: *Maximum acceleration rates for each vehicle type in the Headingley AIMSUN network (values for cars and LCVs taken from Wyatt (2017), HGV/bus from this analysis).*

Vehicle Type	Maximum Acceleration Rates (m/s2)			
	Mean	Standard Deviation	Minimum	Maximum
Car / Taxi - AM	1.63	0.10	1.51	1.88
Car / Taxi - IP	1.69	0.10	1.54	1.85
Car / Taxi - PM	1.53	0.10	1.27	1.62
Car / Taxi - EV	1.72	0.15	1.54	1.99
Car / Taxi - NI	*No PEMS data so set to the same values as Car - EV			
LCV – ALL	1.45	0.05	1.4	1.5
HGV, BUS – ALL	*1.31*	*0.13*	*1.07*	*1.54*

Table 6-4b: *Normal deceleration rates for each vehicle type in the Headingley AIMSUN network (values for cars and LCVs taken from Wyatt (2017), HGV/bus from this analysis).*

Vehicle Type	Normal Deceleration Rates (m/s^2)			
	Mean	Standard Deviation	Minimum	Maximum
Car / Taxi - AM	1.30	0.18	1.03	1.67
Car / Taxi - IP	1.36	0.15	1.16	1.64
Car / Taxi - PM	1.18	0.11	1.06	1.36
Car / Taxi - EV	1.49	0.12	1.35	1.67
Car / Taxi - NI	*No PEMS data so set to the same values as Car – EV			
LCV – ALL	1.05	0.13	0.90	1.15
HGV, BUS – ALL	*0.99*	*0.14*	*0.75*	*1.20*

Table 6-4c: *Maximum deceleration rates for each vehicle type in the Headingley AIMSUN network (values for cars and LCVs taken from Wyatt (2017), HGV/bus from this analysis).*

Vehicle Type	Maximum Deceleration Rates (m/s^2)			
	Mean	Standard Deviation	Minimum	Maximum
Car / Taxi - AM	2.66	0.46	2.23	4.17
Car / Taxi - IP	2.97	0.49	2.17	3.93
Car / Taxi - PM	2.44	0.22	2.20	2.83
Car / Taxi - EV	2.43	0.05	2.36	2.50
Car / Taxi - NI	*No PEMS data so set to the same values as Car – EV			
LCV – ALL	2.38	0.08	2.29	2.44
HGV, BUS – ALL	*2.09*	*0.36*	*1.48*	*2.60*

Table 6-5: *Comparison to bus dynamics figures from Zhang et al (2012).*

Parameter	Mean	Standard Deviation
Maximum Acceleration	1.70	0.21
Normal Deceleration	2.42	0.35

Leeds ring road between 8am and 2pm. The weather on the data collection day was overcast with no rain.

As already discussed, the AIMSUN traffic model has fewer vehicle dynamics parameters than other microsimulation traffic models. The three key parameters governing vehicle dynamics in this model are maximum acceleration, normal deceleration and maximum deceleration (see table 6-3 for definitions). These parameters affect car-following, lane changing, travel time and queue discharge.

From analysing the collected bus dynamics data, we conclude that overall acceleration and deceleration behaviours are more uniform in buses than cars, as anticipated. This is evidenced by the mean, minimum and maximum of the three key parameters calculated with a lower value for buses than cars or LCVs (see Tables 6-4a-c). The values of the standard deviation indicate that the spread of accelerating and decelerating behaviour is similar to that of cars. This indicates that there is not uniformity across bus drivers or trips. With a much heavier vehicle and the same drivers employed to drive at all times of day, it was assumed that acceleration rates would not vary significantly at different times of day.

Comparing our values to those of Zhang et al. (2012) (see Table 6-5), it is clear that the values for the parameters in question are significantly higher than our estimates. The key reason for this will be difference in interpretation of the definition (see Table 6-3), which is not clearly defined in calculation terms in the user manual. Aside from this, there are several factors that could cause discrepancies between the results, however, the likelihood of drivers in London driving significantly more aggressively is unlikely given the traffic conditions and weight of the vehicles in question.

6.3.4 Simulink H/EV Energy and Emissions Model

The trajectories from the Leeds network traffic model, along with the fleet mix are run through the TU-Graz PHEM emissions model for all vehicles except hybrid and electric vehicles that are run through the Simulink H/EV Energy and Emissions Model. The details of the process of calculating the vehicle emissions from the PHEM model are given in Appendix 6-F.

The Simulink H/EV Energy and Emissions Model was originally designed by Riley (2017). This microscale CO_2 emission model (model architecture outlined in Figure 6-8) was built using real world PAMS (Portable Activity Measurement System) data and designed to model the Toyota Prius Hybrid vehicle at a 1 Hz frequency. The model needs input of a vehicle drive cycle with corresponding data on road grade to output fuel consumption at the same frequency.

This model has several key advantages over other microscale emission models[13]. Primarily, the mix of first principle and empirical methods used to build the model, with the option to incorporate complex vehicle architectures and adapt the model to test changes in vehicle design, results in high quality output with a fast run time, ideal for running vehicle trajectories through from microsimulation traffic models such as AIMSUN. To put this in context, for the model to compile and run over 24 hours of data at 1 Hz takes under twenty five seconds. To this end, the original model was adapted to model the Toyota Prius PHEV and Nissan Leaf BEV. The trajectories fed into this model are between 10 and 450 seconds, the TfL drive cycle is run through the model ahead of each vehicle trajectory to condition the battery and vehicle system.

The model was built from on road test measurements taken from the vehicle CAN. This is

[13] Note that the PHEM emissions model does not have a hybrid vehicle module available at the time of publication.

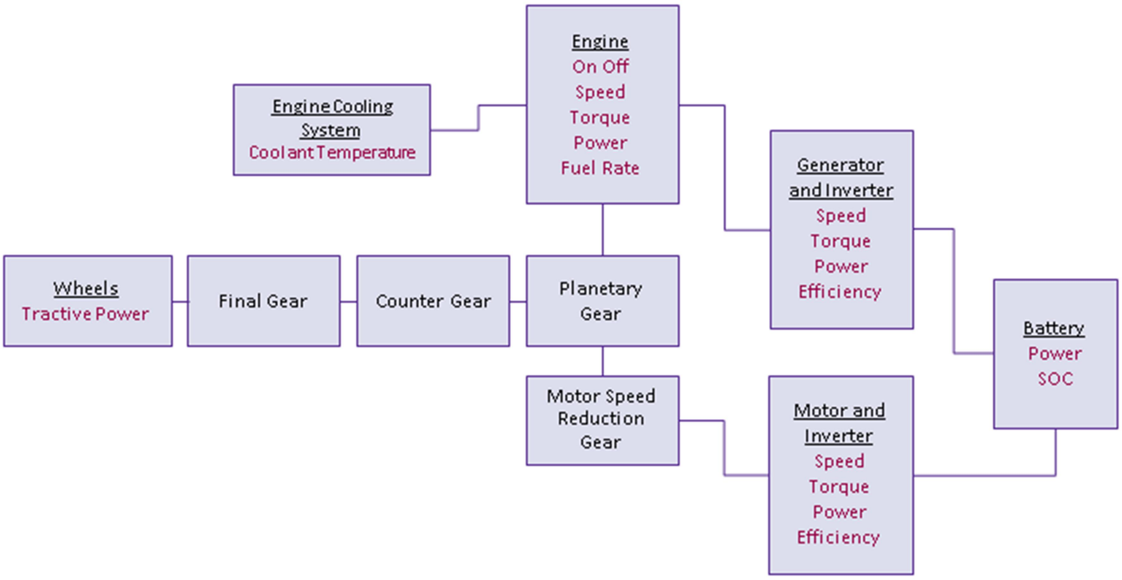

Figure 6-8: *Toyota Prius powertrain overview. (Models underlined and parameters calculated within each model in pink) (Riley, 2017).*

costly and time consuming, and therefore many models use chassis dynamometer data instead (Kim et al., 2012a; Kim et al., 2012b). Chassis dynamometer data cannot take many external variables into account and is often collected within carefully controlled laboratory conditions; therefore, it is easier to fit the model but there is a larger error when modelling on road vehicle trajectories. Therefore, the real-world data approach is particularly advantageous when utilising the model to estimate CO_2 emissions from traffic microsimulation vehicle trajectories as in this study. Note that because NO_x emissions from hybrid and electric vehicles is negligibly low but the complexity to estimate these emissions on a second by second basis is very complex, it was not deemed necessary to build the model with the capability to model NO_x emissions.

The hybrid model has been independently tested against other data sets, demonstrating an error margin well below 5% (Riley, 2017), see Figure 6-9 for comparison of the model to real world data and other vehicle types. Many models in the literature have not been thoroughly independently validated (Rakha et al., 2004; Smit et al., 2006), and without this step the microscale model can be over fitted to the data from the building stage. The Toyota Prius plug-in model is based on the 2012 vehicle design with a 4.4 kWh battery. The Nissan Leaf Electric Vehicle model is a variation on the Toyota Prius hybrid model. This model uses the same fuzzy logic framework but is simpler due to the battery electric powertrain. The Nissan Leaf model is based on the 2010 vehicle release with a 24 kWh battery.

6.4 RESULTS AND DISCUSSION OF THE LEEDS NETWORK EMISSIONS MODELLING

The results of the coupled microsimulation traffic and emissions model show that network level CO_2 emissions could fall by 2.3% by 2020, 16.8% by 2030 and 31.6% by 2040 (based on 2015 baseline) with hybrid and electric vehicles paving the way for decarbonisation of the fleet (see Figure 6-10a for total CO_2 emissions over the 24-hour period). Similarly, network level NO_x emissions could fall by 35.3% by 2020, 88.6% by 2030 and 95.0% by 2040 (based on 2015 baseline) due to the increased adoption of low carbon vehicles coupled with more stringent

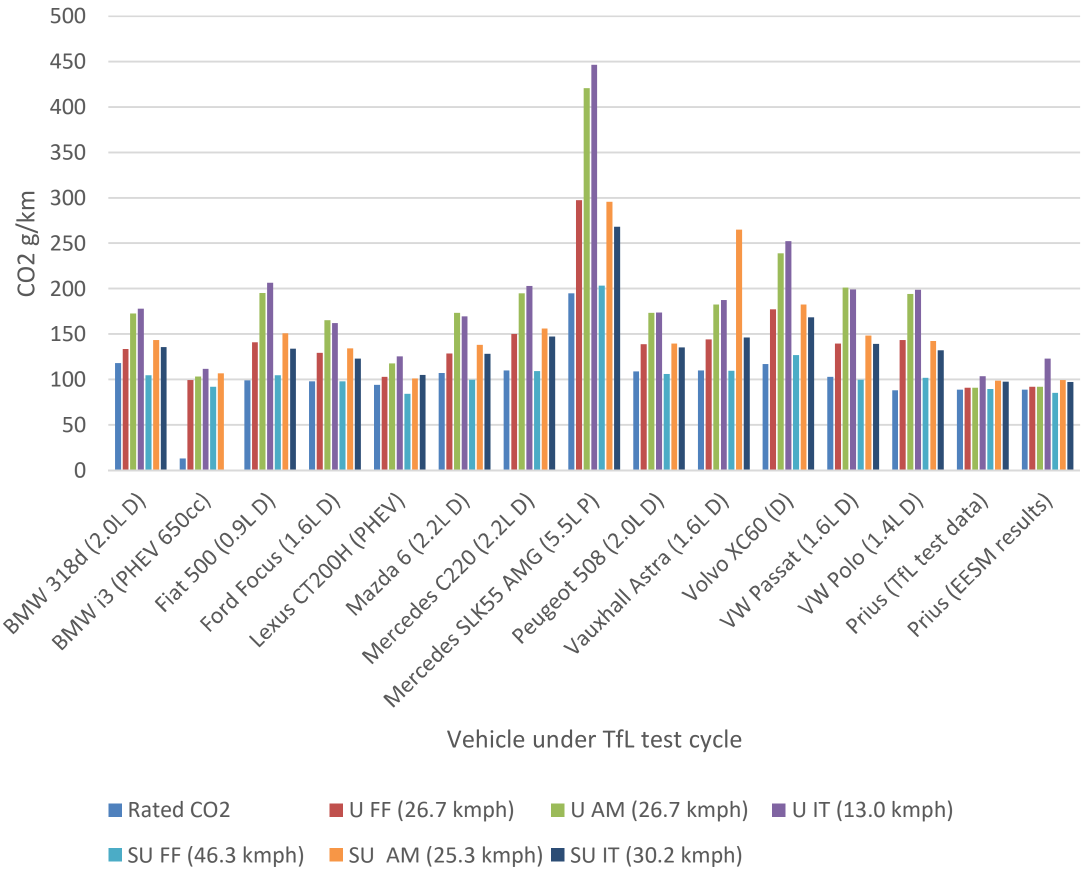

Figure 6-9: *Comparison of Toyota Prius model with TfL drive cycle data (data sourced from TfL). U FF - Urban Free flow, U AM – Urban AM (e.g. peak congestion), U IT – Urban Inter Peak, SU FF – Suburban Free flow, SU AM – Suburban AM, SU IT – Suburban Inter Peak. The speed represents the average speed of the part of the test cycle. EESM results indicate 'Simulink H/EV Energy and Emission model' estimates.*

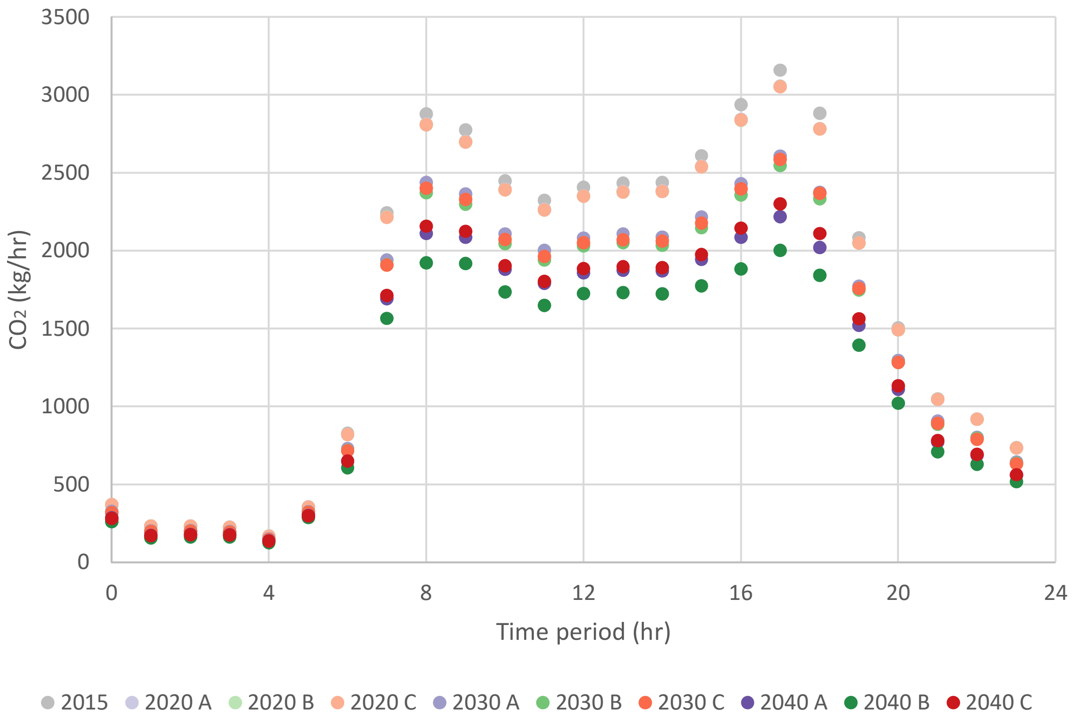

Figure 6-10a: *Total network CO_2 emissions over the 24-hour period (Note that scenario A represents Business as Usual, scenario B corresponds to Battery Bonanza and scenario C represents Diesel Persists).*

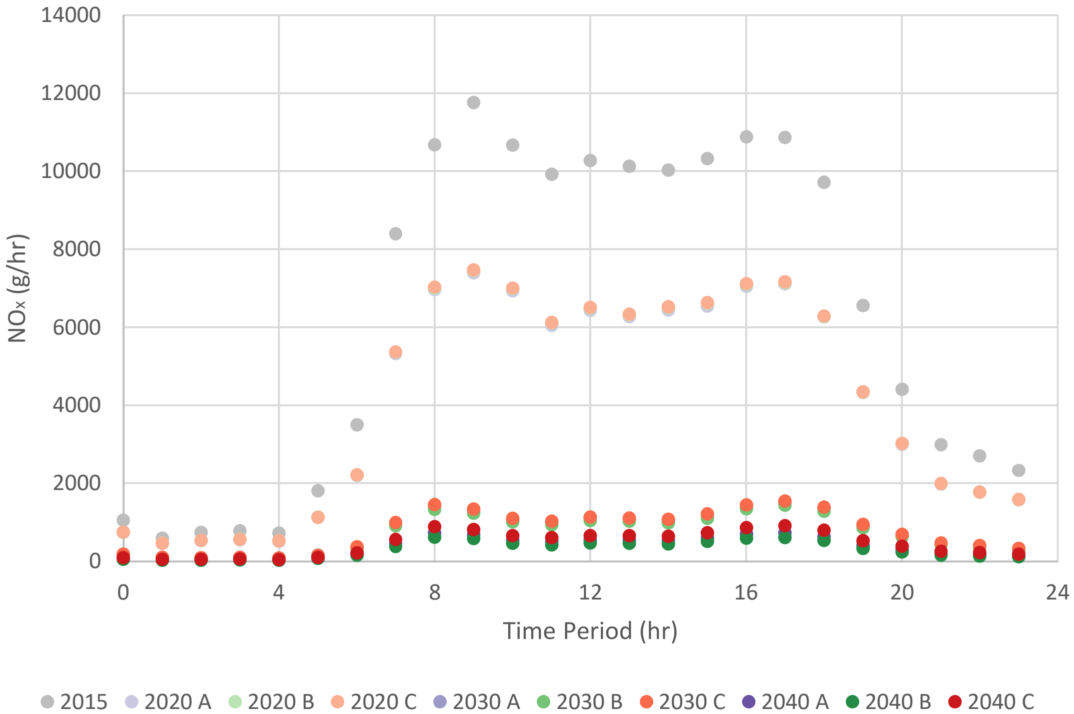

Figure 6-10b: *Total network NO_x emissions over the 24-hour period (Note that scenario A represents Business as Usual, scenario B corresponds to Battery Bonanza and scenario C represents Diesel Persists).*

Euro standards for different types of diesel vehicles (see Figure 6-10b for total NO_x emissions over the 24-hour period). However, this section illustrates how deeper conclusions can be drawn concerning the effect of congestion on emission factors of different classes of Euro standard vehicle, the effect of greater numbers of P/H/EVs in traffic at different times of day and the ability to analyse vehicle emissions by road segment. This level of analysis would not be possible by using a simpler model as the higher resolution is required for these insights.

6.4.1 The Effect of Congestion on CO_2 and NO_x Emission Factors

Road congestion occurs when vehicle traffic volumes approaches road capacity, at this point average vehicle speeds fall. Road improvements that increase capacity lead to reduced time delays from increased traffic speeds but these effects are only experienced in the short term. Higher vehicle speed leads to reduced travel time costs, increasing the attractiveness of travel. This increases travel from other routes and modes, encouraging longer and more frequent vehicle trips. This increased traffic volume is referred to as generated traffic (Litman, 2015). Induced travel represents a proportion of generated traffic; induced travel accounts for the increase in total vehicle trips and distance travelled, not including the traffic diverted from other routes. Congestion usually becomes self-limiting as drivers are deterred from using the road network. This is evidenced in Leeds by the city cordon where vehicle flow has increased by less than 5% in 10 years (Department for Transport, 2015a). This evidences the assumption that with the current road layout and policies in place, the vehicle flows are not expected to change significantly between now and 2040.

Over the course of a day, there are different levels of congestion on the traffic network. This is clearly illustrated in the traffic microsimulation model by slower vehicle speeds at times when there are high numbers of vehicles moving around the road network (see Figure 6-11). In the Leeds network traffic microsimulation network model, there is a clear ‘rush hour’ where there are more vehicles on the network leading to stop-start congested traffic. One of the key advantages of the modelling approach used in this thesis is the ability to capture the difference in emissions from different states of congestion and the weighting due to the different vehicle flows at these times. A simpler method, such as vehicle drive cycles, could have been used in this chapter to estimate emissions, but using a simpler could not capture the spatial and temporal aspects of the network level emissions. Using the microsimulation method, further analysis could reveal emission hotspots and the difference between junctions and links across the road network.

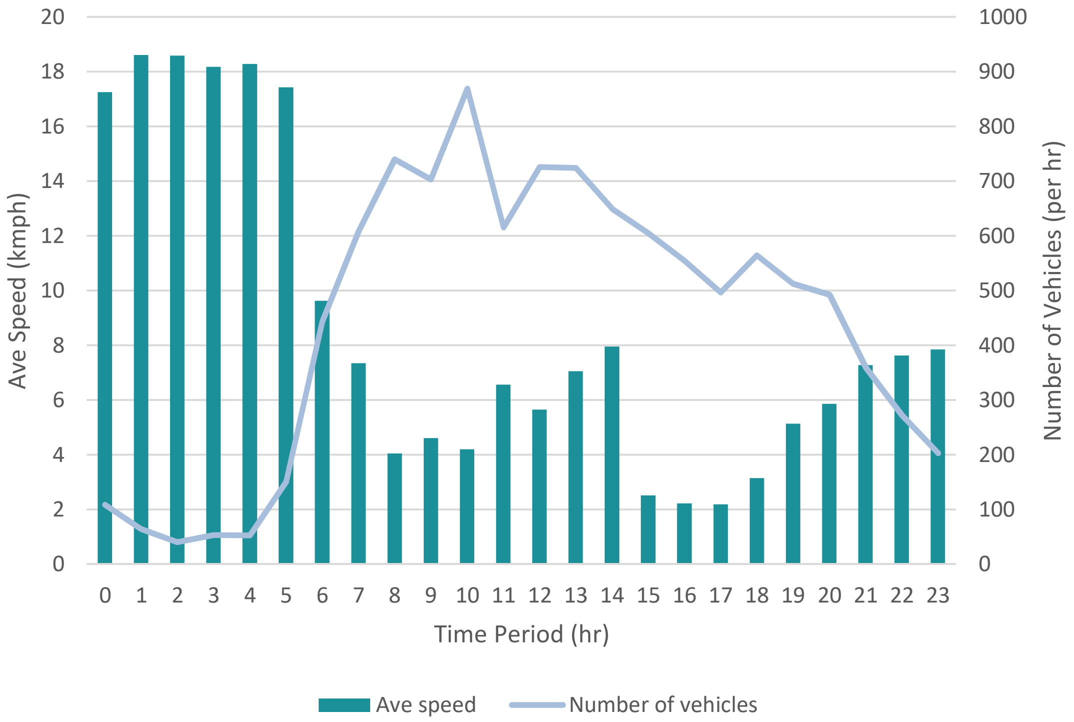

Figure 6-11: *Average vehicle speed and number of vehicles passing a point on the A660 throughout the 24-hour period on a specific point on the A660 (on Otley Road Southbound near junction with Shaw Lane).*

The CO_2 emission factor of vehicles of different fuel type varies throughout the 24-hour period of the model (see Figure 6-12a). As expected, petrol cars were found generally to have higher emission factors than diesel cars, this was approximately 4% greater over all traffic flow conditions. The average emission factors of petrol cars increase by 34% between times of peak congestion (e.g. 18:00) and free flow (e.g. 01:00), this figure is slightly lower for diesel cars at 30%. The average emission factor of petrol and diesel cars is nearly double that of HEVs. For HEVs there is only a 10% increase between free flow and congested conditions, and the emission factor is between 17% and 44% lower than the emission factor of the lowest emitting petrol or diesel Euro standard vehicle. The average emission factor of PHEVs was found to be 28% lower than the average HEV emission factors. This illustrates the greater inefficiency of petrol and diesel vehicles in stop start traffic.

NO_x emissions predominantly stem from diesel vehicles. The introduction of higher Euro standard vehicles (as discussed in Chapter 2), and the retirement of old diesel vehicles leads to significant reductions in NO_x emissions in the short to medium term. By 2030 all Euro 1-4 diesel vehicles are scrapped, with most diesel cars registered as either Euro 6d or 6dT, this is turn leads to a drop in 87% on total network level NO_x emissions (from 2015 baseline values)

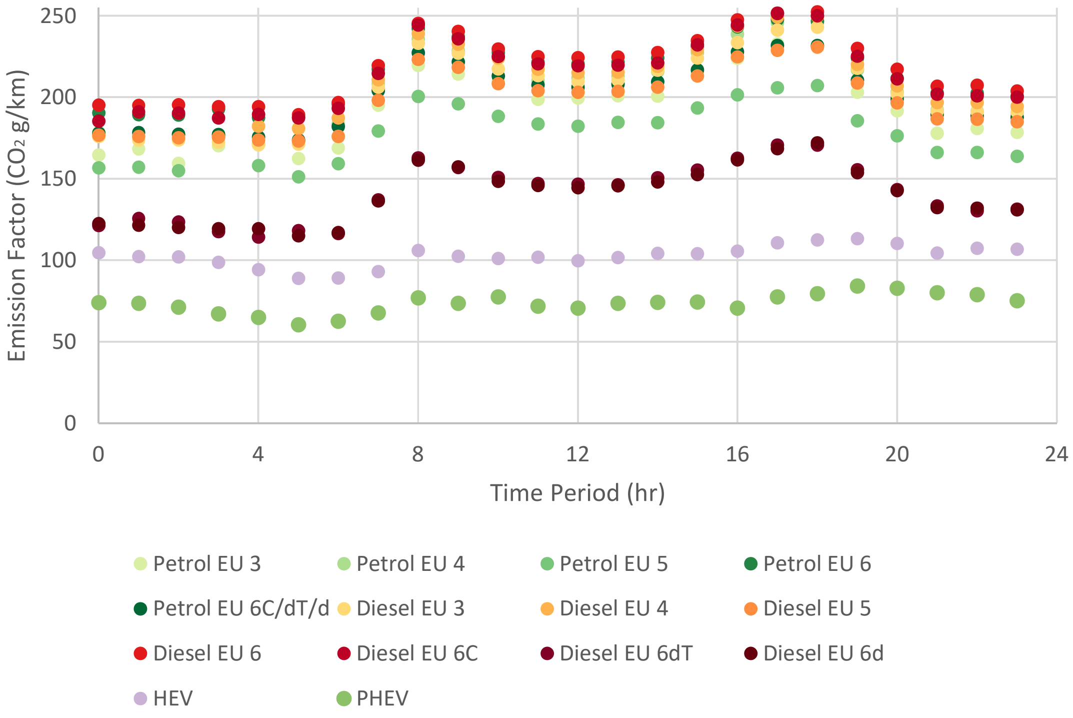

Figure 6-12a: *Variation of CO_2 emission factors of different Euro standard vehicles through the course of the 24-hour period.*

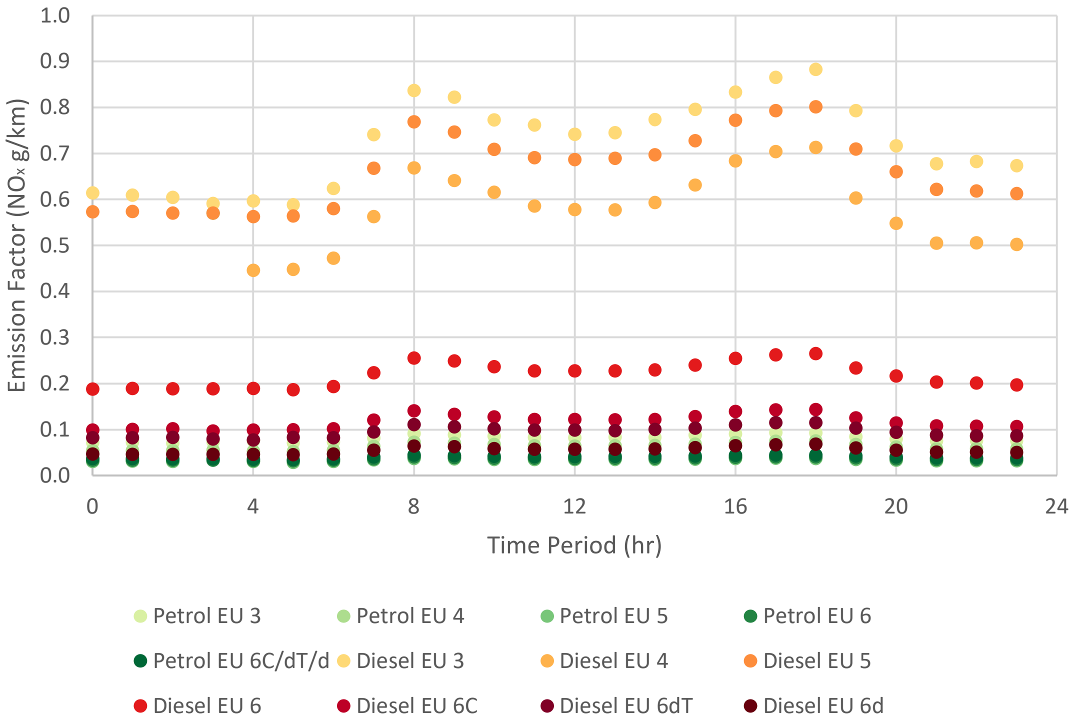

Figure 6-12b: *Variation of NO_x emission factors of different Euro standard vehicles through the course of the 24-hour period.*

compared to the 35% reduction seen in 2020 (see Figure 6-10b). The effect of the increasing adoption of HEVs/PHEVs/BEVs in the car fleet was found to make a smaller difference to total NO_x emissions than the mass adoption of Euro 6 vehicles.

The CO_2 emission factors of the different Euro standard cars vary through the day with different traffic conditions (see Figure 6-12a for details of the variation of CO_2 emission factors of different Euro standard vehicles through the course of the 24-hour period). Vehicle weight plays a part in this, with Euro 6 vehicles generally heavier than Euro 5, this accounts for the increase in emission factor for Euro 6 compared to Euro 5. In the PHEM emission model, the average kerbside weight and power of a Euro 5 diesel car was chosen as 1565 kg with a 105 kW engine whereas for a Euro 6 diesel vehicle this figure is 1615 kg with a 128 kW engine, these values were chosen to reflect the 2015 Leeds car fleet (calculated from the ANPR survey data). Average kerbside weight across the car fleet is anticipated to remain constant in future, as this historically has been a result of increased safety design and automation of vehicle features. For Diesel cars, Euro 6d vehicles were found to have a lower emission factors in free flow conditions than Euro 6dT, but this is approximately equal in congested conditions.

Similarly, the NO_x emission factors of the different Euro standard cars vary through the day (see Figure 6-12b for details of variation of NO_x emission factors of different Euro standard cars through the course of the 24-hour period). NO_x emissions for petrol cars are around 20% that of diesel cars. The emission factor of Euro 5 diesel cars is 3.0 times greater than Euro 6 diesel cars. The average emission factor of Euro 6C diesel cars is half that of Euro 6 diesel cars. The emissions factor of 6dT diesel cars falls by 20% compared to Euro 6C, again halving from the transition from 6dT to 6d. The average emission factors of Euro 6d diesel cars is less than 10% that of Euro 5 diesel cars.

The emission factor of BEVs and PHEVs varies less during the day but is dependent upon the assumed carbon intensity of the electricity grid. The carbon intensity of the electricity grid is forecast to drop from 2015 to 2040, therefore the emission factors for PHEVs and BEVs will decrease over time. The emission factor of BEVs range from 0.337 to 0.352 kWh per km, this translates to 1.82 g CO_2/km to 10.24 g CO_2/km depending on the level of decarbonisation in the future. This compares to a range of emission factors of between 70.5 g CO_2/km to 95.9 g CO_2/km in 2020 over the period of a day for PHEVs, to 59.4 g CO_2/km to 77.9 g CO_2/km in 2040 when carbon intensity of the electricity grid has fallen. Note that EVs are assumed in this thesis to be charged using the base load generation rather than dedicated generation, therefore the figures reflect the decarbonisation of the electricity sector. If dedicated generation figures are used, e.g. infrastructure is built/operated specifically to support the increasing charging demands of greater numbers of EVs, the emission factors of these vehicles would increase significantly (see Marmiroli et al. (2018) for further discussion of this point).

6.4.2 The Effect of Higher Numbers of P/H/EVs in Traffic

Because of the greater efficiency of hybrid and electric vehicles during congested periods, the role out of these vehicles has a more pronounced effect during congested periods than at times of free flow (see Figure 6-12a). For example, at 03:00 – a time of traffic free flow, the change in total hourly network CO_2 emissions from 2015 to 2040 reduces by 24% whereas at 09:00 - during a congested period - it reduces by 26%. Over the 24 hour period, in the scenario with the highest fleet share of P/H/EVs (Battery Bonanza - representing 32.4% HEV, 16.3% PHEV and 12.8% BEV car vkm share), the total CO_2 emissions falls by 31.6%; in this scenario in peak traffic periods such as 09:00 and 17:00 there is a greater reduction of network CO_2 emission (36.1% and 36.6% respectively compared to the 2015 baseline) due to this increased efficiency of hybrid and electric vehicles in congested traffic. It is worth noting that total network level CO_2 emissions are ten times greater at peak times than during night-time hours.

Due to the different makeup of the fleet in the different future scenarios modelled, at each time period (e.g. 2020, 2030 etc) there is a variation in the network level emissions forecast. By 2020 the difference between the reduction in CO_2 across the three scenarios is negligible (<1%), because HEV car vkm share varies between 1.79% to 2.35%, PHEV between 0.25% and 0.32% and BEV between 0.17% and 0.23%. By 2030 this increases to approximately 2%, because HEV car vkm share varies between 8.43% to 16.25%, PHEV between 1.02% and 3.32% and BEV between 0.94% and 5.81%. Finally, by 2040 this figure is at 7%. because HEV car vkm share varies between 15.51% to 34.06%, PHEV between 3.61% and 16.30% and BEV between 3.26% and 12.85% (see Figure 6-6 and Appendix 6-C for figures/tables of fleet scenarios). Over the course of the day, there is greater variation between these scenarios, for example at 16:00, the difference in scenarios at 2040 is closer to 10% because the effect of higher levels of P/H/EVs in traffic on emissions is non-linear.

Similarly, network level NO_x emissions fall by different amounts depending on the scenario in this study, but the variation between scenarios is smaller than discussed for CO_2 reductions, this is because higher Euro standard diesel vehicles are modelled with significant NO_x reductions (see Figure 6-12b for NOx emission factors throughout the day). By 2020, the NO_x emissions reductions across the three scenarios differ by less than 0.5%, by 2030 this increases to 1%, and this is still higher by 2040 at 3%. This shows that NO_x levels are mainly dependent on scrapping older vehicles/purchasing new vehicles (across the whole road fleet) with a

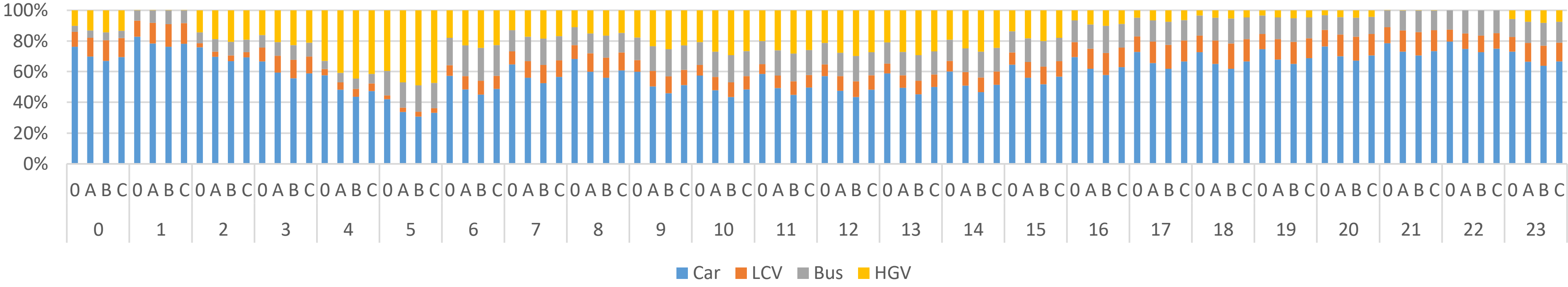

Figure 6-13a: *Contribution of CO_2 emissions by vehicle type. '0' represents 2015 baseline case, 'A', 'B' and 'C' represent the scenarios Business as Usual, Battery Bonanza and Diesel Persists respectively in 2040.*

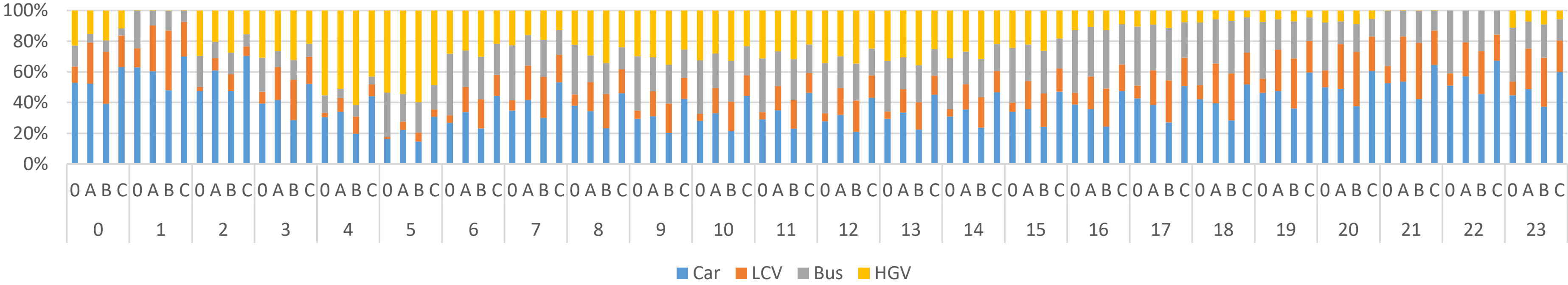

Figure 6-13b: *Contribution of NO_x emissions by vehicle type. '0' represents 2015 baseline case, 'A', 'B' and 'C' represent the scenarios Business as Usual, Battery Bonanza and Diesel Persists respectively in 2040.*

higher Euro standard rather than opting for P/H/EVs. However, the absolute reduction of network level NO_x emissions is greater by 2040 than that of CO_2 (95% reduction of NO_x versus 31.6% reduction of CO_2 in 2040 in Battery Bonanza scenario compared to 2015 baseline levels).

6.4.1 The Contribution of Different Vehicle Types to Network Level CO_2 and NO_x Emissions

The microsimulation model accounts for different vehicle types such as cars, buses, LCVs and HGVs. Vehicles other than cars account for approximately 59% of CO_2 and 30% of NO_x emissions at peak times such as 09:00 rising to 76% and 48% at night time (e.g. 02:00) (see Figure 6-13a for emissions contribution of different vehicle types in 2015 and 2040). The scrappage model accounts for the renewal of vehicles of all sizes, replacing them with vehicles of a higher Euro standard depending on their age according to scrappage curves. For example, buses represent around 15% of total network CO_2 over the period of a day in the baseline scenario rising to 22% in 2040 with the expected lower contribution of carbon emissions from cars.

The percentage contribution of cars over different scenarios, across all times of day varies. Compared to the 2015 baseline scenario, by 2040 in the Battery Bonanza scenario cars contribute 18% less to total CO_2 emissions. Only approximately half the reduction is achieved in the Diesel Persists scenario illustrating the need to switch to P/H/EVs.

Cars contribute 14.6% to 70.5% of NO_x emissions depending on time of day and scenario (see Figure 6-13b). Unsurprisingly, in the Diesel Persists scenario NO_x contribution from cars is greater (40%), whereas in Battery Bonanza scenario it is much less (25%), illustrating the effect of P/H/EVs on NO_x emissions. During night-time hours cars represent most of the traffic therefore most NO_x is emitted by cars, however, at peak time periods with greater numbers of buses in the traffic fleet this drops. Between 06:00 and 23:00 buses contribute around 40% of emissions in 2015, this shows the potential to dramatically cut NO_x levels if electric buses were adopted on the Headingley route.

6.4.4 Road Segment Level Analysis

So far in this section, it has been shown that the microsimulation coupled traffic and emissions model can be used to estimate vehicle emissions over the network at different times of day with different traffic mixes. Because this model is so detailed, analysis can be taken one step further to illustrate how emission factors change at traffic bottlenecks within a time period for different parts of the network. To demonstrate this, a route is chosen (see Figure 6-14) that

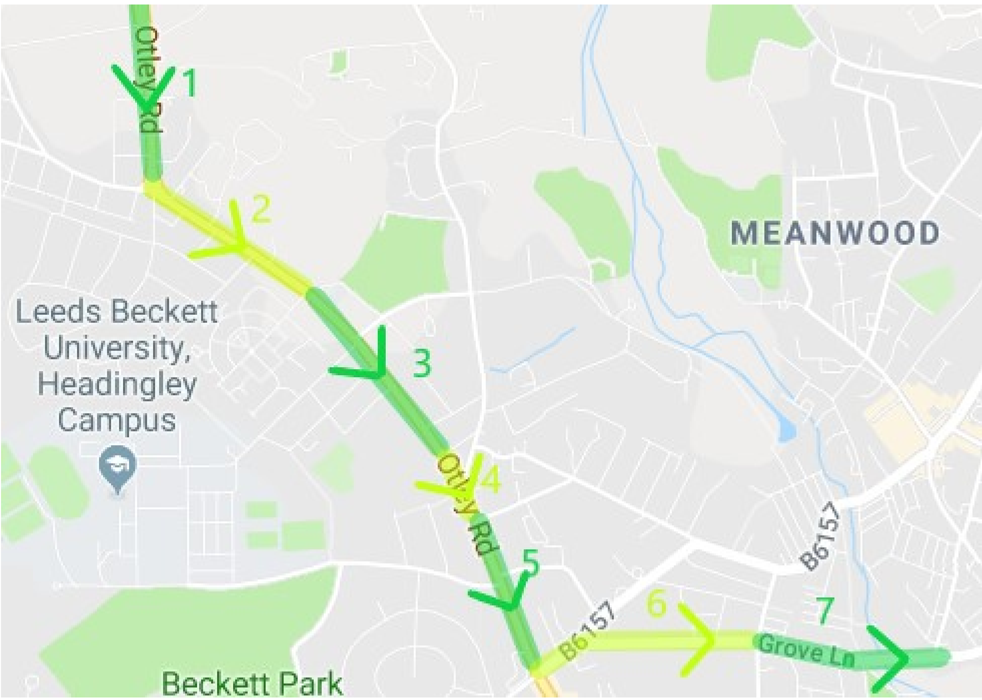

Figure 6-14: *Illustration of selected road segments on the traffic model network (Note that 26 road segments are aggregated into 7 for simplicity, these are south/east direction of travel only) (©Copyright GoogleTM 2015)* **.**

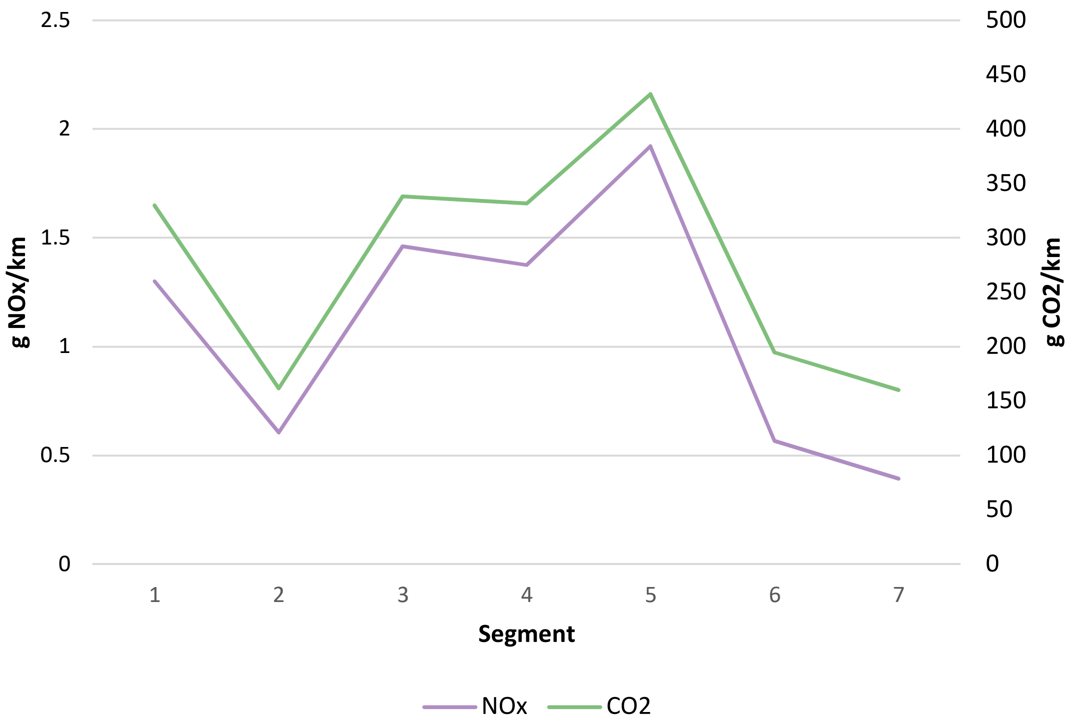

Figure 6-15: *CO_2 and NO_x emission factors averaged across all vehicles on each road segment for 07:00.*

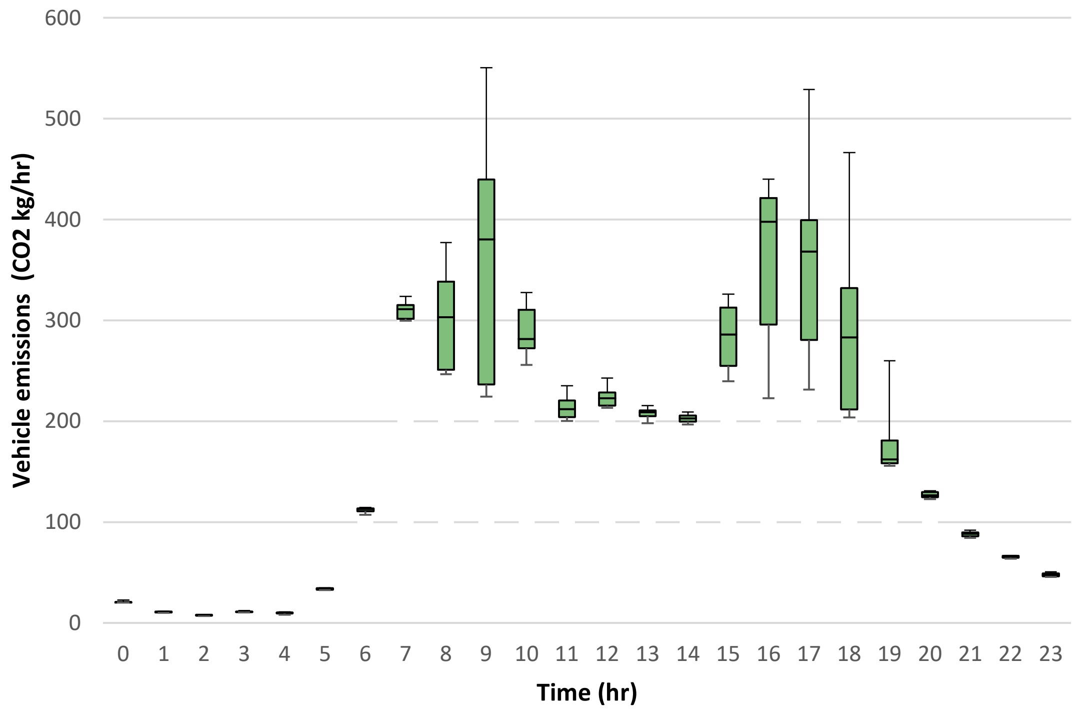

Figure 6-16a: *Box and whisker diagram illustrating the spread of total CO_2 emissions on the road segments specified in Figure 6-14 across different random seeds.*

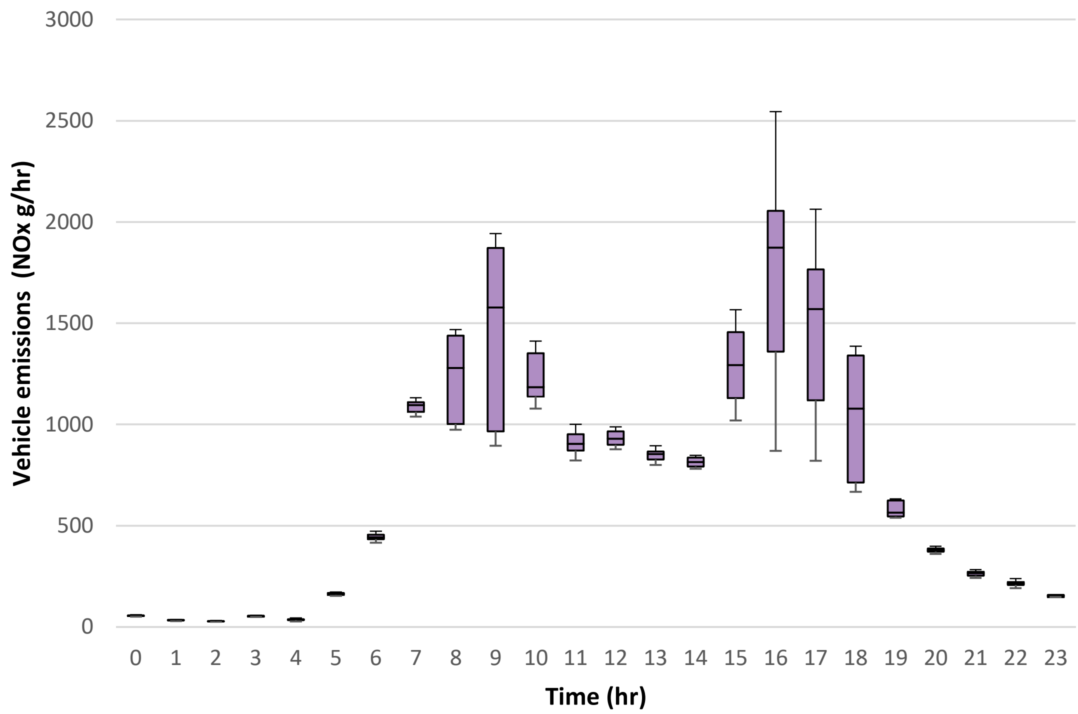

Figure 6-16b: *Box and whisker diagram illustrating the spread of total NO_x emissions on the road segments specified in Figure 6-14 across different seeds.*

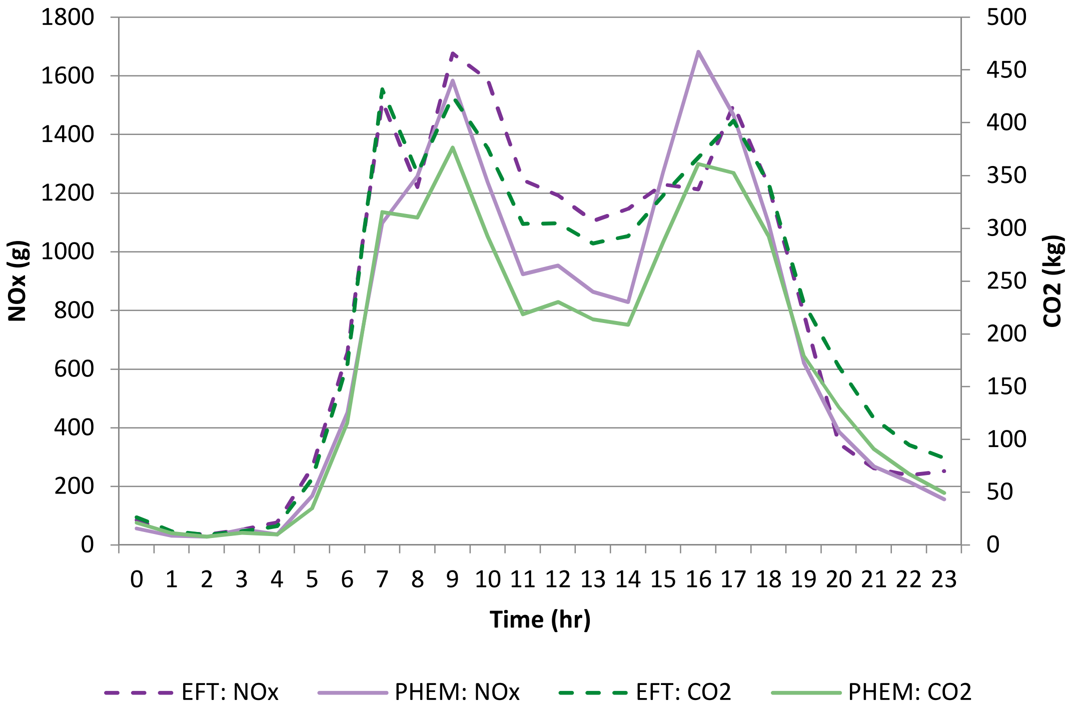

Figure 6-17: *Total NO_x and CO_2 summed over the seven road segments in Figure 6-14 for EFT and PHEM models.*

incorporates different traffic conditions within an hour period (07:00). The average CO_2 emission factor was found to change throughout the specified route (see Figure 6-15 for average emission factors of all vehicles for each road segment). The average CO_2 emission factor increases as vehicles approach the junction (located at the intersection of section 5 and 6) which often has long queues on the approach, then the average emission factor drops off rapidly as the vehicles return to free flow along road segments 6 and 7. The average emission factor on road segment 5 was found to be 2.9 times that of road segment 1. The same trends are mimicked by the average NO_x emission factor. Future analysis could exploit this aspect of this modelling methodology more fully, allowing for identification of key junctions that have a significant contribution to network level emissions and assessing how these emissions could be reduced.

6.4.5 The Stochastic Nature of Traffic

The traffic model in this analysis illustrates vehicles flows on an average September day calibrated with vehicle flow data from a single week. However, this modelling methodology has the advantage over simpler models that it can capture the stochastic nature of traffic across the network using the AIMSUN feature of random seeds. Random seeds are used to determine lane selection, traffic management actions, vehicle path selection and vehicle

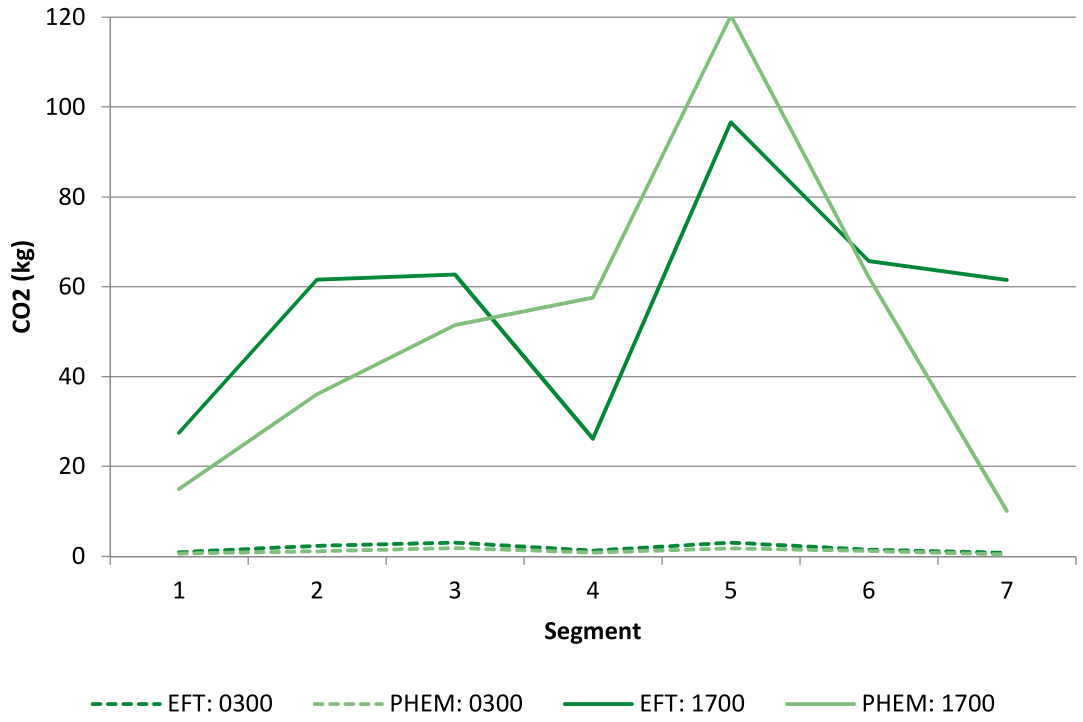

Figure 6-18a: *Total CO_2 on each of the seven road segments in Figure 6-14 at 03:00 and 17:00.*

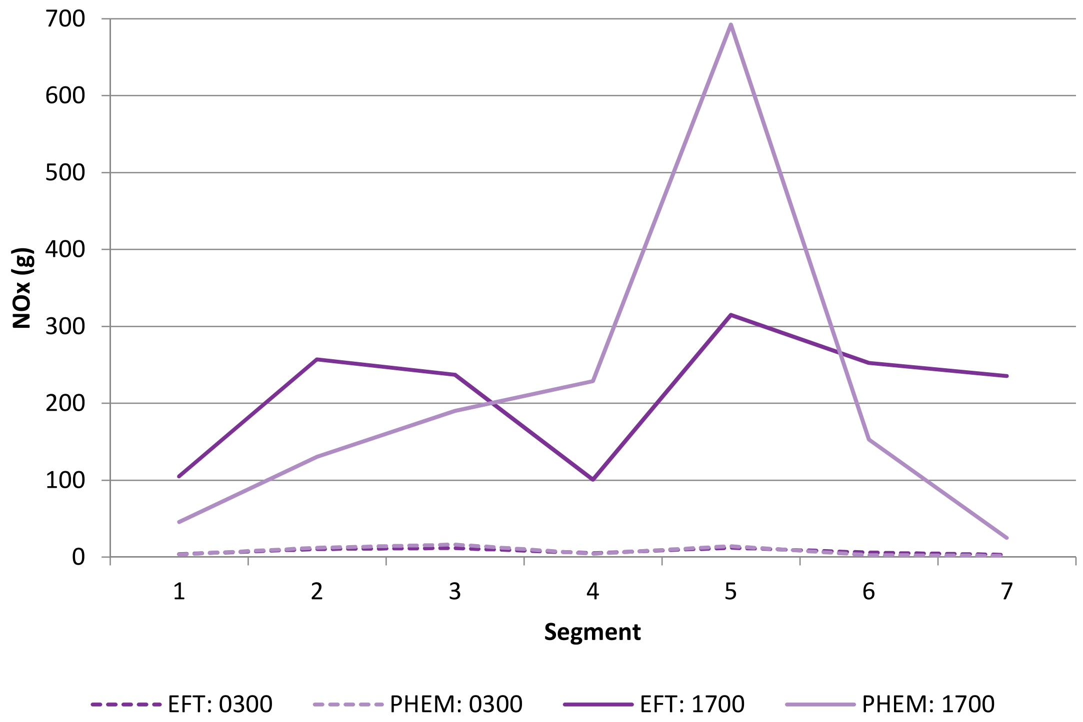

Figure 6-18b: *Total NO_x on each of the seven road segments in Figure 6-14 at 03:00 and 17:00.*

generation in the traffic model (as specified in the AIMSUN user manual (TSS, 2013b)). The model used in this analysis is run with 10 different random seeds, illustrating how traffic varies over ten different days.

By examining the same road segments that were specified in Section 6.4.4 (see Figure 6-14) across the different random seeds, the difference between the days modelled can be illustrated (see Figure 6-16a and 6-16b). As already discussed in this section, in congested periods vehicle emissions are greater. The variation in traffic congestion is illustrated by the greater spread of CO_2 and NO_x emissions across different seeds during the am and pm rush hour.

6.4.6 Comparison to the Emissions Factors Toolkit Model

As discussed in Section 6.2.2, the Emissions Factors Toolkit (EFT) model is an average speed model that is one of the most widely used emission models in the UK and therefore it is pertinent to compare the vehicle emissions output from this study to EFT. In the EFT, the vehicle emissions are calculated as a function of average speed over a link, it is a simpler model than the microsimulation methodology used in this research. The road segments in Figure 6-14 are used as the comparison area for the EFT model for the base year (2015) fleet mix. This was run over the period of 24 hours with the same Euro standard fleet mix as that specified in the PHEM model (although this was constant across the 24-hour period for EFT due to the model limitations). Overall, the EFT model was found to estimate higher CO_2 and NO_x emissions than the PHEM model(see Figure 6-17). This is mainly as a result of the topography of the road network. The EFT model does not incorporate gradient into the emissions estimate and the road segments chosen have a continual downhill road grade. The discrepancies between the models are greater at peak times than non-peak periods, especially in the evening. If we consider the seven road segments individually for 03:00 and 17:00 e.g. peak and off peak (see Figure 6-18a), it is clear that the EFT model is estimating higher CO_2 emissions than the PHEM model on free flow links (e.g. road segments 1-3) by as much as 70% and underestimating emissions on congested links (e.g. road segments 4 and 5) by as much as 20%. Note that due to the gradient, this lower emissions estimation from EFT would be significantly greater if the congestion was on a flat or increasing road grade. The difference between the model estimates are even greater for NO_x (see Figure 6-18b), with an estimate of up to 97% greater than the PHEM model on free flow links and lower estimate of up to 47% than the PHEM model on congested links.

In addition, the EFT cannot estimate energy consumption from BEVs or PHEVs. Therefore, for future fleet scenarios, it is not capable of estimating the impact on emissions of increasing numbers of hybrid and electric vehicles in the road fleet. Because of the inclusion of road grade, the ability to capture congested behaviour on the traffic network, and capability to incorporate hybrid and electric vehicle energy and emissions, this section illustrates why the modelling approach described in this chapter of the thesis is a better approach to estimating network level vehicle emissions across different times of day for both the base year and in future fleet scenarios.

The other vehicle emission models discussed in Section 6.2.2 such as MOVES, AIMSUN and HBEFA would produce different results to the modelling undertaken with PHEM. As discussed in Section 6.2.2 the MOVES model is a microsimulation model and has been found to produce similar results to the PHEM model (see Wyatt (2017), therefore it is likely that MOVES would reproduce the same trends as the PHEM model. The AIMSUN and HBEFA models are more aggregate models and therefore it is speculated that the results would be more likely to mimic those of the EFT rather than the higher resolution PHEM modelling results. With the different approaches used by the different models, without running the data through these models it is difficult to quantify how results would vary between them.

6.5 SUMMARY AND CONCLUSIONS

Estimating the effect of a diverse set of future road fleet scenarios on traffic emissions allows us to draw tangible conclusions about the effect of different levels of hybrid and electric vehicles on emissions of CO_2 and NO_x . By utilising a method that fully captures the changing emission levels, conclusions can be drawn both at an aggregate level but also at a greater temporal and spatial resolution. Using a coupled microsimulation traffic and emissions model on a network level over a 24-hour period is still a novel approach to estimating vehicle emissions, but with growth of data availability and computing power, this is likely to change in coming years. The approach used in this chapter is unique, in that it couples two different microsimulation emission models together to approximate fuel efficiency and pollutant emissions from both conventional and hybrid/electric vehicles. This is important because hybrid and electric vehicles are more efficient than conventional vehicles in stop-start traffic, and therefore this needs to be incorporated for representative emissions estimates.

On an individual vehicle and highly aggregate level, the benefits of hybrid and electric vehicles compared to petrol and diesel ICEV have been well documented (for example see Chen et al. (2018), Liu et al. (2018), and Guensler et al. (2017)). These benefits include lower NO_x, and higher fuel efficiency especially under stop start conditions. Because of the small number of hybrid and electric vehicles in most vehicle markets, most traffic emission models do not have dedicated modules for estimating emissions of low carbon vehicles or models are aggregated such that they cannot appreciate how emission factors of all vehicle types vary with changing traffic conditions. The microsimulation coupled traffic and an emission modelling is an emerging simulation toolkit, which relies on extensive data collection to build the model, and computing power to run it. Therefore, this is the best representation of the benefits of future fleet scenarios from an emissions perspective.

Although the future scenarios of the fleet are inherently uncertain, if an aggregate emissions model is used the errors will propagate and we cannot draw meaningful conclusions from the results. This approach allows us to have appreciation for the different financial scenarios and their potential effect on adoption, whilst giving an analytical application in assessing network level emissions at a microsimulation level.

From this analysis, levels of CO_2 and NO_x spike in congested traffic with emission factors of petrol and diesel cars increasing by over 30%. Therefore, policy should aim to curb use of diesel vehicles and incentivise hybrid and electric vehicles during these times. Although this analysis primarily focuses on cars (which account for approximately 66% of CO_2 and 36% of NO_x), limiting emissions from larger vehicles such as buses and HGVs will bring significant benefits to urban air quality. The main value in this chapter is the quantitative assessment of the effect of more EVs and fewer diesels in the fleet. Clearly it was already known that these trends would produce a positive result for CO_2 and NO_x emissions, but the work in this chapter shows the extent of this across a city road network. By using this modelling method, it was revealed that by scrapping vehicles of older Euro standards, and curbing increases in kerbside vehicle weight, there could be significant benefits for air quality. Additionally, the methodology adopted allows for more in-depth analysis temporally and spatially as well as accounting for the stochastic nature of traffic. This enables an assessment of the effect of changes in the vehicle fleet at different times of day and different locations across the network. Such an insight is highly valuable to policymakers who are assessing measures such as clean air zones, low emission zones and electrification of bus fleet and the extent to which they could contribute to cleaner air at different times of day across different locations in the city.

In the next chapter the conclusions from each part of this thesis will be brought together to answer the research questions set out in the first section of this work. This chapter completes the story of the thesis, such that the TCO analysis was utilised as the basis for future road fleet scenarios, and the effect on network level emissions was assessed using these scenarios.

CHAPTER 7: SUMMARY AND CONCLUSIONS

7.1 THESIS SUMMARY

Electrification of the transport sector offers the opportunity to utilise the increasing share of renewable energy generation whilst reducing national oil dependency. Battery Electric Vehicles (BEVs), Plug-in Hybrid Electric Vehicles (PHEVs) and Hybrid Electric Vehicles (HEVs) offer a low-carbon low-pollution alternative to conventional petrol and diesel technology. Battery technology has improved over the past decade, with economies of scale and streamlining of manufacturing processes leading to falling electric vehicle costs. Market share of hybrid and electric vehicles is now growing, with many countries incentivising vehicles through both fiscal and non-fiscal incentives. Establishing the cost effectiveness of these vehicle types, understanding how costs may change in the future and estimating the effect of greater numbers of hybrid and electric vehicles on pollutant emissions at a city scale can inform and direct low-carbon transport policy.

Historic vehicle ownership cost analysis in this thesis ascertains the cost effectiveness of hybrid and electric vehicles in light of the current fiscal incentives on offer across several different geographic regions. This thesis concludes that in all regions the incremental TCO of hybrids and electric vehicles compared to conventional vehicles has reduced between the year of introduction and 2015 subject to the assumptions made in this analysis, confirming the original research hypothesis. Year on year hybrid electric vehicle TCO was found to vary least in the UK due to the absence of subsidies. Financial subsidies have enabled BEVs to reach cost parity in the UK, California and Texas, but this is not the case for PHEVs, which have not received as much financial backing. The value of this regional analysis highlights the variation of monetary incentives available across different regions and the effect on the comparative vehicle TCO. However, the cost ratio of EVs to ICEVs varies across the different regions more than anticipated.

Electrification of the fleet is already growing with hybrid and electric vehicle ownership costs falling. This thesis finds that depending on the vehicle size segment, hybrid and electric private vehicle ownership costs could reach cost parity with conventional petrol vehicles by 2025. Future vehicle costs will be affected by changes in several variables: primarily fuel price, battery price, and taxes. In fact, VED tax changes in 2017 affect PHEV purchasers greater than those who purchase other vehicle types. Based on this analysis, with falling battery costs, BEV uptake could be strong in the medium and large+ size segments but financial subsidies and tax policy would have to support this. Private car TCO and market share were found to be more closely linked than company car cost and market share; such that private car market share is more reactive to changing cost. The historic variation in company car cost was found to be more dependent on changing BIK tax rates than vehicle prices. With other additional factors such as greater range of new BEVs and the expansion of the supporting charging infrastructure, it is highly likely that the electrification of the fleet will continue.

Policymakers are looking to plan for the future, therefore this thesis investigates how market diffusion modelling can be used to model future road fleet scenarios . This thesis illustrates the shortcomings of the widely employed standard market diffusion modelling approach such as the Bass, Gompertz and Logistic models, demonstrating how fitted modelling parameters are sensitive to the number of years of calibration data and the saturation level chosen. An extended generalised Bass modelling framework based on vehicle ownership costs can be utilised to ascertain how different external market conditions could affect the composition of the future car fleet. This approach outputs vehicle market share of hybrid and electric vehicles and can be used to test the effect of different fiscal incentives on future market share. This approach illustrates one adoption pathway to the 2040 target of 100% hybrid and electric vehicle market share, indicating that market share could accelerate in the near future. It is clear that one option available to policymakers is to support the plug-in vehicle grant, which could ensure continuing adoption of EVs. By ensuring diesel vehicle ownership costs are greater than conventional petrol cars, the dieselisation of the fleet could slowly be reversed.

Estimating the effect of future fleet scenarios on network level vehicle emissions is important for urban transport policy. This thesis demonstrates how hybrid and electric vehicles can contribute to cleaner urban air quality and lower carbon dioxide emissions especially at times of high congestion. This analysis found that CO_2 emission factors of hybrid and electric vehicles are less than half that of diesel and petrol ICEVs in times of peak congestion. Therefore, the increased adoption of hybrid and electric vehicles by 2040 along with the scrappage of older vehicles leads to the reduction in network level CO_2 and NO_x emissions of up to 31.6% and 95% respectively. The advantages of using the microsimulation methodology are extensive, enabling in-depth analysis into spatial emission hotspots, the effect of the stochastic nature of traffic, and the variation of vehicle emissions throughout the day. Therefore, a coupled microsimulation traffic and vehicle emissions model is the most appropriate method to capture the temporal and spatial effects of this future vehicle fleet. With more aggregate methods such as the Emission Factor Toolkit, the temporal and spatial effects cannot be assessed. By incentivising the scrappage and use of older diesel vehicles of all sizes, the majority of the air quality benefits can be realised within the next five years. After that, EVs can contribute significantly to decarbonising and improving urban air quality.

7.2 HOW THE RESEARCH IN THIS THESIS ADDRESSES THE RESEARCH QUESTIONS

R1. Are hybrid and electric vehicles cheaper now than when they were first introduced to the mass market?

Hybrid and electric vehicle technology has been falling in price since introduction of these vehicle types to the mass market. In fact, new EV models have recently been announced with similar MSRP to conventional petrol/diesel ICEVs. Each year, the cost of manufacturing the novel drivetrain, battery and vehicle components has fallen from more efficient production processes. Some of this cost reduction has been passed onto the consumer, although profit margins of hybrid and electric vehicles are also increasing. Historically, manufacturers such as Toyota have made a loss during the early years of production, but as sales grow this is changing. Simultaneously, hybrid and electric vehicle technology is developing, the EVs available now are more advanced than the first models available on the market. Changes in battery capacity, installation of advanced driver assistance systems and modifications to meet increasingly stringent safety standards, all offset part of the falling capital cost of hybrid and electric vehicles.

In some geographic regions, these vehicles can be more expensive due to import taxes. Changes in manufacturing locations, for example the opening of the Toyota factory in the USA, can cause step changes in price but lead to supply stability in the region. Some countries, such as Brazil, have taken advantage of this tax to produce a financial incentive for EVs. As electrification of the transport sector grows, more countries will start to manufacture EV models and the falling vehicle prices experienced in countries such as the USA could materialise in other markets.

In the UK, vehicle TCO has changed depending on the type of owner. For the private consumer, the costs of hybrid and electric vehicles have fallen since introduction for all vehicle types (as is the case in Japan and the USA). However, this is different for company car drivers, which have seen tax increases for low CO_2 emission vehicles to counter the reducing government tax base. Therefore, over the past decade company car driver costs have increased for EV drivers. Tax increases for vehicles with low rated CO_2 will likely rise as the average vehicle CO_2 of company cars continues to fall. However, the taxes payable are still significantly lower than for conventional petrol and diesel ICEVs, therefore there is still a financial incentive to choose low CO_2 emission vehicles.

These conclusions are largely supported by the literature, with learning rates of hybrid and electric vehicles being well documented (see Safari (2018) and Nykvist and Nilsson (2015)). Because this thesis analyses vehicle TCO using MSRP rather than the cost of manufacture, a learning rate analysis is not directly comparable, rather this approach is from a consumer point of view, emphasising the price fluctuations consumers experience. Most TCO analysis in the literature considers manufacturing costs rather than MSRP (e.g. Al-Alawi and Bradley (2013b), Hutchinson et al. (2014) and Wu et al. (2015)), and by comparing these studies over their different base years we can confirm that cost is falling and will continue to do so. The studies in literature do not consider TCO over multiple historic years, and are therefore not directly comparable; the temporal conclusions in this thesis are therefore much stronger than attempting to compare these studies in the literature.

R2. How do vehicle ownership costs change over different size segments and how does this link to market share?

Generally, larger sized vehicles have greater ownership costs, but there is greater variation across vehicle types for larger size segments. In the small and medium vehicle segments, the comparison vehicles chosen (based on market share) are more similar in terms of engine power/size than in the large and large+ segments. The small and medium vehicle size segments together account for 70% of market share (in the UK; this figure is similar for many European markets) and are more popular in the private car market. The large and large+ vehicle size segments represent a minority of market share and are dominated by the business market. The large vehicle size segment represents vehicle types of luxury, therefore there will be an element of cost in purchase decisions, but other factors such as business practices, brand loyalty and aesthetic value will play a role in vehicle purchase decision. The large+ size segment represents a small proportion of market share and diversity of vehicle types that are not directly comparable, therefore it is difficult to draw conclusions for this size segment. This thesis finds that generally there is a link between TCO and market share over different size segments for the private consumer.

Hybrid and electric vehicles are now generally cheaper over a three-year TCO than conventional petrol/diesel cars. This is true for both private and company car owners across different vehicle size segments. In the larger segments, diesel ICEV TCO has increased compared to petrol ICEVs in the last couple of years. However, in the larger size segments diesel cars are still cost competitive for high mileages. The larger car segments have a higher proportion of company car owners, and with taxes graduated by CO_2 this is a strong policy instrument to decarbonise and de-dieselise a large proportion of the road fleet. Transport policy has made steps in the right direction, for example the increase of the company car diesel surcharge in the autumn budget (Barton, 2017), but this price increase may still not be great enough to deter diesel car adoption. Fleet purchasers are more rational in their decision making processes than private car purchasers. Hybrid and electric vehicles are still significantly cheaper than petrol/diesel ICEVs for the company car owner, and therefore market share continues to rise despite rising costs for low CO_2 emission vehicles.

Most studies in the literature consider vehicles across different size segments (e.g. Alawi and Bradley (2013b), Wu et al (2015) and Levay et al (2017)) with similar findings that larger vehicles have a greater TCO. However, these studies consider only a private car ownership model that is not reflective of the composition of vehicle ownership types across the fleet. These studies have also not considered how market share has changed historically compared to TCO necessitating a model that accounts for multiple purchase years. This thesis builds on the literature base to consider the UK car market in detail – which is similar to many vehicle markets across Europe in terms of vehicle size segment composition, company car popularity and dieselisation of the fleet. By comparing market share of size segments and vehicle types to TCO for both the private and company car owner, this thesis finds that the private market is more reactive to changing ownership costs than the company car market.

R3. How might the evolution of vehicle costs influence the future road vehicle fleet?

It is largely agreed in TCO studies which examine future vehicle costs, such as Hill et al (2012), Wu et al. (2015) and Lee et al. (2016), that vehicle costs for hybrid and electric vehicles will continue to fall, continuing historic trends. The findings in this thesis largely support the existing literature, finding that by 2030 hybrid and electric vehicles could be cost competitive without financial subsidies. Financial motivation is largely responsible for vehicle purchases in vehicle markets across the world- as discussed in Chapter 3 and backed up by the literature (Coffman et al., 2017). Therefore, it is reasonable to assume that changing vehicle costs in the future will influence the composition of new registrations. If hybrid and electric vehicle costs continue to fall, then it is probable that these vehicle types will be more important in the future, especially in the medium term. This thesis uses cost as a proxy for increases in hybrid and electric vehicle fleet share, but there are other factors, that could affect adoption, such as access to charging infrastructure, range anxiety and distrust in new technology, all of which if fully addressed could stimulate sales even if prices are stagnant.

Depending on how companies choose to set their profit margins and governments choose to differentiate company car tax, there is an opportunity to promote clean low carbon vehicles, and decarbonise (and de-dieselise) the fleet. Trends have shown that costs are rising for diesel cars; with uncertainty of depreciation, increasingly stringent DPF testing and regulation limiting diesel vehicle access to urban areas, resulting in a significant fall in diesel ICEV market share. This means that dieselisation is likely to be reversed, but the switch to hybrid and electric vehicles rather than petrol ICEVs should be encouraged by using policy levers. As long as low carbon vehicle TCO is cheaper than for conventional vehicles especially for private owners in the smaller size segments and company car owners in the larger size segments, market share is likely to grow.

R4. How would a future road vehicle fleet containing more hybrid and electric vehicles affect urban network vehicle emissions?

From the modelling work in this thesis, it was found that hybrid and electric vehicles have similar emission factors in congested and non-congested conditions due to their increased efficiency in stop-start conditions, whereas petrol and diesel CO_2 emissions vary by over 30% over the same distance depending on congestion. This means that at times of high traffic flow, with stop-start conditions, on a network level hybrid and electric vehicles deliver an even greater CO_2 and NO_x savings. This non-linear effect illustrates how even small numbers of hybrid and electric vehicles deployed in the fleet can lead to much more significant reductions in CO_2 and NO_x over the course of a day. The impact of increasingly stringent Euro standards will also reduce CO_2 and NO_x emissions significantly in the short term, but electrification of the fleet would make a bigger difference in the long term illustrating how network level CO_2 and NO_x emissions could fall by as much as 31.6% and 95% respectively by 2040.

The network level emission models currently in use (notably the Emissions Factors Toolkit) do not have the capability to adequately capture these non-linear effects of traffic emissions and congestion. In addition, most do not have the means to model hybrid or electric vehicles – a must when examining the effect of the changing vehicle fleet on emissions. However, even if these models disagree quantitatively regarding the percentage of emissions reductions, these models do agree that the deployment of hybrid and electric vehicles will lead to declines in network level CO_2 and NO_x throughout the day.

Contrary to the inherent uncertainties of the cost model and fleet scenarios used, the microsimulation traffic and emissions model is considered more precise in its estimate of second by second vehicle emissions. Errors propagate through a model, therefore if an aggregate emissions model is used, the errors from early stages will compound. The inaccuracies of using aggregate emission factors have been extensively documented (see Chapter 6 for comparison of this modelling approach to the Emission Factors Toolkit) and there would be little use in estimating the effects of these fairly low penetrations of HEV/PHEV/BEVs in the fleet if using these methods.

7.3 LIMITATIONS

Every effort was made in this thesis to explore each avenue fully, however, it is the nature of all research that there are limitations to the methods used, the data collected and the conclusions that can be drawn, especially within the timeframe allocated for the PhD. Time permitting, some of these limitations could be addressed, whereas others are fundamental to the methodology chosen or the data available.

7.3.1 Methodological Limitations

The TCO methodology underpins the key conclusions from this thesis. TCO is a useful measure, but even a sensitivity analysis cannot fully demonstrate the range of ownership costs across vehicle models, user behaviour and purchase method. The results of this thesis are subject to the large number of assumptions made regarding the inclusion of the constituent parts in the TCO calculation and the values assumed for these components. The sensitivity and scenario analysis in Chapters 3 and 4 aimed to investigate how the variation in these components affects the results. Because the TCO framework and the values of the constituent parts are not standard across the literature, we conclude that it is necessary to recognise that these findings are clearly dependent on the assumptions made.

There are significant uncertainties in future cost and adoption of hybrid and electric vehicles but the scenarios outlined in this thesis attempt to provide an overview of these. There are limitations in scenario modelling, in that all future scenarios and projections will likely be wrong. One of the aims in the thesis is to understand how the different cost scenarios could affect fleet mix and the effect on network level vehicle emissions rather than attempt to explicitly project future vehicle market share.

When applying the coupled traffic and emissions model, there are numerous small errors that could contribute to the overall modelling error and limit the model applicability than described here, but this section aims to give the reader an appreciation of the main limitations rather than an exhaustive discussion.[14] The commonly quoted phrase 'all models are wrong but some are useful' seems particularly pertinent at this point. Models are designed to be simplifications of the real world, such that it is cheaper and quicker to build and simulate these models rather than carry out real world experiments on this scale - if these experiments are even possible to execute. As a result, there is always a trade-off between computing time and model complexity when designing a representation of the real world.

The traffic model is designed to simulate a representative weekday in September. Traffic varies with the day of the week, the month, and the weather (amongst other factors), with events such as sports fixtures, vehicle accidents or road works all causing abnormal traffic flows. Limitations such as these are typical of all traffic models. Averaging over different random seeds aims to address the stochastic nature of traffic to model a 'typical' day.

The vehicle flow data available was not all collected within the same 24-hour period. The data used in the model has been collected over a number of different months and years, in some cases with minor flow inconsistency between data sets. If more than one data set was available for a particular entry/exit point, the data selected was chosen based on a similar month rather than year of the modelled day. In addition, there is not data available for some entry/exit points (these were mainly minor roads). The Leeds city cordon vehicle count has shown that the number of vehicles entering and exiting the inner ring road has varied by around 5% in the past twenty years (Department for Transport, 2015a). This evidences the assumption that with the current road layout and policies in place, the vehicle flows are not expected to change significantly between now and 2040. This contradicts the DfT Road Traffic Forecasts 2018 (Department for Transport, 2018), which project urban traffic growth. However, with the high levels of congestion across most of the day, it is unlikely with the current policies in place that this could materialise.

Updating the Leeds Network model from Version 1 to Version 2, the traffic model has been incrementally improved. Although every effort has been made to fully calibrate the model, the lack of data to validate using journey time analysis is a key area for improvement. The amount of data needed to calibrate journey times across different times of day requires a large data set with journeys over many days throughout the 24-hour period.

Driving behaviour is non-uniform across the vehicle fleet and significantly affects vehicle tailpipe emissions. AIMSUN uses random seeds along with vehicle dynamics parameters to account for this stochastic behaviour, such that vehicles do not drive uniformly within the

[14] For an in-depth discussion of the limitations of this modelling approach please see Wyatt et al (2017).

traffic model. However, there is little guidance on how to calculate vehicle dynamics parameters from the AIMSUN user manual and the literature. An inaccurate interpretation could affect the outputs and therefore the conclusions drawn from the model. Detailed information from the software developers would give clarity and ensure that these parameters were accurately calculated for the model.

The vehicle emissions estimates made by PHEM have been independently validated (as discussed in section 6) and the Simulink H/EV Energy and Emissions Model has also been independently validated (see Section 6.3.6), therefore the estimates of second-by-second tail pipe emissions are as accurate as possible. These models calculate emissions for a specific vehicle specified, but clearly by estimating all the vehicles within the category (e.g. passenger car, taxi etc) with the same attributes there will be errors. PHEM specialises in modelling vehicles by Euro standard, with the capacity to vary vehicle characteristics such as weight. Although these parameters could be changed to take different vehicle size segments into account, because the original testing used a particular vehicle model it is ill advised to change the vehicle weights significantly within the PHEM vehicle attributes. Analysis of the ANPR Leeds fleet shows a concentration of vehicle sizes around the medium vehicle segment, therefore it is anticipated that the over representation of emissions from small cars will be compensated by the under representation from large cars.

In the past twenty years the average vehicle weight of cars has increased across all size segments (as discussed in Chapter 2). This is mainly as a result of increased safety features as well as additional electrification of previously manual vehicle attributes (e.g. windows). In the future there are several options to reduce vehicle weight by using different materials (e.g. carbon fibre or high strength steel) (Lewis et al., 2014), or by redesigning the body to use less materials (e.g. Tesla model 3) (Bower, 2018). These options increase vehicle design and/or manufacture costs. To date, most of these options have only been utilised on EVs where weight reduction is important, but it is unlikely that these changes will be applied across the board unless the material costs reduce significantly. Other vehicle attributes can also change tailpipe emissions, such as occupancy and vehicle age, the values used to represent the 'average' vehicle in the fleet have the potential to change in the future.

The Simulink H/EV Energy and Emissions Model is based on a particular vehicle type (the Toyota Prius HEV/PHEV, and the Nissan Leaf). At present the Toyota Prius and the Nissan Leaf are the most popular HEV and BEV models respectively in the UK (Next Green Car, 2018). The most popular PHEV in the UK is the Mitsubishi outlander, which is much larger than the modelled Toyota Prius PHEV (Next Green Car, 2018). There are fewer HEV/PHEV/BEV models available than conventional petrol/diesel ICEVs, therefore the HEV/PHEV/BEV fleet is more homogeneous at present. As a result, the error in calculating vehicle emissions from these vehicle types will be smaller than for the other vehicles' emissions calculated in PHEM. In the future fuel economy and efficiency will probably increase, however, the model does not have the capacity to anticipate this.

In summary, this modelling approach has limitations - as does every modelling approach. However, this approach is arguably more robust for assessing urban, congested network than using aggregated tailpipe emissions estimates. More aggregate methods are less reliable at assessing stop-start congested conditions, when emissions of CO_2 and NO_x are greatest. On the whole, from understanding the limitations of the model, and having an appreciation of where the key uncertainties lie, the modelling conclusions can be drawn with greater certainty.

7.3.2 Policy Limitations

One of the main limitations of this thesis is the focus on cost as a key driver to low carbon vehicle adoption. It is discussed in Section 2.2.2 that there are a number of other factors that contribute to vehicle purchase decisions such as demographic, situational and psychological factors. In recognising that adoption is not purely motivated by economic rationality, this can inform how policy can be optimally designed to stimulate adoption of EVs.

The analysis in this thesis indicates that vehicle ownership costs and market share are linked. Therefore, this shows that fiscal incentives could play a role in incentivising hybrid and electric vehicle adoption. This aligns with the findings from other studies such as Yan et al. (2016) that reductions in the initial capital cost are effective in increasing adoption. However, providing capital cost reduction is expensive for policymakers, with ethical issues over subsidising middle class household vehicle purchases. Therefore, it is imperative that these grants are regularly reassessed and then phased out as EVs break out of the niche market.

With nearly half of new car registrations attributed to the business market, changing company car tax is a key policy mechanism to push for the decarbonisation of the fleet. By creating a larger differentiation between CO_2 emission tax bands, this could accelerate the decarbonisation of the road fleet. At present, the majority of PHEV market share consists of Mitsubishi Outlanders in the business car segment. Policy can be designed to mitigate this and shift business purchasers towards either fully electric vehicles or smaller size segment PHEVs.

The trends in increasing vehicle weight and size over the past decade have not positively contributed to the decarbonisation of the road fleet. If these trends continue, this adds another challenge in reducing transport CO_2 emissions. Transport policy can play a significant role in nudging vehicle purchasers away from the larger vehicle segments, policy levers should be designed to try to stabilise or reverse this trend.

In many countries, lack of reliable information regarding vehicle cost is an additional purchase barrier. This could be addressed by creating an impartial resource such that potential purchasers can at least assess their fuel saving (and air pollution contribution) against depreciation costs given their annual mileage and share of urban/motorway driving.

In light of recent evidence illustrating the effects of urban air pollution on public health; introducing incentives for replacing diesel vehicles with hybrid/electric vehicles should be prioritised, especially in the business market that accounts for disproportionate diesel market share in the UK. Replacing high urban-mileage diesel vehicles with petrol-HEVs such as the Toyota Prius should be one of the first steps taken to cut urban air pollution.

Vehicle purchase incentives need to account for market segmentation. Attributes of adopters are different at distinct stages of technology adoption (as discussed in Section 2.2.2). The first EV purchasers (which form the 'niche market') have different attributes to those who adopt the technology when it is more mature. This begs the question of whether past car market adoption behaviour is a good indicator of future adoption patterns; this is a clear limitation of the conclusions drawn from this thesis. To investigate this, further analysis into more mature markets such as Norway should be undertaken. To continue to stimulate EV adoption, the policies in place need to account for this market segmentation, adapting to incentivise consumers with different attributes.

In light of the findings in this thesis, and the literature in vehicle purchasing behaviour, to optimally design transport policy that will steer vehicle purchasers towards low carbon vehicles, a range of policy instruments need to be employed. Fiscal incentives such as reductions in VED can play a key role in persuading purchasers towards low carbon vehicles, but non-fiscal policy levers are important in complimenting these incentives to influence car-purchasing decisions. Policymakers need to be aware on a local and national level of non-fiscal incentives such as access to HOV lanes, priority parking, and information programs. Importantly, incentives need to be phased in and out as appropriate for the different market segments to support adoption of hybrid and electric vehicles from the niche to the mass market.

7.4 FUTURE WORK

In the process of writing this thesis, many more questions emerged in each topic; each chapter in itself could have been extended to fill the entire thesis. This thesis fits into a large body of literature that has been rapidly expanding over the last decade with the advent of mass market EV deployment.

The TCO analysis in Chapter 3 focuses on countries with different attributes and market share of HEVs. Japan was included for its high market share of HEVs, but this analysis would be stronger if Norway was included as well because of the high EV market share. The depreciation rate used across countries/regions was static for each individual country. There is uncertainty around resale of EVs, and if data was available, tracking depreciation rates across countries and vehicle types would be valuable. This would also be important for diesel vehicles that have depreciated quicker in the last couple of years. EV charging costs are not uniform across public chargers. In some cities, such as Dundee, EV chargers are currently free, but in most cities charging using electricity from public charging infrastructure is charged at a higher cost than home charging. Future work would investigate this aspect of recharging the EV and look at its effect on TCO. Social discount rates were used in this analysis because private discount rates are variable amongst individual consumers. A further investigation into private discount rates for hybrid and electric vehicles would be an interesting extension, charting how this has changed over time. Parking charges vary across cities: a sensitivity analysis looking at the impacts of parking subsidies for low emission vehicles would be useful for city level policy makers. At present the share of LPG vehicles in the fleet is very small (<2%) but for completeness including LPG cars in the TCO analysis would be an interesting extension.

The regression analysis in Chapter 3 established the link between TCO and market share for the private owner. Future work should include investigating a lagged model and additional factors in the regression analysis. For example, an interesting extension of the current work would be investigating the neighbourhood effect in adoption of HEVs. Additionally, a separate panel regression should be run for the UK across the different size segments. The regression analysis currently considers the constituent components on an aggregate basis, by splitting these components, the effect of the different incentives on adoption could be investigated further adding to the extensive literature on this topic.

In Chapter 4, the TCO of different cars is investigated for the UK market across different vehicle segments. Due to lack of available data, the focus of this chapter was the UK, if reliable cost data was available across different vehicle size segments, and for future cost scenarios, further work would extend this analysis to cover the same geographic regions as in Chapter 3. Tesla's are highly competitive with other bestselling EVs in several of the world's vehicle markets; further work should compare Tesla TCO across these markets against an appropriate conventional petrol car. Further work could include regression analysis on TCO for business purchases; this would add quantitative evidence to the conclusions drawn regarding purchasing behaviour in this segment.

The future cost scenarios examined do not include step changes in battery size and chemistry e.g. development of solid state battery technology etc. In future, consumers may be able to choose the battery size of their vehicle, the impact of step changes in battery size will no doubt affect adoption, where potentially reduced range anxiety could offset this increased cost. Road pricing is a policy that is deemed politically unfeasible at present, but there is mounting discussion over not 'whether' but 'when' this policy will be introduced. An extension to this scenario analysis would be to include exploration of road pricing and its effect of TCO and the future fleet.

Time constraints resulted in a lack of robust sensitivity analysis for the extended model in Chapter 5. A natural extension to the work presented in Chapter 5 would include Monte Carlo simulation of the different cost attributes effect on fleet share. A Monte Carlo simulation places a probability on each parameter and therefore is a more insightful sensitivity analysis. An extensive exploration of the different model parameters for the extended model would also strengthen the analysis in this chapter. The clear extension to the first three results chapters of the thesis is to include the adoption of other electric vehicle types such as vans, trucks and buses in the modelling framework. The model could also be applied to evaluate other policies such as scrappage rates for diesels. A comprehensive comparison to other future vehicle fleet scenarios would be an interesting conclusion to this chapter. However, the assumptions governing these models are not often publically available and are therefore challenging to analyse.

The analysis in this thesis predominantly focuses on CO_2 and NO_x emissions. Particulate Matter (PM) emissions from vehicles are still a concern because of the negative effects on human health. As discussed in Chapter 2, with better vehicle emissions control technology, tailpipe PM emissions could become insignificant compared to non-tailpipe PM emissions (e.g. from tyres and brakes). A limitation to this thesis is the lack of inclusion of PM emissions in the vehicle emissions modelling. Further work should address this limitation to understand the contribution from hybrid and electric vehicles as these vehicle types become a higher proportion of the fleet.

The AIMSUN traffic model was calibrated for vehicle flows along the guidance specified by DfT. The next step is for the model to be validated with journey times recorded from the real world. The stochastic nature of the model, means there would need to be hundreds of journeys logged to compare it with simulated journeys over key road segments for each hour of the day. With such data, statistical significance could be ascertained for simulated journey times, but clearly such data would be difficult and costly to attain. In this study, the vehicle dynamics of HGVs was assumed to be the same as buses. An extension to this work would include vehicle dynamics data collection and analysis from HGVs operating within the Leeds ring road. Finally, with large scale telematics data now available, the modelling could be extended to include real, observed trajectories for calibration of journey times and vehicle dynamics. A useful extension to the analysis presented in Chapter 6 would be a full comparison to the other vehicle emission models to ascertain the different results from these models and why these discrepancies exist. The methodology used in this chapter can be utilised further to analyse emission hotspots and the effect of changing the vehicle fleet at this greater resolution. Further work should include a more in depth analysis of the model results both temporally and spatially to evidence the full value of using this modelling approach.

7.5 FINAL REMARKS

Hybrid and electric vehicles are a strong contender to decarbonise the transport fleet and cut urban air pollution. Electrification of the fleet is set to rise; and with falling battery costs, investment in public charging infrastructure, and public opinion demonising diesel cars, conditions are primed for consumers to make the switch to hybrid or electric. The non-linear effects of hybrid and electric vehicles on CO_2 and NO_x emissions in traffic is a key motivating factor for policymakers to incentivise adoption of these vehicle types in congested urban areas. Such evidence paves the way for the introduction of Clean Air Zones, Ultra Low Emission Zones and congestion charging, to significantly improve the lives of everyone who lives in congested urban areas.

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APPENDICES

Appendix 2-A: *Definitions of vehicle size segments for the UK, EU and USA (Van Miert, 1999; U.S. Government Publishing Office, 2016).*

UK	EU	US
A: Mini	A: Mini	Minicompact
B: Supermini	B: Supermini	Subcompact
C: Medium Car	C: Medium Car	Compact
D: Large Car	D: Large Car	Mid-size
E: Executive F: Luxury	E: Executive F: Luxury	Large
G: Sports	S: Sports	Two-Seater
H: Multipurpose	M: Multipurpose	Minivan Cargo Van Passenger Van
I: Dual Purpose	J: Dual Purpose	Small Sport Utility Vehicle Standard Sport Utility Vehicle

Appendix 2-B: *Definitions of vehicle purchase class (Society of Motor Manufacturers and Traders, 2017).*

Purchase class	Definition
Business	If the vehicle is being sold to/registered for a company that operates up to 24 vehicles, it should be designated a business sale unless it is a "demonstrator" in which case it should always be "Fleet".
Fleet	If the vehicle is being sold to/registered for a company that operates a fleet of 25 or more vehicles, or is a demonstrator, it should be designated a fleet sale. This includes dealer demonstrators and Motability-leased vehicles.
Private	If the vehicle is being sold primarily for the personal use of a private individual, it should be designated a private sale.

Appendix 3-A: *Vehicle specification for comparison vehicles (2015 model year).*

	Powertrain type	Battery capacity (kWh)	Power (bhp)	Engine size (l)	Fuel Economy (MPG)	Vehicle length (mm)	Weight (kg)
Toyota Corolla (Petrol)	Conventional petrol ICE	–	130	1.8	42.2 (A)	4638	1295
Ford Focus (Petrol)	Conventional petrol ICE	–	103	1.6	38 (M)	4358	1270
Ford Focus (Diesel)	Conventional diesel ICE	–	93	1.6	51 (M)	4358	1338
Toyota Prius	Full parallel Hybrid HSD	1.3	120	1.8	56.7	4540	1395
Toyota Prius plug-in	Plug-in Hybrid HSD	6.4	122	1.8	90.8$*$	4481	1449
Nissan Leaf electric	Full Electric	24.0	107	–	141.7$*$	4445	1471

Note: A indicates Automatic transmission, M Manual transmission system. HSD stands for Hybrid Synergy Drive. $*$ MPG equivalent

Sources: (Idaho National Laboratory, 2014; Edmunds, 2015; Parkers, 2017)

Appendix 3-B: *TCO component breakdown for the year 2015 (accompany output to Figure 3-2 all costs converted to £2015 for easy comparison).*

Geographic region	Cost component	Petrol	Diesel	HEV	PHEV	BEV
Japan	Depreciation	3410	–	5648	6848	6368
	Tax	1078	–	315	315	315
	Maintenance	358	–	323	323	276
	Insurance	2652	–	2652	2652	2652
	Petrol cost	1556	–	1158	535	–
	Electric cost	–	–	–	79	796
California	Depreciation	4323	–	5921	6629	4849
	Tax	196	–	196	196	196
	Maintenance	384	–	314	314	268
	Insurance	792	–	713	792	792
	Petrol cost	1821	–	1353	625	–
	Electric cost	–	–	–	98	982
Texas	Depreciation	4323	–	5029	6119	7119
	Tax	147	–	147	147	147
	Maintenance	352	–	318	318	268
	Insurance	691	–	691	691	691
	Petrol cost	1602	–	1191	550	–
	Electric cost	–	–	–	90	897
UK	Depreciation	6717	7223	9080	12755	9078
	Tax	369	57	0	0	0
	Maintenance	354	742	319	319	273
	Insurance	783	783	783	783	783
	Petrol cost	4062	3146	2733	1263	–
	Electric cost	–	–	–	65	653

Appendix 4-A: *Vehicle specification for comparison vehicles (2015 model year) (Compiled from Parkers (2017) and Autoevolution (2017)).*

Powertrain type	Size segment		Release year	Battery capacity (kWh)	Power (bhp)	Engine size (l)	Fuel Economy (MPG)	Vehicle length (mm)	Weight (kg)
Petrol/Diesel ICEV	Small	Ford Fiesta	1976	-	80/67	1.25/1.4	49/67	3950	1041/1011
HEV	Small	Toyota Yaris	2010	0.8	99	1.5	80	3905	1085
BEV	Small	Renault Zoe	2012	22	86	-	111*	4084	1468
Petrol/Diesel ICEV	Medium	Ford Focus	1997	-	83/93	1.5/1.5	47/74	4358	1264/1338
HEV	Medium	Toyota Prius	2000	1.3	120	1.8	83	4460	1375
PHEV	Medium	Toyota Prius Plug-in	2011	4.4	97	1.8	133*	4645	1450
BEV	Medium	Nissan Leaf	2010	24	107	-	114*	4445	1567
Petrol/Diesel ICEV	Large	BMW 5 series	1972	-	181/181	2.0/2.0	41/58	4899	1595/1620
HEV	Large	Lexus GS 300h	2005	1.3	223	2.5	60	4850	1730
PHEV	Large	Mercedes C350e	2014	6.4	288	2.0	71*	4686	1785
Petrol/Diesel ICEV	Large+	Kia Sportage	1993	-	133/134	1.5/2.0	44/49	4440	1380/1600
HEV	Large+	Lexus RX 450h	2004	2.4	308	3.5	54	4890	2100
PHEV	Large+	Mitsubishi Outlander PHEV	2013	12	200	2.0	74	4695	1845
BEV	Large+	Mercedes B class (electric)	2013	28	177	-	84	4358	1725

*Note: There have been no BEV models introduced to date in the large car category, and no PHEV models in the small car category. * denotes MPGe (equivalent of MPGe for EVs).*

Appendix 4-B i: *Benefit in Kind (BIK) rates for Petrol cars 2002-2020.CO_2 given in g/km for Lower Bound (LB) and Upper Bound (UB).*

CO_2 LB	CO_2 UB	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
0	0	15	15	15	15	15	15	15	15	0	0	0	0	0	5	7	9	13	16	*
1	50	15	15	15	15	15	15	15	15	5	5	5	5	5	5	7	9	18	16	15
51	54	15	15	15	15	15	15	15	15	5	5	5	5	5	5	7	9	18	16	16
55	59	15	15	15	15	15	15	15	15	5	5	5	5	5	5	7	9	18	16	17
60	64	15	15	15	15	15	15	15	15	5	5	5	5	5	5	7	9	18	16	18
65	69	15	15	15	15	15	15	15	15	5	5	5	5	5	5	7	9	18	16	19
70	74	15	15	15	15	15	15	15	15	5	5	5	5	5	9	11	13	18	19	20
75	95	15	15	15	15	15	15	15	15	10	10	10	10	11	13	15	17	19	22	21
80	84	15	15	15	15	15	15	15	15	10	10	10	10	11	13	15	17	20	23	22
85	89	15	15	15	15	15	15	15	15	10	10	10	10	11	13	15	17	21	24	23
90	94	15	15	15	15	15	15	15	15	10	10	10	10	11	13	15	17	22	25	24
95	99	15	15	15	15	15	15	15	15	10	10	10	11	12	14	16	18	20	23	25
100	104	15	15	15	15	15	15	15	15	10	10	11	12	13	15	17	19	21	24	26
105	109	15	15	15	15	15	15	15	15	10	10	12	13	14	16	18	20	22	25	27
110	114	15	15	15	15	15	15	15	15	10	10	13	14	15	17	19	21	23	26	28
115	119	15	15	15	15	15	15	15	15	10	10	14	15	16	18	20	22	24	27	29
120	124	15	15	15	15	15	15	15	15	10	10	15	16	17	19	21	23	25	28	30
125	129	15	15	15	15	15	15	15	15	15	15	16	17	18	20	22	24		29	31
130	134	15	15	15	15	15	15	15	15	15	16	17	18	19	21	23	25	26	30	32
135	139	15	15	15	15	15	15	15	15	16	17	18	19	20	22	24	26	27	31	33
140	144	15	15	15	15	15	15	16	16	17	18	19	20	21	23	25	27	28	32	34
145	149	15	15	15	16	16	16	17	17	18	19	20	21	22	24	26	28	29	33	35
150	154	15	15	16	17	17	17	18	18	19	20	21	22	23	25	27	29	30	34	36
155	159	15	15	17	18	18	18	19	19	20	21	22	23	24	26	28	30	31	35	37
160	164	15	16	18	19	19	19	20	20	21	22	23	24	25	27	29	31	32	36	37

Appendix 4-B i continued…

CO_2 LB	CO_2 UB	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
165	169	15	17	19	20	20	20	21	21	22	23	24	25	26	28	30	32	33	37	37
170	174	16	18	20	21	21	21	22	22	23	24	25	26	27	29	31	33	34	37	37
175	179	17	19	21	22	22	22	23	23	24	25	26	27	28	30	32	34	35	37	37
180	184	18	20	22	23	23	23	24	24	25	26	27	28	29	31	33	35	36	37	37
185	189	19	21	23	24	24	24	25	25	26	27	28	29	30	32	34	36	37	37	37
190	194	20	22	24	25	25	25	26	26	27	28	29	30	31	33	35	37	37	37	37
195	199	21	23	25	26	26	26	27	27	28	29	30	31	32	34	36	37	37	37	37
200	204	22	24	26	27	27	27	28	28	29	30	31	32	33	35	37	37	37	37	37
205	209	23	25	27	28	28	28	29	29	30	31	32	33	34	35	37	37	37	37	37
210	214	24	26	28	29	29	29	30	30	31	32	33	34	35	35	37	37	37	37	37
215	219	25	27	29	30	30	30	31	31	32	33	34	35	35	35	37	37	37	37	37
220	224	26	28	30	31	31	31	32	32	33	34	35	35	35	35	37	37	37	37	37
225	229	27	29	31	32	32	32	33	33	34	35	35	35	35	35	37	37	37	37	37
230	234	28	30	32	33	33	33	34	34	35	35	35	35	35	35	37	37	37	37	37
235	239	29	31	33	34	34	34	35	35	35	35	35	35	35	35	37	37	37	37	37
240	244	30	32	34	35	35	35	35	35	35	35	35	35	35	35	37	37	37	37	37
245	249	31	33	35	35	35	35	35	35	35	35	35	35	35	35	37	37	37	37	37
250	254	32	34	35	35	35	35	35	35	35	35	35	35	35	35	37	37	37	37	37
255	259	33	35	35	35	35	35	35	35	35	35	35	35	35	35	37	37	37	37	37
260	264	34	35	35	35	35	35	35	35	35	35	35	35	35	35	37	37	37	37	37
265	+	35	35	35	35	35	35	35	35	35	35	35	35	35	35	37	37	37	37	37

*Notes: For 2000/2001, the BIK percentage was set at a flat rate of 25% for all vehicles. *For zero emission vehicles, if the battery electric range is under 30 miles the BIK is 14%, 30-39 miles BIK 12%, 40-69 miles 8%, 70-129 miles 5%, greater than 130 miles 2%.*

Appendix 4-B ii: *Benefit in Kind (BIK) rates for Diesel cars 2002-2020. CO_2 given in g/km for Lower Bound (LB) and Upper Bound (UB).*

CO_2 LB	CO_2 UB	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
0	0	15	15	15	15	18	18	18	18	3	3	3	3	3	8	10	12	16	19	*
1	50	15	15	15	15	18	18	18	18	8	8	8	8	8	8	10	12	21	19	18
51	54	15	15	15	15	18	18	18	18	8	8	8	8	8	8	10	12	21	19	19
55	59	15	15	15	15	18	18	18	18	8	8	8	8	8	8	10	12	21	19	20
60	64	15	15	15	15	18	18	18	18	8	8	8	8	8	8	10	12	21	19	21
65	69	15	15	15	15	18	18	18	18	8	8	8	8	8	8	10	12	21	19	22
70	74	15	15	15	15	18	18	18	18	8	8	8	8	8	12	14	16	21	22	23
75	95	15	15	15	15	18	18	18	18	13	13	13	13	14	16	18	20	22	25	24
80	84	15	15	15	15	18	18	18	18	13	13	13	13	14	16	18	20	23	26	25
85	89	15	15	15	15	18	18	18	18	13	13	13	13	14	16	18	20	24	27	26
90	94	15	15	15	15	18	18	18	18	13	13	13	13	14	16	18	20	25	28	27
95	99	15	15	15	15	18	18	18	18	13	13	13	14	15	17	19	21	23	26	28
100	104	15	15	15	15	18	18	18	18	13	13	14	15	16	18	20	22	24	27	29
105	109	15	15	15	15	18	18	18	18	13	13	15	16	17	19	21	23	25	28	30
110	114	15	15	15	15	18	18	18	18	13	13	16	17	18	20	22	24	26	29	31
115	119	15	15	15	15	18	18	18	18	13	13	17	18	19	21	23	25	27	30	32
120	124	15	15	15	15	18	18	18	18	13	13	18	19	20	22	24	26	28	31	33
125	129	15	15	15	15	18	18	18	18	18	18	19	20	21	23	25	27	3	32	34
130	134	15	15	15	15	18	18	18	18	18	19	20	21	22	24	26	28	29	33	35
135	139	15	15	15	15	18	18	18	18	19	20	21	22	23	25	27	29	30	34	36
140	144	15	15	15	15	18	18	19	19	20	21	22	23	24	26	28	30	31	35	37
145	149	15	15	15	16	19	19	20	20	21	22	23	24	25	27	29	31	32	36	37
150	154	15	15	16	17	20	20	21	21	22	23	24	25	26	28	30	32	33	37	37
155	159	15	15	17	18	21	21	22	22	23	24	25	26	27	29	31	33	34	37	37

Appendix 4-B ii continued…

CO_2 LB	CO_2 UB	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
160	164	15	16	18	19	22	22	23	23	24	25	26	27	28	30	32	34	35	37	37
165	169	15	17	19	20	23	23	24	24	25	26	27	28	29	31	33	35	36	37	37
170	174	16	18	20	21	24	24	25	25	26	27	28	29	30	32	34	36	37	37	37
175	179	17	19	21	22	25	25	26	26	27	28	29	30	31	33	35	37	37	37	37
180	184	18	20	22	23	26	26	27	27	28	29	30	31	32	34	36	37	37	37	37
185	189	19	21	23	24	27	27	28	28	29	30	31	32	33	35	37	37	37	37	37
190	194	20	22	24	25	28	28	29	29	30	31	32	33	34	36	37	37	37	37	37
195	199	21	23	25	26	29	29	30	30	31	32	33	34	35	37	37	37	37	37	37
200	204	22	24	26	27	30	30	31	31	32	33	34	35	35	37	37	37	37	37	37
205	209	23	25	27	28	31	31	32	32	33	34	35	35	35	37	37	37	37	37	37
210	214	24	26	28	29	32	32	33	33	34	35	35	35	35	37	37	37	37	37	37
215	219	25	27	29	30	33	33	34	34	35	35	35	35	35	37	37	37	37	37	37
220	224	26	28	30	31	34	34	35	35	35	35	35	35	35	37	37	37	37	37	37
225	229	27	29	31	32	35	35	36	35	35	35	35	35	35	37	37	37	37	37	37
230	234	28	30	32	33	35	35	36	35	35	35	35	35	35	37	37	37	37	37	37
235	239	29	31	33	34	35	35	36	35	35	35	35	35	35	37	37	37	37	37	37
240	244	30	32	34	35	35	35	36	35	35	35	35	35	35	37	37	37	37	37	37
245	249	31	33	35	35	35	35	36	35	35	35	35	35	35	37	37	37	37	37	37
250	254	32	34	35	35	35	35	36	35	35	35	35	35	35	37	37	37	37	37	37
255	259	33	35	35	35	35	35	36	35	35	35	35	35	35	37	37	37	37	37	37
260	264	34	35	35	35	35	35	36	35	35	35	35	35	35	37	37	37	37	37	37
265	+	35	35	35	35	35	35	36	35	35	35	35	35	35	37	37	37	37	37	37

*Notes: For 2000/2001, the BIK percentage was set at a flat rate of 25% for all vehicles. *For zero emission vehicles, if the battery electric range is under 30 miles the BIK is 14%, 30-39 miles BIK 12%, 40-69 miles 8%, 70-129 miles 5%, greater than 130 miles 2%.*

Appendix 4-C: *VED rates for vehicles considered in this study (VED prices given in £2017) (Compiled from GOV.UK (2017c), Department for Transport (2015b), Parkers (2017) and Spritmoniter (2018)).*

Size Segment	Vehicle Type	Representative vehicle	Tax before 1st April 2017	Tax after 1st April 2017 (first year)	Tax after 1st April 2017 (flat rate)	Type Approval CO_2 (g/km 2016 model)	Reported CO_2 (g/km 2016 model)
Small	BEV	Renault Zoe	0	0	0	0	0
	HEV	Toyota Yaris	0	15	130	75	109
	Petrol ICE	Ford Fiesta	0	120	140	99	164
	Diesel ICE	Ford Fiesta	0	120	140	82	114
Medium	BEV	Nissan Leaf	0	0	0	0	0
	PHEV	Toyota Prius	0	10	130	49	72
	HEV	Toyota Prius	0	15	130	89	116
	Petrol ICE	Ford Focus	0	120	140	136	172
	Diesel ICE	Ford Focus	0	100	140	109	129
Large	PHEV	Mercedes C 350e	0	10	440	54	138
	HEV	Lexus GH 450h	150	190	130	138	196
	Petrol ICE	BMW 5 series	150	200	140	139	214
	Diesel ICE	BMW 5 series	30	160	140	109	146
Large+	BEV	Mercedes B class	0	0	0	0	0
	PHEV	Mitsubishi Outlander	0	10	440	42	90
	HEV	Toyota RAV4	30	150	130	145	217
	Petrol ICE	Kia Sportage	150	200	140	149	209
	Diesel ICE	Kia Sportage	30	160	140	135	163

Appendix 4-D: *Eligibility for the plug-in vehicle grant (Compiled from GOV.UK (2017c) and Morris (2016))* .

Vehicle type	Eligibility April 2011 to March 2016	Eligibility April 2016 to March 2020
Category 1 cars		
CO_2 emissions <50g/km and can travel at least 112km (70 miles) with zero CO_2 emissions.	The grant will pay for 25% of the purchase price for these vehicles, up to a maximum of £5000.	The grant will pay for 35% of the purchase price for these vehicles, up to a maximum of £4500.
Category 2 cars CO_2 emissions <50g/km and can travel at least 16km (10 miles) with zero CO_2 emissions.	The grant will pay for 25% of the purchase price for these vehicles, up to a maximum of £5000.	The grant will pay for 35% of the purchase price for these vehicles, up to a maximum of £2500.
Category 3 cars		
CO_2 emissions >50 and <75g/km and can travel at least 32km (20 miles) with zero CO_2 emissions.	The grant will pay for 25% of the purchase price for these vehicles, up to a maximum of £5000.	The grant will pay for 35% of the purchase price for these vehicles, up to a maximum of £2500.

Note: From 2016 Category 2 or 3 cars with a recommended retail price over £60,000 are not eligible for a grant. This table was correct until November, after an announcement by the government in September 2018 that the vehicle grant would change, the maximum allowed subsidy falling to £3500 for BEVs with Category 2 and 3 vehicles no longer eligible.

Appendix 5-A: *Details of equation methods (basic equations sourced from (Mcmanus and Senter, 2009), generalisations derived).*

Diffusion Method	Differential Equation	Standard equation	Definitions
Bass	$$\frac{dA}{dt} = \left(p + q\frac{A(t)}{M}\right)\left(M - A(t)\right)$$	$$A(t) = M\left(\frac{1 - e^{-t(p+q)}}{1 + \frac{p}{q}e^{-t(p+q)}}\right)$$	*A:* cumulative sales *t:* time (months) *p:* innovation constant *q:* imitation constant *M:* saturation point *I*: Initial vehicle cost *R*: Running cost per mile β_1: Initial cost coefficient β_2: Running cost coefficient
Generalised Bass	$$\frac{dA}{dt} = \left(p + q\frac{A(t)}{M}\right)\left(M - A(t)\right)x(t)$$ where $$x(t) = 1 + \beta_1\left(\frac{P(t) - P(t-1)}{P(t)}\right) + \beta_2\left(\frac{G(t) - G(t-1)}{G(t)}\right)$$	$$A(t) = M\left(\frac{1 - e^{-(p+q)(t+\beta_1\ln(P)+\beta_2\ln(G))}}{1 + \frac{p}{q}e^{-(p+q)(t+\beta_1\ln(P)+\beta_2\ln(G))}}\right)$$ where $P(t) = \frac{I_{EV}}{I_{ICE}}$ and $G(t) = \frac{R_{ICE}}{R_{EV}}$	
Logistic	$$\frac{dA}{dt} = \frac{L_2}{L_1}A(t)^2$$	$$A(t) = \frac{L_1}{1 + e^{-L_2(t-L_3)}}.$$	*A:* cumulative sales *t:* time (months) L_1: Saturation point L_2: slope parameter L_3: time to peak sales *I*: Initial vehicle cost *R*: Running cost per mile β_1: Initial cost coefficient β_2: Running cost coefficient
Generalised Logistic	$$\frac{dA}{dt} = \frac{L_2}{L_1}A(t)^2x(t)$$ where $$x(t) = 1 + \beta_1\left(\frac{P(t) - P(t-1)}{P(t)}\right) + \beta_2\left(\frac{G(t) - G(t-1)}{G(t)}\right)$$	$$A(t) = \frac{L_1}{1 + e^{-L_2(t+\beta_1\ln(P(t))+\beta_2\ln(G(t))-L_3)}}$$ where $P(t) = \frac{I_{EV}}{I_{ICE}}$ and $G(t) = \frac{R_{ICE}}{R_{EV}}$	

Appendix 5-A continued…

Gompertz	$\frac{dA}{dt} = G_2 A(t) e^{-G_2(t-G_3)}$	$A(t) = G_1 e^{-e^{-G_2(t-G_3)}}$	*A:* cumulative sales *t:* time (months) *G₁*: saturation point *G₂*: slope parameter *G₃*: time to peak sales *I*: Initial vehicle cost *R*: Running cost per mile β_1: Initial cost coefficient β_2: Running cost coefficient
Generalised Gompertz	$\frac{dA}{dt} = G_2 A(t) e^{-G_2(t-G_3)} x(t)$ where $x(t) = 1 + \beta_1 \left(\frac{P(t) - P(t-1)}{P(t)}\right) + \beta_2 \left(\frac{G(t) - G(t-1)}{G(t)}\right)$	$A(t) = G_1 e^{-e^{-G_2(t+\beta_1 \ln(P(t)) + \beta_2 \ln(G(t)) - G_3)}}$ where $P(t) = \frac{I_{EV}}{I_{ICE}}$ and $G(t) = \frac{R_{ICE}}{R_{EV}}$	

Appendix 5-B i: *Historic UK car market share (Society of Motor Manufacturers and Traders, 2017).*

Year	HEV	Petrol	Diesel	PHEV	BEV
2000	0.01182	85.89375	14.0902	0	0
2001	0.029303	82.17505	17.75618	0	0
2002	0.013216	76.38462	23.5044	0	0
2003	0.04181	72.51268	27.32194	0	0
2004	0.0959	67.2979	32.53781	0	0
2005	0.236339	62.9407	36.80251	0	0
2006	0.381984	61.27878	38.31868	0	0
2007	0.664391	59.06609	40.24169	0	0
2008	0.721692	55.69072	43.56671	0	0
2009	0.734086	57.52118	41.72714	0	0
2010	1.089546	52.76496	46.10916	0.001034	0.008223
2011	1.205149	48.12366	50.56502	0.000155	0.056561
2012	1.243367	47.83741	50.80091	0.022987	0.061723
2013	1.303639	48.77352	49.78123	0.029981	0.110918
2014	1.570887	47.82718	50.07896	0.252298	0.270429
2015	1.770721	48.75092	48.48565	0.615074	0.377216
2016	2.070606	48.9558	47.74208	0.849975	0.381167
2017	2.992777	53.33023	41.95355	1.226238	0.535185

Appendix 5-B ii: *UK car market share: Business as Usual scenario.*

Year	HEV	Petrol	Diesel	PHEV	BEV
2017	2.23	48.51	47.57	1.23	0.46
2018	2.20	61.15	34.59	1.20	0.86
2019	3.69	64.58	28.66	1.36	1.71
2020	5.77	54.69	36.74	1.50	1.29
2021	8.66	57.06	32.06	1.52	0.69
2022	11.29	58.28	27.83	1.70	0.90
2023	13.18	58.42	25.23	1.98	1.20
2024	16.80	51.14	28.65	2.16	1.24
2025	18.06	52.62	26.29	2.04	0.99
2026	17.82	54.00	24.66	2.36	1.17
2027	18.41	54.77	22.44	2.82	1.55
2028	19.12	54.71	21.10	3.33	1.74
2029	19.74	54.88	19.18	4.05	2.15
2030	20.54	53.68	18.12	4.76	2.90
2031	22.68	50.14	17.51	6.03	3.65
2032	22.36	49.43	16.66	7.12	4.43
2033	23.96	45.63	15.82	8.81	5.78
2034	26.16	41.95	15.53	10.55	5.81
2035	28.66	38.45	14.87	12.38	5.64
2036	31.42	32.08	14.50	15.49	6.51
2037	33.28	26.83	14.17	18.36	7.36
2038	36.86	19.86	13.88	21.43	7.97
2039	38.05	15.53	13.62	24.50	8.30
2040	37.72	11.53	13.38	28.31	9.07

Appendix 5-B iii: *UK car market share: Battery Bonanza scenario.*

Year	HEV	Petrol	Diesel	PHEV	BEV
2017	3.38	50.98	43.96	1.15	0.52
2018	3.87	67.64	26.74	1.12	0.62
2019	5.60	72.18	19.84	1.22	1.17
2020	7.02	75.48	14.56	1.32	1.63
2021	9.51	74.88	11.57	1.55	2.48
2022	11.71	73.92	9.27	1.80	3.30
2023	13.31	72.11	7.86	2.23	4.49
2024	15.15	69.72	6.64	2.80	5.69
2025	15.98	67.32	5.77	3.66	7.26
2026	16.15	65.13	5.16	4.67	8.89
2027	16.86	60.70	4.51	6.15	11.78
2028	17.74	55.83	4.09	7.65	14.69
2029	18.81	48.57	3.62	9.87	19.12
2030	17.56	45.57	5.28	13.43	18.16
2031	18.36	56.17	4.80	10.57	10.10
2032	19.09	52.44	4.32	12.75	11.40
2033	21.21	45.74	3.89	15.69	13.47
2034	23.03	39.61	3.63	18.53	15.20
2035	24.44	31.69	4.38	23.20	16.30
2036	26.47	34.24	3.64	22.06	13.59
2037	28.40	26.16	3.08	26.32	16.05
2038	30.55	17.11	2.61	31.12	18.60
2039	31.67	8.97	1.12	36.62	21.62
2040	30.94	1.53	0.00	43.98	23.55

Appendix 5-B iv: *UK car market share: Diesel Persists scenario.*

Year	HEV	Petrol	Diesel	PHEV	BEV
2017	2.75	66.26	29.07	1.44	0.48
2018	2.28	65.22	30.51	1.37	0.62
2019	3.56	62.80	31.20	1.53	0.90
2020	4.51	59.87	32.79	1.72	1.11
2021	6.28	53.43	37.97	1.68	0.63
2022	7.49	52.14	37.83	1.80	0.73
2023	8.11	50.15	38.87	1.98	0.88
2024	9.03	47.17	40.53	2.23	1.05
2025	9.20	46.25	41.64	2.05	0.86
2026	8.85	45.51	42.48	2.22	0.94
2027	8.81	44.31	43.41	2.42	1.05
2028	9.05	42.92	44.20	2.62	1.21
2029	9.19	41.05	45.18	2.89	1.69
2030	9.54	39.42	46.03	3.10	1.91
2031	10.86	36.56	46.97	3.44	2.17
2032	10.53	35.46	47.89	3.71	2.42
2033	11.98	31.84	48.89	4.16	3.13
2034	13.03	28.89	49.80	4.57	3.71
2035	14.91	24.52	50.70	5.17	4.71
2036	16.09	20.60	51.69	5.93	5.70
2037	16.80	16.75	52.65	6.76	7.04
2038	17.79	12.46	53.61	7.76	8.38
2039	18.02	8.24	54.58	9.06	10.10
2040	17.73	4.34	55.54	10.52	11.87

Appendix 6-A: *Definition of Vehicle Specific Power (VSP).*

VSP is defined as the instantaneous power per unit mass of the vehicle (kW/t) (Jimenez-Palacios, 1999). In other words, for a vehicle to move, the power from the engine must overcome certain key forces including aerodynamic drag, rolling resistance and the road gradient (Heisler, 2002). These factors are accounted for in the VSP equation derived by Jimenez-Palacios (Jimenez-Palacios, 1999).

$$\text{Vehicle Specific Power} = \frac{\frac{d}{dt}(KE + PE) + F_{rolling} \cdot v + F_{aerodynamic} \cdot v}{m}$$

Where, m is the vehicle mass (t), v is the vehicle speed (m/s), a is the vehicle acceleration (m/s^2), KE is the Kinetic Energy (J), PE is the Potential Energy (J).

This can be simplified to[15],

$$VSP = = v \cdot (1.1 \cdot a + 9.81 \cdot grade(\%) + 0.132) + 0.000302 \cdot (v + v_w)^2 \cdot v$$

Jimenez-Palacios showed that VSP is proportional to engine power therefore there is a strong relationship between VSP and vehicle emission (Jimenez-Palacios, 1999).

[15] See Wyatt (2017) for full derivation of this.

Appendix 6-B i: *Leeds fleet share: Business as Usual scenario.*

Year	HEV	Petrol	Diesel	PHEV	BEV
2015	0.607079	55.70724	43.65668	0.021003	0.008001
2016	0.658416	54.82277	44.46733	0.027723	0.023762
2017	0.766599	53.7678	45.31855	0.09705	0.049996
2018	0.873524	53.61687	45.24561	0.164999	0.098999
2019	1.095522	53.65366	44.7809	0.255622	0.214299
2020	1.435762	53.23736	44.68178	0.350139	0.294954
2021	2.11862	52.76674	44.29037	0.47384	0.350434
2022	2.883019	52.7683	43.34602	0.591341	0.411327
2023	3.84626	52.66375	42.25346	0.736007	0.500522
2024	5.041648	52.33659	41.1442	0.888734	0.588832
2025	6.233818	52.39539	39.70144	1.019355	0.649997
2026	7.576613	52.60695	37.88844	1.194798	0.733192
2027	8.720038	52.79057	36.29829	1.366666	0.824437
2028	9.876988	53.05773	34.57429	1.567525	0.923469
2029	10.94156	53.25411	32.97781	1.79126	1.03526
2030	12.04327	53.49274	31.20209	2.063774	1.198126
2031	13.4525	53.52431	29.11212	2.470641	1.440426
2032	14.58511	53.56374	27.26106	2.889495	1.700597
2033	15.91928	53.07317	25.44726	3.471944	2.088349
2034	17.20953	52.46045	23.7677	4.125452	2.436864
2035	18.22406	51.64317	22.69874	4.735289	2.698738
2036	19.55306	50.19921	21.5784	5.62322	3.046114
2037	20.96794	48.42333	20.45778	6.700356	3.450603
2038	22.55878	46.00687	19.58541	7.967164	3.881765
2039	24.2398	43.15248	18.8103	9.47288	4.324541
2040	25.75579	40.31097	17.9464	11.18034	4.8065

Appendix 6-B ii: *Leeds fleet share: Battery Bonanza scenario.*

Year	HEV	Petrol	Diesel	PHEV	BEV
2015	0.607079	55.70724	43.65668	0.021003	0.008001
2016	0.710898	54.79064	44.44598	0.023763	0.028713
2017	0.884227	53.87609	45.09264	0.089207	0.057837
2018	1.085121	54.09686	44.57245	0.152383	0.093177
2019	1.433802	54.64304	43.51858	0.233521	0.171057
2020	1.847764	55.55281	42.00951	0.31589	0.274025
2021	2.595335	56.53968	39.94367	0.442761	0.478559
2022	3.382954	57.62214	37.71522	0.568023	0.711661
2023	4.348629	58.52226	35.34312	0.733237	1.052758
2024	5.406419	59.54741	32.63143	0.936271	1.478468
2025	6.437508	60.55205	29.84827	1.182307	1.979866
2026	7.629565	61.5528	26.57709	1.549755	2.690784
2027	8.65074	61.96621	23.94661	1.955912	3.48053
2028	9.691676	62.08911	21.30587	2.456748	4.45659
2029	10.67709	61.59969	19.04008	3.050971	5.632161
2030	11.54896	60.95248	16.823	3.905355	6.770201
2031	12.59871	61.0662	14.27962	4.640195	7.415272
2032	13.48729	60.86211	12.1861	5.423457	8.041037
2033	14.60603	59.85453	10.18518	6.490825	8.863437
2034	15.67808	58.4975	8.461908	7.661491	9.701023
2035	16.4596	56.68825	7.640551	8.842813	10.36879
2036	17.48134	54.83366	6.703181	10.07384	10.90798
2037	18.60097	52.44714	5.794878	11.57449	11.58252
2038	19.80496	49.26262	5.191861	13.36107	12.37949
2039	21.08243	45.41438	4.585227	15.55606	13.3619
2040	22.20784	41.19679	4.046225	18.15382	14.39533

Appendix 6-B iii: *Leeds fleet share: Diesel Persists scenario.*

Year	HEV	Petrol	Diesel	PHEV	BEV
2015	0.607079	55.70724	43.65668	0.021003	0.008001
2016	0.687136	54.74906	44.4945	0.037624	0.031683
2017	0.825401	54.70488	44.29228	0.118615	0.058817
2018	0.934679	54.77628	43.99884	0.196059	0.094147
2019	1.147415	54.67711	43.72285	0.297905	0.154718
2020	1.404377	54.5804	43.38535	0.405328	0.224548
2021	1.888801	53.78702	43.50837	0.540734	0.275077
2022	2.383084	53.32513	43.30311	0.66316	0.325517
2023	2.955137	52.56081	43.2863	0.807122	0.390632
2024	3.558628	51.90275	43.10767	0.964633	0.466316
2025	4.131738	51.49644	42.7586	1.094494	0.51873
2026	4.751405	50.97834	42.42832	1.255748	0.586195
2027	5.254517	50.38959	42.31213	1.397714	0.646054
2028	5.750914	49.81021	42.18245	1.545586	0.710846
2029	6.189863	49.08479	42.23635	1.688619	0.800376
2030	6.620326	48.3432	42.28705	1.845009	0.904416
2031	7.223388	47.33835	42.3502	2.045916	1.042146
2032	7.671978	46.4777	42.44919	2.227457	1.173679
2033	8.277459	45.06496	42.83027	2.45707	1.370241
2034	8.858465	43.7096	43.15998	2.687669	1.584293
2035	9.337813	42.32913	43.63793	2.883953	1.811178
2036	9.970058	40.46933	44.27738	3.158091	2.125139
2037	10.63122	38.09983	45.26202	3.473846	2.533079
2038	11.34382	35.54838	46.23357	3.850743	3.023481
2039	12.06792	32.68805	47.27383	4.326904	3.643294
2040	12.71648	29.76927	48.2732	4.881358	4.359692

Appendix 6-C i: *Leeds traffic share: Business as Usual scenario.*

Year	HEV	Petrol	Diesel	PHEV	BEV
2015	0.778634	43.49966	55.69998	0.015499	0.006231
2016	0.839375	42.50452	56.61748	0.021347	0.017282
2017	0.976023	41.39623	57.5214	0.06937	0.036975
2018	1.125238	41.04946	57.62661	0.124794	0.073896
2019	1.385267	41.81078	56.44801	0.195853	0.160098
2020	1.810513	41.862	55.8234	0.274923	0.229168
2021	2.63371	42.29428	54.4282	0.367073	0.276734
2022	3.563049	42.66251	52.99537	0.456274	0.322796
2023	4.784974	43.21179	51.05082	0.565777	0.386642
2024	6.326273	43.66166	48.87207	0.686565	0.453439
2025	7.855649	43.53925	47.31237	0.787918	0.504817
2026	9.562641	44.26033	44.69782	0.916455	0.562749
2027	11.07155	44.34107	42.91264	1.044214	0.630527
2028	12.57147	44.59764	40.91708	1.205626	0.708178
2029	14.12411	45.28976	38.38292	1.400875	0.802339
2030	15.62997	45.67559	36.13214	1.620904	0.941404
2031	17.45682	45.82669	33.64568	1.938502	1.132296
2032	19.04605	45.67047	31.66335	2.28146	1.338671
2033	20.57747	44.7072	30.37302	2.715828	1.626489
2034	22.20764	43.8068	28.8446	3.231618	1.909339
2035	23.84422	42.69792	27.54103	3.760176	2.156655
2036	25.65934	41.04134	26.3927	4.469158	2.437455
2037	27.54147	39.0241	25.36751	5.330721	2.736203
2038	29.78508	36.47398	24.23923	6.398501	3.103206
2039	32.04624	33.74171	23.04388	7.66704	3.501117
2040	34.05486	30.80726	22.14306	9.086574	3.908252

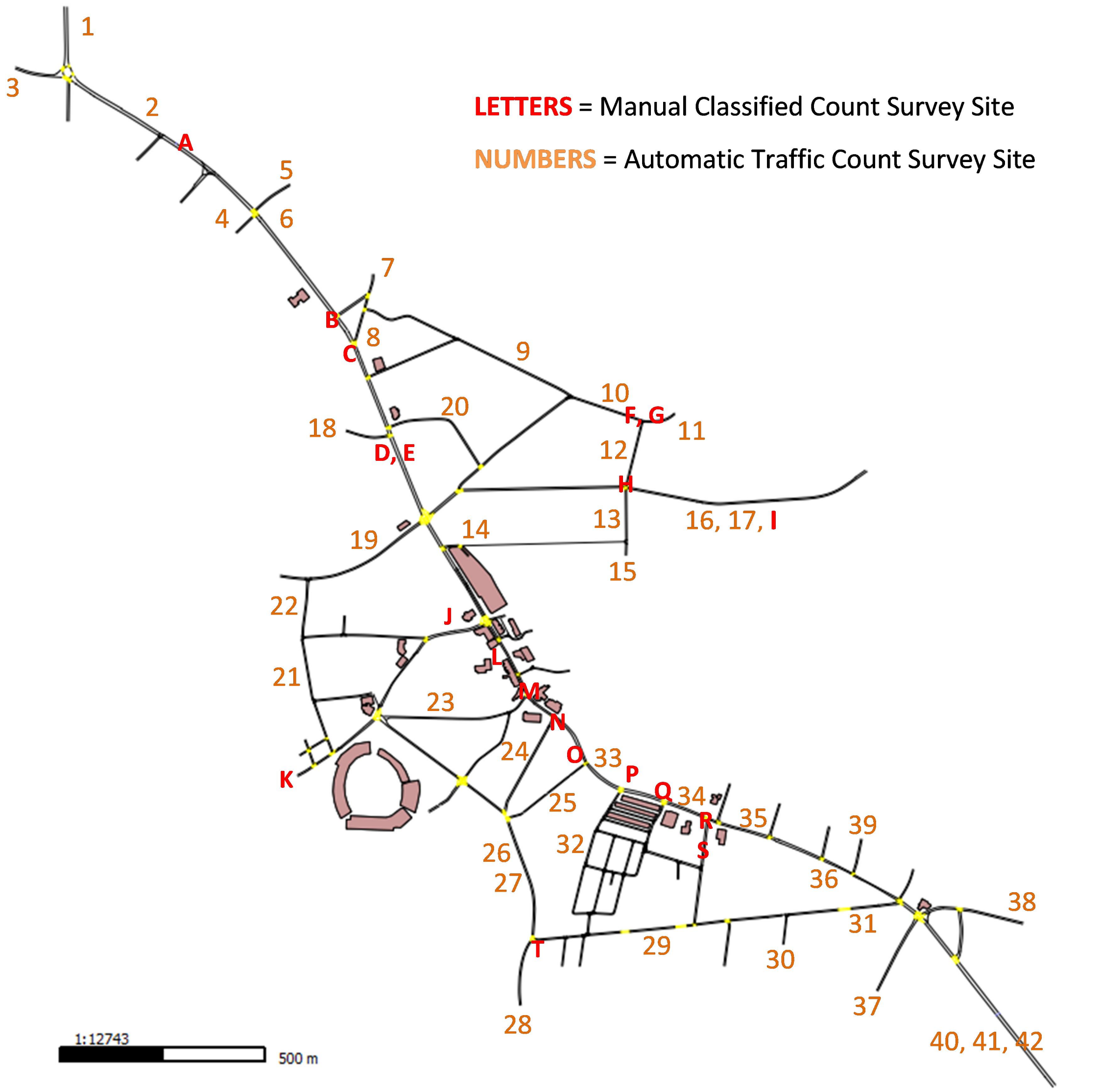
Appendix 6-C ii: *Leeds traffic share: Battery Bonanza scenario.*

Year	HEV	Petrol	Diesel	PHEV	BEV
2015	0.778634	43.49966	55.69998	0.015499	0.006231
2016	0.898538	42.46605	56.59611	0.018637	0.020671
2017	1.116544	41.52474	57.25229	0.063609	0.042813
2018	1.387267	41.634	56.79285	0.115111	0.070767
2019	1.813773	42.99678	54.88058	0.178909	0.129954
2020	2.347779	44.66761	52.52598	0.248582	0.210045
2021	3.265014	46.90152	49.12906	0.342597	0.361808
2022	4.249445	48.51744	46.25071	0.440089	0.542312
2023	5.508841	50.36432	42.75164	0.568484	0.806714
2024	6.941432	52.50339	38.67747	0.731817	1.145883
2025	8.350431	53.54583	35.62195	0.928008	1.553782
2026	9.990646	55.18443	31.48855	1.219437	2.11694
2027	11.48024	55.72304	28.46239	1.554971	2.779357
2028	13.03819	55.93815	25.40589	1.993854	3.623921
2029	14.74321	56.21555	21.77022	2.554731	4.716291
2030	16.25017	55.68476	18.94229	3.316303	5.806477
2031	17.80389	56.10911	15.61002	4.001233	6.475754
2032	19.30706	55.77884	13.06799	4.741916	7.104192
2033	20.76834	54.11271	11.72914	5.642371	7.747438
2034	22.28833	52.50067	10.12336	6.651036	8.436611
2035	23.7901	50.3828	8.865928	7.799182	9.161983
2036	25.27418	48.19897	7.929935	8.923997	9.672916
2037	26.90128	45.38613	7.187721	10.26374	10.26113
2038	28.74494	41.74186	6.613311	11.9118	10.98808
2039	30.61431	37.67694	5.934728	13.91221	11.86181
2040	32.35332	33.22184	5.27322	16.303	12.84862

Appendix 6-C iii: *Leeds traffic share: Diesel Persists scenario.*

Year	HEV	Petrol	Diesel	PHEV	BEV
2015	0.778634	43.49966	55.69998	0.015499	0.006231
2016	0.871878	42.4194	56.65789	0.028127	0.022707
2017	1.045564	42.51844	56.30729	0.084973	0.043737
2018	1.206702	42.49925	56.07353	0.148815	0.071699
2019	1.464488	42.98316	55.20293	0.230078	0.119351
2020	1.789555	43.56656	54.15061	0.319035	0.174244
2021	2.375395	43.51393	53.4738	0.420658	0.21622
2022	2.975684	43.20044	53.05446	0.514741	0.254677
2023	3.706461	42.9141	52.45034	0.625011	0.304087
2024	4.498734	42.94935	51.44539	0.747467	0.359059
2025	5.226951	42.18981	51.33131	0.848424	0.403499
2026	6.021639	42.03003	50.53315	0.965695	0.449483
2027	6.645722	41.23846	50.55341	1.067349	0.495065
2028	7.270542	40.57991	50.41596	1.188134	0.545458
2029	7.884144	40.19265	49.98932	1.315609	0.618275
2030	8.432986	39.35494	50.07732	1.434246	0.700504
2031	9.156981	38.4322	50.02117	1.582688	0.806958
2032	9.736572	37.18618	50.44996	1.721096	0.906186
2033	10.32834	35.40569	51.35822	1.869719	1.038038
2034	10.95125	33.73165	52.10194	2.025664	1.189496
2035	11.56125	31.93945	52.96964	2.168105	1.361562
2036	12.30272	29.92189	53.82589	2.355544	1.593956
2037	13.06435	27.69365	54.78175	2.577289	1.882956
2038	13.89198	25.21641	55.791	2.854091	2.246522
2039	14.69655	22.70311	56.6816	3.203488	2.715257
2040	15.41245	20.07377	57.63707	3.614355	3.262357

Appendix 6-D: *Locations of all Manual Classified Count (MCC) and Automatic Traffic Count (ATC) locations on the Leeds network.*



Appendix 6-E i: *Details of traffic microsimulation calibration*

Turning movements and vehicle flows are calibrated hourly. For calibration, the GEH statistic is calculated for each of the 26 calibration points for each hourly vehicle flow. The GEH statistic is a goodness of fit test used to compare two sets of traffic data (e.g. 'modelled' traffic flow versus 'observed' real-world count). The GEH statistic formula is:

$$\mathrm{GEH} = \sqrt{\frac{2(\mathrm{M} - \mathrm{C})^2}{\mathrm{M} + \mathrm{C}}}$$

where M is the hourly 'modelled' traffic flow and C is the 'observed' real-world count. The model was validated according to the guidelines provided by DfT (see Appendix 6-E ii) with 97% of cases with GEH<3. Note this was a very time-intensive step of the modelling, with the model run over a thousand times to tweak the vehicle flows and turning movements to ensure the criteria were met.

Appendix 6-E ii: *Link flow validation criteria and acceptability guidelines (DfT, 2014).*

Description of Criteria	Acceptability Guidelines
Individual flows within 100 veh/h counts for flows less than 700 veh/h Individual flows within 15% of counts for flows from 700 to 2 700 veh/h Individual flows within 400 veh/h of counts for flows more than 2 700 veh/h Individual flows with a GEH statistic < 5	>85% of cases

Appendix 6-F i: *Calculating Vehicle Emissions with PHEM*

PHEM has an Advanced User Interface that facilitates the estimation of vehicle emissions at a network level. Utilising trajectories and road gradient from the microsimulation traffic model, fleet emissions can be estimated across all vehicle types (car, bus, LCV, HGV) within the Headingley network. The details of the inputs and outputs of the model are given in Appendix 6-F ii.

To calculate these network level estimates in PHEM, an '.ADV' job file must be prepared that consists of a '.FZP' drive cycle file, a '.FLT' fleet data file and a '.STR' route section file. The '.FZP' file consists of the simulated vehicle activity data generated by the AIMSUN Headingley network, the '.STR' file describes the road links and junctions on the simulated Headingley network and the '.FLT file' details the Headingley network vehicle fleet composition for each hourly time period for every simulation year. For the Headingley network model, a separate '.ADV' file was needed for each hour of the simulation for each simulation year and every random seed (a total of 2400 files).

The '.FZP' drive cycle file describes the second-by-second activity of each vehicle simulated in the network. This includes attributes such as time, latitude, longitude, velocity, vehicle ID, road gradient, vehicle Type ID and section. This is generated from the AIMSUN API and processed in MATLAB to align the data with the input file structure. In PHEM Advance each recorded drive cycle ('.FZP' file) is labelled with a vehicle type ID that matches with the vehicle category. This ID number is defined in the drive cycle file ('.FZP') file, but the vehicle Euro standard, size and fuel type are assigned by a random number generator in PHEM. This ensures that the overall composition of the modelled fleet is the same as the composition specified in the '.FLT' file for each vehicle type ID (Luz and Hausberger, 2015).

The '.FLT' fleet data file details the fleet composition hourly for each vehicle type by fuel type (petrol/diesel), Euro emission standard category (Euro 0 – 6d) and also by vehicle weight class (LCV and HGV categories only). For the base year (2015), the '.FLT' files are created from analysis of the ANPR survey and for the other years, this was calculated by the fleet scenarios.

The '.STR' files enable calculation of total vehicle emissions on each road section and junction. The '.STR' file assigns an identification number to each road section, which corresponds to the Section ID in the '.FZP' files. A total of 519 '.STR' files were created for the Headingley simulation model.

For each individual vehicle sub-category a '.GEN' file compiles the relevant engine and catalyst map ('.MEP' and '.MAP'), full load curve ('.FLD') and vehicle specification ('.VEH') files. The

'.VEH' files contain average parameters for that vehicle category, including vehicle mass, cross sectional area, rated engine power, rated engine speed, and engine idling speed. For this study, the '.VEH' files contain the Headingley network average vehicle parameters.

When the '.ADV' job file is run, PHEM calculates output files that contain detailed emission and power information for each vehicle ('.mod'), average values per vehicle ('.vehicle.sum'), and average values per road segment ('.segment.sum'). The .mod file details second-by-second emission estimates for each vehicle in g/h for Fuel Consumption, NO_x, CO, HC, PM, and NO. The '.vehicle.sum' file aggregates the .mod files, to present total emissions estimates (g/h), along with time in the simulation (s), distance travelled (km) and average speed (km/h). Finally, the '.segment.sum' files present emission estimates for each road section in the network, along with the number of vehicles passing through the section, the total distance covered in the section (km) and the total time spent by vehicles on the section (h).

Appendix 6-F i: *Outline of PHEM model files.*