Energy Consumption and Carbon Emissions of Electric Vehicles Under Real Driving Conditions

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Abstract

This thesis investigates the energy consumption of electric vehicles (EVs) under real-world driving conditions and the associated carbon emissions during charging, which are influenced by electricity grid mix, travel demand and energy consumption. Existing methods of road measurements of EVs used unscheduled trips, making the results particular to the test location and difficult to compare. Besides shifting to EVs, additional actions enable further decarbonisation of road transport resulting from changes in travel demand and charging flexibility. The analysis uses data collected from an EV operated on UK roads for almost four years, and the evaluation of the energy consumption was carried out following a real driving cycle (RDC) schedule. The results show EV specific energy consumption (SEC) is highly influenced by changes in ambient temperature, nearly doubling from operation at moderate temperatures of around 20°C to operation at temperatures as low as 0°C due to the corresponding loads required by heating and air conditioning systems. Short trips below 16 km caused nearly 10% SEC average increase in comparison with longer ones, showing more awkward effects in motorway operation with SEC rise up to 29%. Traffic conditions and driving behaviour also demonstrated a high influence on SEC, increasing it by 40% and 16%, respectively, from the most favourable to the most unfavourable condition. A model was developed to investigate carbon emissions projections of passenger vehicles considering the expected large EV market penetration and the impact of changes in road traffic using a set of scenarios based on vehicle ownership and usage. A reduction of 22% in EVs cumulative carbon emissions by 2050 can be achieved by targeting 23% lower vehicle number and 17% usage, while an opposite scenario increases EV cumulative carbon emissions by 28%. The regional differences in energy consumption and carbon emissions were modelled under different charging scenarios, showing carbon emission reduction varies from 4% to 33% between the regions when switching to delayed charging, shifting the charging outside peak hours. An optimised charging that moves charging events to periods of low grid carbon intensity reduces carbon emissions from 6% to 55%, affected by region grid carbon intensity and energy consumption.

Keywords: Electric vehicles; ambient temperature; driving behaviour; road grade; regional differences; charging time

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Contents

List of Figures

List of Tables

Nomenclature

Abbreviations

BESS	Battery Energy Storage System
BEV	Battery Electric Vehicle
BMS	Battery Management System
BTM	Battery Thermal Management
CAN	Controller Area Network
CAZ	Clean Air Zone
DfT	Department of Transport
EV	Electric Vehicle
GB	Great Britain
GHG	Greenhouse Gas
GPS	Global Positioning System
HDOL	High Dynamic Operation Limit
HEV	Hybrid Electric Vehicle
HVAC	Heating, Ventilation and Air Conditioning

ICE	Internal Combustion Engine
LDOL	Low Dynamic Operation Limit
LEZ	Low Emission Zone
NEDC	New European Driving Cycle
OBD	On-Board Diagnosis
PHEV	Plug-in Hybrid Electric Vehicle
RDC	Real Driving Cycle
RDE	Real Driving Emissions
RPA	Relative Positive Acceleration
SEC	Specific Energy Consumption
SOC	State of Charge
TTW	Tank to Wheel
UF	Utility Factor
UK	United Kingdom
ULEZ	Ultra Low Emission Zone
V2G	Vehicle to Grid
VSR	Vehicle Survival Rate
WLTP	Worldwide Harmonised Light Vehicle Test Procedure
WTT	Well to Tank
ZEV	Zero Emission Vehicle

Symbols

$(v{\cdot}a)_i$	instantaneous product of vehicle speed and acceleration, (m^2/s^3)
$(v{\cdot}a^+)_i$	Instantaneous product of vehicle speed and a^+ (m^2/s^3)
Δt	Time step interval (s)
a^+	Positive accelerations only ($a_i > 0.1$ m/s^2).
$AE_{Electricity,j}$	Total electricity production emissions in a year j ($MtCO_2$)
$AE_{Fuel,j}$	Total fuel production emissions in a year j ($MtCO_2$)
$AE_{Tailpipe,j}$	Total tailpipe emissions in a year j ($MtCO_2$)
$AE_{Total,j}$	Total carbon emissions from all vehicles in a year j ($MtCO_2$)
a_i	Instantaneous acceleration (m/s2)
b	Weibull distribution parameter
$C_{battery}$	Usable battery capacity (kWh)
$c_{electricity}$	Annual carbon emissions from electricity production to charge an EV (Kg)
c_{fuel}	Annual carbon emissions for fuel production (kg)
CI	Electricity grid carbon intensity (g/kWh)
c_{ice}	Annual carbon emissions from an ICE vehicle or HEV (kg)
$c_{k,m,j}$	Annual carbon emissions from a vehicle of powertrain type k and model year m in a year j (kg)
c_{phev}	Annual carbon emissions from a PHEV (kg)

$c_{phev,cd}$	Annual carbon emissions of a PHEV in charge depleting mode (kg)
$c_{phev,cs}$	Annual carbon emissions of a PHEV in charge sustaining mode (kg)
$c_{tailpipe}$	Annual carbon emissions from the tailpipe (kg)
d	Distance covered in each operation mode (m)
D	Vehicle mileage (km)
$D_{1st,j}$	Mileage for a first-year registration vehicle in a year j (km)
$D_{avg,j}$	Average vehicle mileage in year j (km)
d_{trip}	Trip distance (km)
$D_{\alpha,j}$	Vehicle mileage of age α in a year j
E_{aux}	Energy needed to operate the auxiliary devices (kWh)
EC	Energy required to charge a vehicle (kWh)
E_{cons}	Net consumed energy (kWh)
E_{drv}	Energy required by drivetrain (kWh)
E_{loss}	Total energy losses (kWh)
E_{reg}	Recovered energy during regenerative braking (kWh)
E_{tot}	Trip total consumed energy (kWh)
E_{tra}	Tractive energy required to drive the vehicle (kWh)
i	Time step (s)
I_i	Battery Current (A)
k	Powertrain type

L	Service life
m	Vehicle model year
n	Trip duration (s)
N_j	Total number of vehicles in year j
$N_{k,m,j}$	Number of vehicles of vehicle type k and model year m in a year j
$N_{m,j}$	Number of vehicles sold in year m that are still operating in year j
$N_{sale,j}$	Number of new vehicles needed in year j to meet the demand
$N_{sale,m}$	Number of vehicles during first registration at year m
$N_{scrap,m,j}$	Number of vehicles leaving the stock of year model m in year j
$N_{\alpha,j}$	Total number of vehicles of age α in a year j
RPA	Relative positive acceleration (m/s^2)
SEC_{trip}	Trip specific energy consumption (kWh/km)
S_{max}	Maximum EV driving range (km)
SP_{α}	Survival probability of a vehicle at age α (%)
TE	tailpipe carbon emissions per km of an ICE vehicle (gCO_2/km)
$U_{electricity}$	Electricity upstream impact factor (%)
U_{fuel}	Fuel production upstream impact factor (%)
V_i	Battery voltage (V)
v_i	Instantaneous vehicle speed (km/h)
VKT_j	Total vehicle kilometre travel for all vehicles in a year j (km)

VSR_{α}	Vehicle survival rate by age
α	Vehicle age (years)
$\beta_{T\&D}$	Electricity transmission and distribution losses (%)
ε	Mileage decay rate (km)
η_{batt}	Battery efficiency (%)
η_{chg}	Charging efficiency (%)

Chapter 1

Introduction

1.1 Background

The transportation sector receives increasing attention from governments worldwide, as it is largely responsible for global environmental pollution, greenhouse gas (GHG) emissions and energy consumption [1]. The environmental and energy concerns have promoted the widespread development of electric vehicles (EVs) [2]. Policy incentives and regulations at national and international levels are the main drivers of reducing transport sector emissions [3]. Several governments and organisations are implementing various strategies to reduce the transport sector emissions through policies and initiatives that cover fuel efficiency, model shift, travel demand and electrification, with the main focus on the latter as electricity could be generated from renewable energy sources [4].

Besides the environmental impact, shifting to low carbon emission economies avoids the associated risks of fossil fuel scarcity and supply and price instability [5]. Recent global events have shown that continued reliance on fossil fuels makes the United Kingdom (UK) susceptible to geopolitical issues [6]. Therefore, increasing the uptake of vehicles that can be powered by domestic renewable energy sources is vital for the UK's future energy security as it reduces the reliance on imports [7]. In 2019, the UK became the first major economy to pass legislation for reaching net-zero GHG emissions by 2050, compared with the previous target of at least 80% reduction from

1990 levels, based on the Committee on Climate Change recommendation [8]. The UK government has also announced to end the sale of new petrol and diesel vehicles in 2030, a decade earlier than previously planned, and by 2035 all new vehicles must be zero emissions at the tailpipe to reduce road transport emissions [9].

Figure 1.1 shows the GHG emissions produced by source in the UK from 1990 to 2019 [10]. The total GHG emissions across all sectors in 2019 decreased by 44% from 1990, with some sectors having significant reductions in emissions, notably the Energy Supply sector, as illustrated by Figure 1.1. However, the reduction in emissions from the transport sector has stagnated with less than 5% reduction in 2019 from 1990 levels. Since 2016, the transport sector has become the largest contributor to GHG emissions, surpassing the Energy Supply sector emissions.

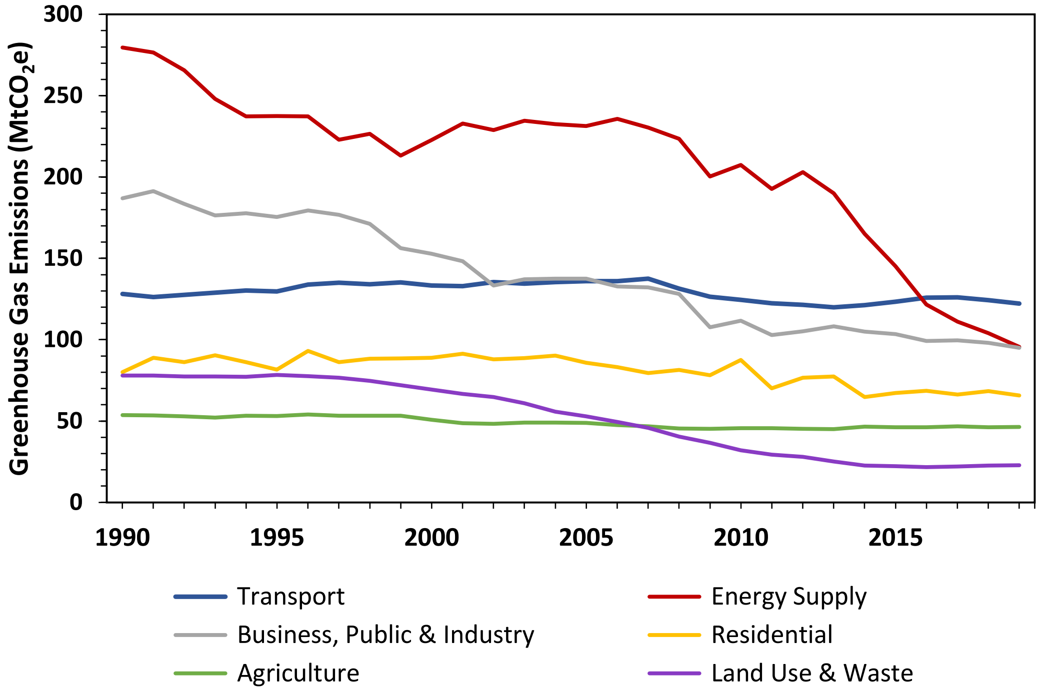

Figure 1.1: UK greenhouse gas emissions by source from 1990 to 2019, adapted from BEIS [10].

Vehicle manufacturers have continuously improved internal combustion engines (ICEs) efficiency and emissions, however these factors alone are unable to reduce transport emissions [11], as the transport sector contribution to GHG emissions continues to rise, reaching 27% of the total (Figure 1.2). As a result, eliminating all tailpipe emissions from road vehicles has become a priority of the UK government, as it is fundamental to the decarbonising transport sector since road transport accounts for 91% of UK annual domestic transport emissions [12], with passenger cars accounting for 56% of all transport GHG emissions in 2019 (Figure 1.2). As a result, the government has introduced policies and economic incentives to promote EVs.

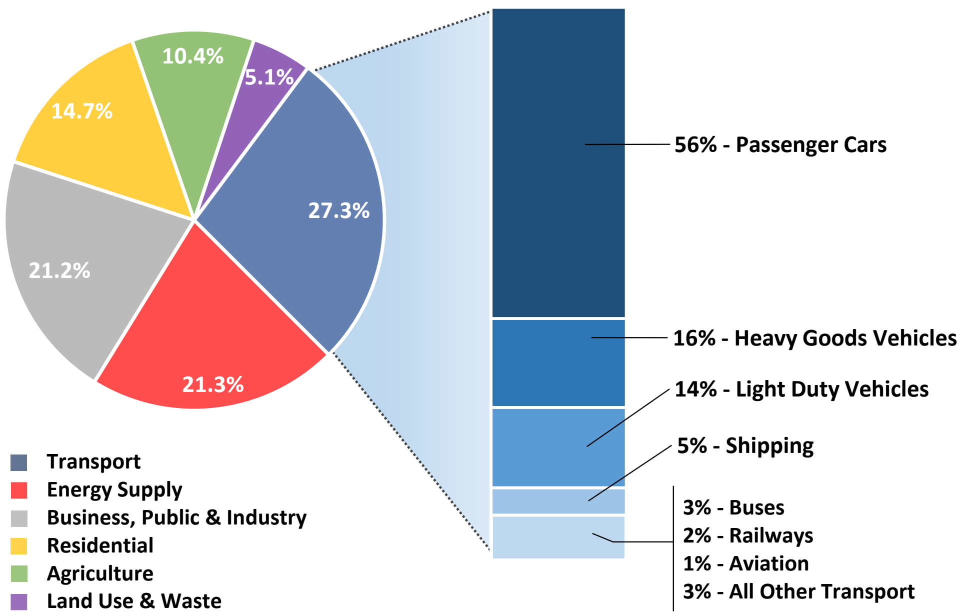

Figure 1.2: Breakdown of UK greenhouse gas emissions by source in 2019, adapted from BEIS [10].

Nevertheless, EVs suffer from constraints related to long charging periods and limited driving range, which affect their adoption on a large scale as a competitive alternative to ICE vehicles [13, 14]. In addition, consumer awareness and growth in confidence in EVs as a new technology needs to be addressed with reliable information. As an example, a study incorporating the impact of traffic congestion hours and the mean acceleration factor showed that the actual driving range differs by more than 25% below the manufacturer datasheet [15]. These drawbacks underline the need to understand the relevant factors that influence the energy consumption of EVs during operation [16].

While EVs have been widely considered a greener alternative to ICE vehicles, their impact during the use phase can be measured by the carbon emissions emitted from the electricity production while charging their batteries. However, there have been some concerns about the actual reduction of carbon emissions from EVs, as it highly depends on the electricity generation mix of each country, and since the reduction of emissions from EVs maybe be followed by an increase in emissions from power generation [17]. The environmental benefits provided by EVs are directly related to their energy consumption, which is mainly estimated using current legislative driving cycles [18]. The differences between real-world driving conditions and standard test schedules under controlled laboratory conditions result in significant variations in energy consumption, emissions and range [19]. For this reason, the development of real-world driving cycles for specific regions can provide more representative results from both experiments and simulation [20].

1.2 Aim and Objectives

The overall aim of this thesis is to investigate the energy consumption of an EV under different driving and ambient conditions based on data collected from real-world driving and investigate the associated carbon emissions with EV charging in the UK. The specific objectives of the study are:

- Evaluate the energy consumption of an EV based on data collected from real-world driving and identify key factors that influence the variation in energy consumption and the expected driving range during different conditions and seasons.

- Analyse EV data and energy consumption from selected trips attending the specification and boundary conditions of a real driving cycle based on a standard real-world test procedure representative of driving on the UK roads to provide a better method to measure EV energy consumption and range.

- Investigate the dynamic relation between the stock of vehicles and carbon emissions by developing a vehicle fleet turnover model that considers the future market size and EV adoption rate.

- Assess the shift in travel demand impacting EV carbon emissions and energy demand through constructing different scenarios of changes in road traffic based on future changes in vehicle ownership and usage.

- Examine the impact on carbon emissions of different EV charging scenarios and explore the possibility of reducing carbon emissions using smart charging, considering hourly variations in the electricity generation profile.

1.3 Main Novelty of the Thesis

This thesis makes the following novel contributions:

- The evaluation of the energy consumption of an EV is carried out following a standard real driving cycle (RDC) schedule based on the European Real Driving Emissions (RDE) test procedure, generally adopted in Europe and other regions for on-road emission analysis, allowing for test reproducibility in other locations and future comparisons. Previous studies on road measurements of EVs used unscheduled trips, making the results particular to the test location and difficult to compare. Unprecedented data of EV energy consumption from trips meeting RDC are compared with results from random driving provides novel information for further RDC/RDE test standard development.

- In this investigation, the effect of short trips under real-world driving on EV energy consumption is assessed and reported for the first time, once this subject has not been addressed in the consulted literature. Short trips below 16 km do not attend the minimum distance required by the standard RDC, but they are very common in urban areas and, therefore, of high research interest.

- The projected carbon emissions from passenger cars are determined considering the latest UK government recently announced policies and regulations, that will affect the vehicle market and road traffic. A model is presented considering the government mandate that compels manufacturers to ensure a percentage of their new car sales are fully electric. The proposed model applies real-world corrections factors based on RDC/RDE test schedules for EVs energy consumption and ICE vehicles.

- The effects of regional differences in electricity grid mix, driving patterns, and ambient temperature on an EV energy consumption and carbon emissions while charging under uncontrolled and smart charging is reported for the first time. Based on the new smart charge points regulations, the impact of a delayed charging strategy on carbon emissions was investigated on a sub-national basis. An optimised charging schedule for minimising related carbon emissions from EV charging was presented in each region.

1.4 Thesis Outline

The remain of this thesis is divided into four more chapters. Chapter 2 presents the current situation of EVs in the UK market and discusses policies that may affect their adoption. The chapter also provides a review of the literature and highlights the main findings. Chapter 3 presents the methodology used in this study and is divided into four main sections. The first section outlines the EV data collection process and the calculation of energy consumption. The second section describes the real driving cycle adopted in this study and its parameters. The third section of this chapter details the model used to investigate road vehicle carbon emissions projection until 2050. Considerations are given to the expected EV market penetration, and the different scenarios constructed to measure travel demand changes in road traffic impacting carbon emissions of vehicles during the use phase through.

The fourth section describes the model developed to evaluate the regional differences in EV energy consumption and carbon emissions during charging. Also, the model evaluates the impact of uncontrolled and smart charging on carbon emissions for each region. Chapter 4 contains the results and discussion based on the work from the previous chapter. Finally, the conclusion of this thesis and recommendations for future work are presented in Chapter 5. The publications that originated from this thesis are listed in the Appendix.

Chapter 2

Literature Review

2.1 Electric Vehicles Market Share

The classification of electrified vehicles can be grouped into three main categories based on the degree of hybridisation: hybrid electric vehicles (HEVs), plug-in hybrid electric vehicles (PHEVs) and battery electric vehicles (BEVs) [21]. HEVs operate by combining an ICE and an electric motor with a battery that can be charged by the ICE or with regenerative braking. PHEVs perform similarly to HEVs, but with a larger battery and the capability to charge the battery by an external source. BEVs only use a battery as an energy source. For the remaining of this thesis, EVs refer to passenger cars that are only run by batteries.

Figure 2.1 shows that the registration of annual new sales of electrified vehicles has been rapidly growing in the UK, accounting for more than a third of the new vehicle market share in 2021 [22]. The number of newly registered BEVs overtook PHEV sales in 2019 and continues to grow, reaching a record of 11% of all new vehicle sales in 2021. Three types of policies are likely to increase EVs adoption: financial incentives, zero-emissions vehicles (ZEV) mandates and strong emissions standards [23]. The UK government started the plug-in car grant scheme in 2011 to help increase EV sales but ended the grant in June 2022 to refocus the funds toward public charging infrastructure [24]. Besides the announcement to end the sale of new petrol and diesel vehicles in 2030, the UK government is also planning to introduce a ZEV mandate in 2024 to provide market certainty for consumers, vehicle manufacturers and charging infrastructure operators [7].

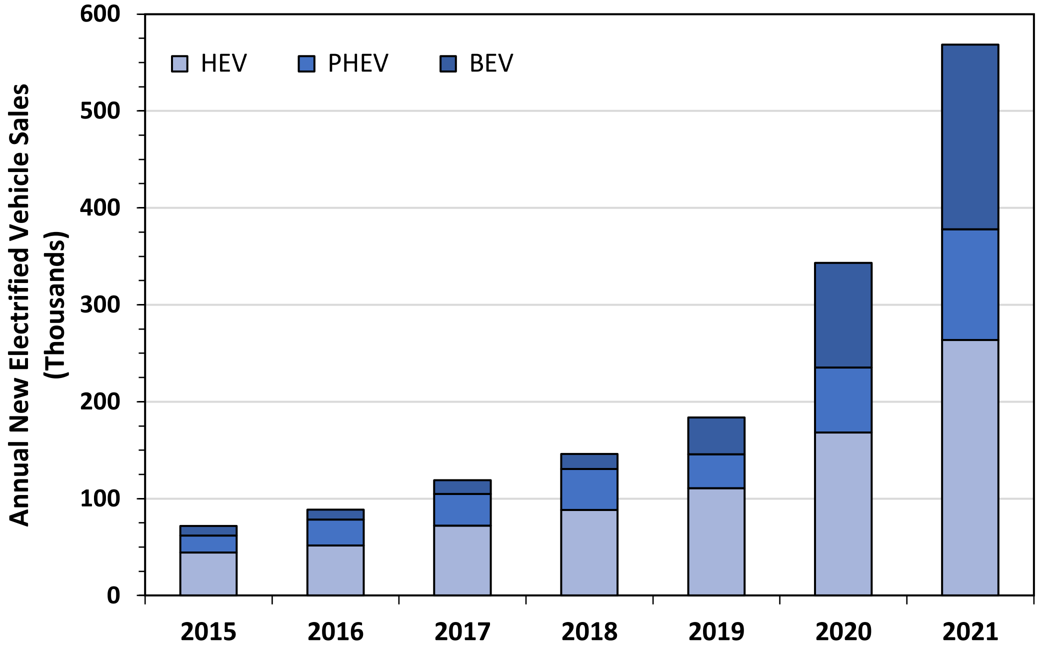

Figure 2.1: Annual new sales of electrified vehicle in the UK from 2015 to 2021, data source from Department of Transport vehicle statistics [22].

The mandate was initially brought up in the Decarbonising Transport plan based on the recommendation by the Climate Change Committee [25]. The mandate requires vehicle manufacturers to have a minimum percentage of overall annual new sales to be zero tailpipe emissions vehicles starting from 2024 and progressively increase to 100% by 2035 [6]. Under the proposed ZEV mandate, vehicles could be awarded a different number of certificates if meeting certain criteria, such as minimum or above-average energy efficiency and established requirements for battery recycling. The aim is that the number of certificates given for each EV will determine the type of vehicle that will exist in the UK over the following decades.

The UK government has introduced several schemes that aim to reduce or restrict the activities of high polluting vehicles in major areas, starting in London with Low Emission Zone (LEZs) in 2008 and later with a more restricted Ultra Low Emission

Zones (ULEZs) scheme [26]. Other local authorities are also setting up Clean Air Zones (CAZs) to meet government requirements for developing plans to reduce pollution to legal limits [27]. For example, Birmingham city council has introduced a CAZ in June 2021, where highly polluting vehicles must pay a fee to enter areas within the city centre. BEVs are fully exempt from the chargers, while ICE vehicles, including hybrids, have to meet either Euro 4 standard for petrol or Euro 6 for diesel vehicles [28]. Introducing CAZs can reduce road traffic by lowering car usage and promoting public transport [29].

The outbreak of coronavirus (COVID-19) led governments worldwide to adopt a series of emergency measures to control the pandemic, including social distancing, border closures and lockdowns, leading to a major reduction in travel demand [30]. The drop in road traffic activities caused a substantial reduction in energy and fuel demand globally [31], but as the lockdown restrictions eased, the road traffic activities began to recover [32].

According to a UK government estimate, the transport sector ─ road transport, railways, shipping and domestic aviation ─ emissions fell by 19% in 2020 compared to 2019 levels due to coronavirus pandemic measures that instructed people to remain at home for large parts of 2020, consequently raising residential emissions by 1% [33]. Regarding vehicle sales, the coronavirus pandemic had a major impact in the UK, as during lockdowns, dealerships and showrooms were required to close, removing the primary method for new vehicles to be sold [34]. Also, multiple lockdowns worldwide imposed by governments result in significant distributions to vehicle production supply chain, leading to shortages in critical vehicle components [35] and hindering vehicle sales [36].

2.2 Real-World and Laboratory Tests

Currently, the advertised specific energy consumption (SEC) and range of an EV are determined based on measurements from legislative laboratory driving cycles, such as the Worldwide Harmonised Light Vehicle Test Procedure (WLTP) replaced the New European Driving Cycle (NEDC) for the official fuel consumption and emissions of new cars in September 2017 [37]. These driving cycles are a standardised procedure aimed at evaluating vehicle performance under controlled laboratory conditions [38].

Variations on EV parameters such as vehicle weight, speed and load from the auxiliaries may have a substantial impact on the EV driving range compared to ICE vehicles because the energy storage of the latter, the fuel tank, is larger and denser [13]. Therefore, the measured energy consumption values provided by car manufacturers can overestimate the actual range of EVs since their testing are carried out under ideal conditions with minimum load. Furthermore, the discrepancy of EV energy consumption measured under real-world driving and the one obtained from laboratory testing can eventually be much higher compared with ICE vehicles. This is especially due to the added load from the auxiliary systems on EV battery. The provision of accurate data of EV energy consumption and range, and identification of related affecting factors are essential to remove customers' anxieties and help to widespread the EV market [15].

The variation in energy consumption of EVs across different seasons and weather conditions has been shown using real-world data of 12 months for several driving application [39]. The results pointed out a significant reduction of 64% in driving range during cold weather in comparison with the standardised driving cycle. However, the reason for the variation in energy efficiency could not be determined due to the lack of data when the auxiliary systems were used. Zhao et al. [40] showed that EV driving range estimated from six legislative driving cycles differs by 20% to 38% compared to a constructed urban driving cycle based on real driving data in China. Data from real-world driving tests of an EV in India showed that energy consumption is 42% to 90% higher than the laboratory affected by changes in traffic congestion conditions [41]. A simulation model showed that laboratory standard driving cycles generally have poor correlation with real-world driving due to the discrepancies in geography, traffic, type of vehicle and size of the city [2].

Several studies constructed fixed speed profile driving cycles for their local areas to overcome the discrepancy in EV energy consumption under laboratory standard driving cycles and real-world, for a better representation of driving in several cities and regions [40, 42-44]. However, these alternative driving cycles are limited to the studied area and do not serve as a general tool to evaluate EV energy consumption [45]. Additionally, the impact of different traffic conditions, operation modes and driving behaviour cannot be studied using pre-defined speed profile cycles. Therefore, these fixed profile driving cycles are never used again in other studies for evaluating EVs real-world energy consumption.

2.3 Factors Influencing Energy Consumption

Different aspects influence the energy consumption of EVs, including traffic conditions, which affect vehicle speed and acceleration, infrastructure, such as road gradient, environmental conditions, such as ambient temperature, and driving behaviour [46]. Two factors affect the driving behaviour of EVs: regenerative braking, which can change the driver style to improve the amount of recovered energy, and powertrain configuration, which performance and noise characteristics give different perceptions to the driver [38]. A survey in the UK identified concerns about the impact of driving behaviour and the use of vehicle features on the range as one of several barriers to increasing the uptake of EVs [47].

Using long-term Global Positioning System (GPS) data collecting every 60 s for driving EVs in Japan, the influence of road gradient on EV energy consumption was explored [48]. Other various factors were considered in the study including trip distance, average speed and air conditioning or heater usage. The trips using heating and air conditioning systems presented average energy consumption per distance twice as larger as the other trips. Other parameters that can be taken into consideration are battery state of charge (SOC) and energy efficiency of regenerative braking [49]. Statistical approaches have been used to analyse the relationship between driving behaviour and EV energy consumption, identifying average speed, battery current and

SOC as important parameters [50]. From the evaluation of data collected in Shanghai, China, changes in trip distance, average speed and temperature have shown a direct impact on EV energy consumption while battery initial SOC had no significant impact on EV efficiency [51].

Data obtained from real-world driving of an EV in Beijing for ten days in three different months (January, April and August) along one year enabled the identification of economical driving speeds around 50 km/h under average ambient temperature in the range from 2°C to 30°C [52]. A combination of microscopic traffic and energy prediction models showed that, if the ambient temperature drops by 12°C, energy consumption increases by 11% at motorway driving speed of 130 km/h and peaks with an increase of 55% at residential driving speed of 30 km/h [53].

The effect of road grade on EV energy consumption has been examined using a mathematical model, showing an increase in energy consumption with uphill driving and decrease in downhill situations [54]. The results from road tests in Japan were used to develop a model to predict the energy consumption of EVs, showing that uphill and downhill road grades up to 2% produce similar energy consumption but, with steeper grades, uphill roads produce higher energy consumption than downhill roads [55]. A sensitivity analysis of EV energy demand showed that varying vehicle mass with a different number of occupants has a rather small influence compared to other factors such as auxiliary demand, especially at speeds below 80 km/h, and it is only relevant in hilly environments [56]. Model simulation showed that tripling battery capacity significantly improved the vehicle range, but dropped the overall efficiency by 12% due to the added weight from increasing the battery size [57].

The environmental conditions have a substantial impact on EV energy consumption, particularly the ambient temperature, which lacks adequate research data to evaluate its impact on the overall EV energy efficiency [55]. Due to changes in atmospheric conditions, the EV driving range varies from 25% to 35% between northern and southern European countries [58]. The climate data of three major cities in the United States was used in a simulation tool to reveal that the utilisation of heating, ventilation and air conditioning (HVAC) system increases EV energy consumption by

9%, 12% and 24% in hot, moderate and cold climates, respectively [59]. Using data collected in Sydney, Australia, several factors related to topography, infrastructure, climate and traffic, including the effects of idling time and stops, which can potentially influence the energy consumption of an EV, have been reviewed and classified [60]. The tests were conducted between July and September with all route lengths around 5 km, leading to the conclusion that topography and the use of HVAC systems have higher effects on the energy consumption than the other factors.

Energy consumption has been analysed under different legislative driving cycles, showing a remarkable drop in range with decreasing temperatures due to the use of the HVAC system [61]. If the HVAC system of an EV is used reasonably, the mean specific energy consumption can be reduced by as much as 9.7% [62]. The sensitivity of EV range to climate effects and driving behaviour was examined, revealing that hot climate causes high peak battery temperature during on-road operation and battery degradation [59]. The use of HVAC has little effect on battery temperature and wear, but significantly increases energy consumption with high impacts on vehicle range as the vehicle is operated over extended year periods.

Predicting EV energy consumption is very complex because it depends on a number of factors including road topology, traffic condition, driving style and ambient temperature [63]. A machine learning framework was used to predict EV energy consumption considering vehicle, environment and driver factors, reaching a mean absolute error of 12.7% compared to real-world results [64]. A road link model is claimed to produce more precise estimate of EV energy consumption than other models, achieving error between 5.0% and 12.6% depending on data availability [46].

2.4 Impact of Ambient Temperature

The effects of temperature on EV energy consumption have also been studied using computer simulation modelling. A simulation model developed to measure the influence of a wide temperature range on EV energy consumption under a legislative driving cycle showed a significant reduction in driving range at cold temperatures, compared with optimal temperatures where the auxiliary demand was at a minimum [58].

The ambient temperature was reported to affect the energy consumption of both EVs and ICE vehicles similarly, as during colder weather the increase in air density leads to an increase in rolling resistance and air drag [65]. In addition, at low temperatures both electric motor and engine lubricants operate outside their optimal range, which translates into a decrease of overall driveline efficiency. A rise in the energy consumption of EVs has been observed due to the use of auxiliary devices to keep the occupants at a comfort level with the use of air conditioning at high-temperature weather and heater at cold weather conditions [66]. The thermal energy from the electric motor in EVs is unable to provide the heating requirement during winter, which notably affects the range due to increase in energy consumption [61].

The relationship between the ambient conditions and driving range using a drive-to-depletion method that involves measuring the covered range by driving the vehicle from the fully charged battery until depleted using battery SOC reading has been examined [67]. The results show a linear correlation between the ambient temperature outside and the EV range, however, the determination of energy consumption was not accurate as the vehicle parameters were extracted at extremely low frequency. The influence of traffic and driving behaviour on energy consumption can be studied using a data sampling rate able to capture the dynamic changes in the driving pattern during the trip. However, a high sampling frequency will increase the data processing load, while a small frequency would filter the data characterising the vehicle acceleration and deceleration [2]. A frequency of 1 Hz to collect vehicle data is sufficient for energy consumption estimation and driving cycle generation [56, 68].

The ambient temperature outside influences the amount of recovered energy during regenerative braking and affects battery efficiency [62]. If the interactive effects between the ambient temperature and the auxiliary load are ignored, it will lead to overestimated energy consumption of the heater in warm weather and underestimated air conditioning in cold weather. Using operation data of heating and cooling systems from different cities in China, laboratory tests of several EV models with different battery types showed that energy consumption increased by 20% and 67% at the ambient temperatures of 30°C and -7°C, respectively, compared with moderate temperatures [69]. The tests also revealed that differences in consumption between vehicle models are caused by the heating and cooling system. For different battery types, the differences were due to charging and discharging performance at low temperature.

2.5 Carbon Emissions During Use Phase

Extensive research has been conducted on measuring the carbon emissions of EVs in different regions. Teixeira et al. [70] performed a study in Brazil evaluating the carbon emissions from gradually replacing ICE vehicles with EVs in a fleet under different scenarios of increasing electricity grid carbon intensity. The results revealed a 9% reduction in carbon emissions in the worst case of electricity generation with a total replacement of the fleet with EVs. Yuan et al. [71] found that the carbon emissions of EVs also depend on the driving behaviour, and for EVs to have reduced emissions over ICE vehicles, they need to operate at speed below 80 km/h and with a driving range up to 250 km, due to the dependency on coal as the primary source of electricity production in China. While for Portugal, Garcia et al. [72] showed that charging behaviour has a significant influence on carbon emissions of EVs. The authors found that charging EVs fleet during off-peak hours, which is the recommended time from an economic perspective, leads to an increase in emissions as a result of using high carbon-intense sources to supply charge EVs.

Raugei et al. [73] used a lifecycle energy analysis model to compare a compact EV with an equivalent ICE vehicle in the UK. The results show that an EV has a 34% lower demand for non-renewable primary energy under current conditions than an ICE vehicle, and further reduction may be expected in the future grid mix due to shifting to a more renewable electric grid. Canals Casals et al. [74] compared EVs GHG emissions to ICE vehicles in several European countries, including the UK, using six laboratory standard driving cycles. They found that, in most cases introducing EVs in the market has the potential to reduce GHG emissions. However, in some counties, EVs do not offer immediate GHG reductions and require improving electricity grid carbon intensity to reduce emissions. According to Rangaraju et al. [75], the discrepancies between laboratory test measurements and real-world conditions should be dealt with to have a correct assessment and comparison of the environmental impact of vehicles.

Onn et al. [76] compared the emissions of several ICE vehicles, HEVs and EVs during the use phase in Malaysia, where fossil fuels dominate the electricity generation mix. The results revealed that the environmental impact of EVs is, on average, 7% higher than HEVs. When using the Japanese JC08 driving cycle, EVs had higher emissions than ICE vehicles. While the result for the EVs can be attributed to the high grid carbon intensity in Malaysia, it can also be linked to the selected driving cycle, which can influence choosing the right vehicle technology with the least amount of environment impact. Some tests procedure will underestimate the reduction of emissions as the characteristics of these driving cycles favour a number of vehicle topologies over the others. With the introduction of vehicle electrification, this effect becomes more noticeable [77].

Accurate projections of road transport carbon emissions are very complex because they rely on a number of variables. Several possible factors can be highlighted, including fleet compositions, transport demand, and improvement in vehicle efficiency [78]. Other parameters that can be considered are government policies, fleet electrification, fuel production, and future electricity grid mix [79, 80].

Several studies have attempted to measure the changes expected in the carbon emissions projections due to the introduction of EVs in the UK under different approaches. During the consulting period of ending the sales of ICE vehicles, a study by Craglia et al. [81] assessed the relative importance of factors influencing future emissions from passenger vehicles. While the analysis considered PHEV sales to continue after 2035, the results showed that the most critical action to reduce future carbon emissions involves shifting to electric powertrains. Although a study by Xu et al. [82] combined the number of BEVs and PHEVs to review the dynamic relation between vehicle stock and carbon emissions in eight countries, including the UK, the results encourage policies to promote growth of the electric vehicle industry to mitigate carbon emissions. An analysis of large scale EVs rollout impact on fuel cost and network investment presented by Calvillo et al. [83] showed that the economic benefit of switching to EVs could potentially offset any losses in fuel tax revenue. According to the authors, the UK electricity has a strong link to the domestic supply chain, so growth in this industry could positively impact the UK economy, unlike the fuel industry, which largely consists of an import supply chain.

According to a study by Raugei et al. [84] that divided the UK vehicle fleet into just two categories, ICE vehicles and EVs, the UK's ambitious targets for fleet electrification and rapid decarbonisation of the grid can contribute to improving energy sovereignty. Fleet electrification reduces non-renewable energy, local air pollution and carbon emissions, but risks a sharp demand for batteries materials. Before the UK government confirmed the dates to end ICE sales, different potential pathways of EVs adoption based on different targets impacting emissions reduction have been investigated [85]. The study concludes that accelerated EV uptake would bring long-term benefits to decarbonise the transport, but it will be important to consider other policies to achieve both near-term and long-term mitigation targets, such as promoting the shift to public transport, car-sharing and reducing travel demand.

Carbon emissions projections for different scenarios of vehicle technologies integration have been modelled [86, 87], concluding that the need to decarbonise the electricity generation or the environmental benefits of low emissions vehicles will be diminished. These studies assumed the new ICE vehicles sold meet the European targets for average fleet emissions. However, the European Union regulation applies a super-credit system where vehicles with emissions below 50 gCO_2/km count multiple times for the average manufacturer vehicles emissions [88]. Therefore, reducing overall calculated fleet emissions while the actual emissions of the average ICE vehicle remain higher than the fleet targets.

The electricity grid carbon intensity changes regularly depending on the hour of the day and season. For example, as noted by Lajunen [89], carbon emissions from electricity generation in Finland are doubled during winter due to the increases in fossil fuel usage compared to the summer. Faria et al. [90] measured the carbon emissions associated with charging EVs in several countries with different electricity generation profiles, from a grid with a high share of renewables to one that mainly depends on fossil fuel sources. The results show that an electricity grid with a large portion of renewables does not necessarily reflect on lowering carbon emissions, as using these sources sometimes requires fossil fuel sources to take over at specific times. The author also emphasised that driving behaviour could limit the benefits EVs will have on reducing emissions, as aggressive driving leads to higher energy consumption, leading to increased emissions.

McLaren et al. [91] covered the analysis of EV emissions under four different charging infrastructures and scenarios, home, time-restricted and workplace charging, with five different electricity grid profiles, from a high to a low carbon-intense electricity generation mix. The results show that workplace charging has the lowest emissions in all scenarios, except in the case of a high carbon electricity mix, while the time-restricted had the higher emissions value in most cases. The authors highlight that the price of electricity at off-peak hours and policies that do not encourage daytime could lead to an increase in emissions.

Li et al. [92] investigated the regional difference in carbon emissions reduction from adopting EVs in China using well to wheel analysis, showing that the reduction varies considerably between the regions and suggesting that policies need to be adjusted to consider the impact of EVs in each region. Onat et al. [93] performed a similar study in the United States with similar results about the difference between each region, where in 24 states, EVs were found to be the least carbon-intensive option. However, as mentioned by Requia et al. [94], there is a substantial gap in the knowledge of EV benefits will have on the environment from a global standpoint, as the majority of previous regional studies were performed in the United States or China. Furthermore, as pointed out by the author, there is a need for studies in other regions, as EV emissions are affected by many factors besides the source of energy generation, such as driving patterns, charging infrastructure, policies, and climate.

A review of the UK Net Zero strategy emphasises the importance of local regions role in meeting the national net zero ambitions, as 30% of GHG emissions reductions rely on local authority involvement, and 82% of all UK emissions are under the influence of local authorities [95]. Taking a regional approach will allow identifying the best path to meet net zero targets considering regional variations in transport and electricity grid [96]. Therefore, to identify further opportunities for decarbonising passenger vehicles, analysis is needed considering the UK region variability in road traffic and electricity grid profile.

2.6 Summary

After reviewing the literature, the following key findings are highlighted:

- The difference between real-world driving conditions and standard test schedules under controlled laboratory conditions results in significant energy consumption and driving range variations of EVs. Although several studies in the literature have identified different factors that influence the variation in energy consumption, there is still a need to identify the most influential factors and better understand the relation between different factors impacting EV energy consumption.

- Previous studies built fixed speed profile driving cycles to overcome the difference in EV energy consumption under real-world and laboratory standard driving cycles. A major issue of this method is that it is limited to the test location and does fit a general tool to measure EV energy consumption. As in real vehicle utilisation, a wide variety of driving conditions are encountered. Therefore, in order to allow future correlations, results need to be built from selected trips attending the specifications and boundary conditions of a representative real driving cycle.

- Previous studies on carbon emissions projection for EVs did not account for the impact the coronavirus pandemic had on road traffic and vehicle supply chain leading to lower vehicle sales than previously expected. To accurately determine carbon emission projections, the analysis should distinguish between different ICE vehicle groups, as each has its emission characteristics from the tailpipe. Similarly, the evaluation should differentiate between electrified vehicle technologies as current policies have a different set of targets for hybrid vehicles and fully electric vehicles.

- Carbon emissions associated with EVs during the use phase are highly influenced by regional electricity grid mix, as it is directly related to emissions produced when charging EVs. Also, the carbon emissions while charging EVs depend on the charging behaviour, regional variations in driving patterns, and climate conditions.

Chapter 3

Methodology

3.1 Electric Vehicle Data Analysis

3.1.1 Data Collection and Processing

This study utilised the driving data of road operation of a Nissan Leaf model, a good representative of a C-segment small family electric vehicle. While the study is based on a single vehicle the analysis is applicable to other EVs in the UK market of close specifications (Table 3.1), such as BMW i3 and Renault Zoe. This model is classified as a compact vehicle, which segment has the largest market share in the UK of 60% [73]. The driving was conducted in the city of Birmingham, the second largest city in the UK, during the period from January 2016 until September 2019. The data was collected at a frequency of 1 Hz, a standard sampling rate for vehicle analysis [97], from the controller area network (CAN) bus by a data logger connected to the vehicle on-board diagnostics (OBD) port. The data logger synchronised the data in real-time and stored it in the cloud, making it accessible by a dedicated ViriCiti monitoring software. These systems that can directly collect vehicle data from the CAN bus and transfer it to a server are rare in tests by research institutes and universities and are primarily used by car manufacturers [98].

The system had a GPS sensor that provided precise vehicle location with the ability to synchronise position and time. The data acquisition device had a very low power consumption, reaching a maximum of 5 W at full load, thus having a negligible impact on the EV overall energy consumption. The main vehicle parameters used in this study were vehicle speed, ambient temperature, trip time step, GPS position, and battery current, voltage and SOC. Prior to the tests the vehicle had a total running distance of 4031 km and, at the end of the test period, the running distance was 19225 km.

Table 3.1: Summary of the main vehicle specifications.

PARAMETER	TYPE OF VALUE
Car model	Nissan Leaf
Vehicle class	C-Segment (compact vehicle)
Battery capacity	24 kWh
Battery chemistry	Li-ion
Maximum motor power	80 kW
Vehicle mass (curb weight/gross weight)	1521/1761 kg

The data exported from the monitoring software was processed and filtered using MATLAB software. For every trip, the distance and duration were calculated using the recorded time interval and vehicle speed. The analysis excluded any trip shorter than 1 km or taking less than 5 minutes. A total of 1,137 trips were evaluated under varying driving conditions across different ambient temperatures outside, ranging from 0°C to 33°C, trip duration taking from 5 min to 1 h 28 min, and travel distance from 1 km to 75.8 km.

Different drivers operated the vehicle under various driving conditions during different times of the day independent from changes in weather conditions. No specific route was selected to ensure that various road types were covered, and the driver had no restriction to use any of the vehicle auxiliaries in order to obtain a realistic representation of the driving characteristics in the UK. Around 65% of the trips started with battery SOC of 70% or higher. The elevation difference between the start and end of each trip was below 100 m for nearly all trips due to the flat nature of the area, limiting the impact of road grade on the overall vehicle energy consumption.

3.1.2 Energy Consumption Calculation

The analysis was done by measuring the SEC for every trip, in kWh/km. This parameter has been used in previous studies to evaluate the economic feasibility of an electric commercial vehicle [99], carbon and pollutant emissions from electricity generation to supply electric passenger cars in Italy [100] and electric buses in China [101]. The consumed energy during the trip was calculated using the battery voltage and current, which was determined using the following equation:

$$\mathrm{E_{tot}} = \frac{1}{3600} \cdot \sum_{i=1}^{n} \mathrm{V_i} \cdot \frac{\mathrm{I_i}}{1000} \qquad i = 1,2,\dots,n \tag{3.1}$$

where E_{tot} is the trip total consumed energy, in kWh, V_i is the battery voltage, in V, I_i is the battery current measured at each time step, in A, i is the time step and n is the total number of readings. Therefore, the specific energy consumption for the trip, SEC_{trip} (kWh/km), can be measured as follows, where d_{trip} is the trip distance, in km:

$$\mathrm{SEC_{trip}} = \frac{\mathrm{E_{trip}}}{\mathrm{d_{trip}}} \tag{3.2}$$

The maximum EV driving range, s_{max} (km), is the total distance the vehicle can cover with a single charge from fully charged battery until depletion state, and is so calculated based on the measured SEC:

$$\mathrm{s_{max}} = \frac{\mathrm{C_{battery}}}{\mathrm{SEC}} \tag{3.3}$$

where $C_{battery}$ is the usable battery capacity observed when it is fully charged (kWh).

The battery usable capacity is restricted by the battery management system (BMS) to protect it from overcharging and discharging events and avoid situations that can compromise the battery pack by reducing its life cycle or leading it to catch fire [102]. To ensure no permanent damage occurs to the battery and avoid deep discharging, the rated capacity cannot be fully accessed or used [13]. Following recommendation from previous authors [103], the usable battery capacity is here adopted as 87.5% of the nominal rated capacity.

The total energy consumed E_{tot} includes the tractive energy required to drive the vehicle, E_{tra} (kWh), the energy needed to operate the auxiliary devices in the vehicle, E_{aux} (kWh), and the total energy losses due to braking, aerodynamic drag, rolling road resistance, friction of the moving components, and electric losses, E_{loss} (kWh). The tractive energy can be split into two parts: one is the energy required by the drivetrain, E_{drv} (kWh), and the other with opposite sign is the recovered energy during regenerative braking, E_{reg} (kWh). Therefore, the sum of these energies gives the total consumed energy written as:

$$\begin{aligned} E_{tot} &= E_{tra} + E_{aux} + E_{loss} = \left(E_{drv} - E_{reg}\right) + E_{aux} + E_{loss} \\ &= E_{cons} - E_{reg} \end{aligned} \tag{3.4}$$

where E_{cons} (kWh) is the net consumed energy by drivetrain, losses and auxiliary system:

$$E_{cons} = E_{drv} + E_{aux} + E_{loss} \tag{3.5}$$

The effect of temperature on battery performance is not within the scope of this thesis, but it has been reported that a decrease in temperature increases the battery internal resistance and, therefore, decreases the amount of energy that can be extracted from the battery [104]. On the other hand, high temperatures do not affect battery charging and discharging performance but may cause a rapid increase in battery degradation and self-discharging [105].

The battery is expected to lose between 2% to 5% of its rated capacity in two years if the user drives the vehicle for 45 km/day [106]. In the current study, the EV had an initial odometer reading of 4031 km in January 2016 and, at end of testing in September 2019, the reading was around 19225 km, corresponding to about 11 km/day. Furthermore, the method applied here relies on the battery voltage and current to calculate the energy consumption independent from the actual battery capacity, unlike the method of using battery SOC. As in the case of using SOC, if battery degradation and actual usable capacity are not accounted for in the calculation the result will be an inaccurate measurement of energy consumption. Therefore, battery degradation during the test period is here assumed to be negligible as the travel distance per day was very low. Likewise, the ageing of other vehicle components was not considered due to its minimal impact. For instance, the electric motor of an EV is likely to operate over 20,000 h or 15 years without degrading power delivery or efficiency [107]. This lifespan is much above that of conventional vehicles, which ranges between 6,000 h and 8,000 h [108].

The impact of driving state on energy consumption was determined by dividing each trip to kinematic segments representing different driving modes, then calculating the trip time percentage the vehicle was driven in each mode. These driving modes are identified in Table 3.2 according to vehicle acceleration (a) and speed (v) conditions in each time step, using the same criteria previously adopted by other authors [109].

Table 3.2: Driving mode defining conditions.

DRIVING MODE	CONDITION
Acceleration	$a > 0.14$ m/s^2
Deceleration	$a < -0.14$ m/s^2
Cruising	$v \geq 1$ km/h and $|a| \leq 0.14$ m/s^2
Idling	$v < 1$ km/h and $|a| \leq 0.14$ m/s^2

Figure 3.1 provides an overview of the types of trip profiles collected from real-world driving and where the NEDC and WLTP driving cycles would be positioned for comparison. The six parameters ─ distance, duration, average speeds, acceleration and decelerations ─ commonly used to compare driving cycles show the variety of trip profiles obtained from the real-world dataset, unlike fixed laboratory driving cycles. Short trips are widely represented in the data, with more than 88% of trip distances in real-world data being less than the NEDC distance of 11 km and 95% below 23 km of the WLTP. Average speeds with and without stops for real-world trips are much lower than NEDC and WLTP because most of the driving occurred in urban environments, typically with lower speeds and frequent stops. Acceleration and deceleration parameters representing driving behaviour indicate less aggressive driving for real-world trips than NEDC or WLTP. However, lower average deceleration values in real-world trips might lead to lower energy recovered during regenerative braking.

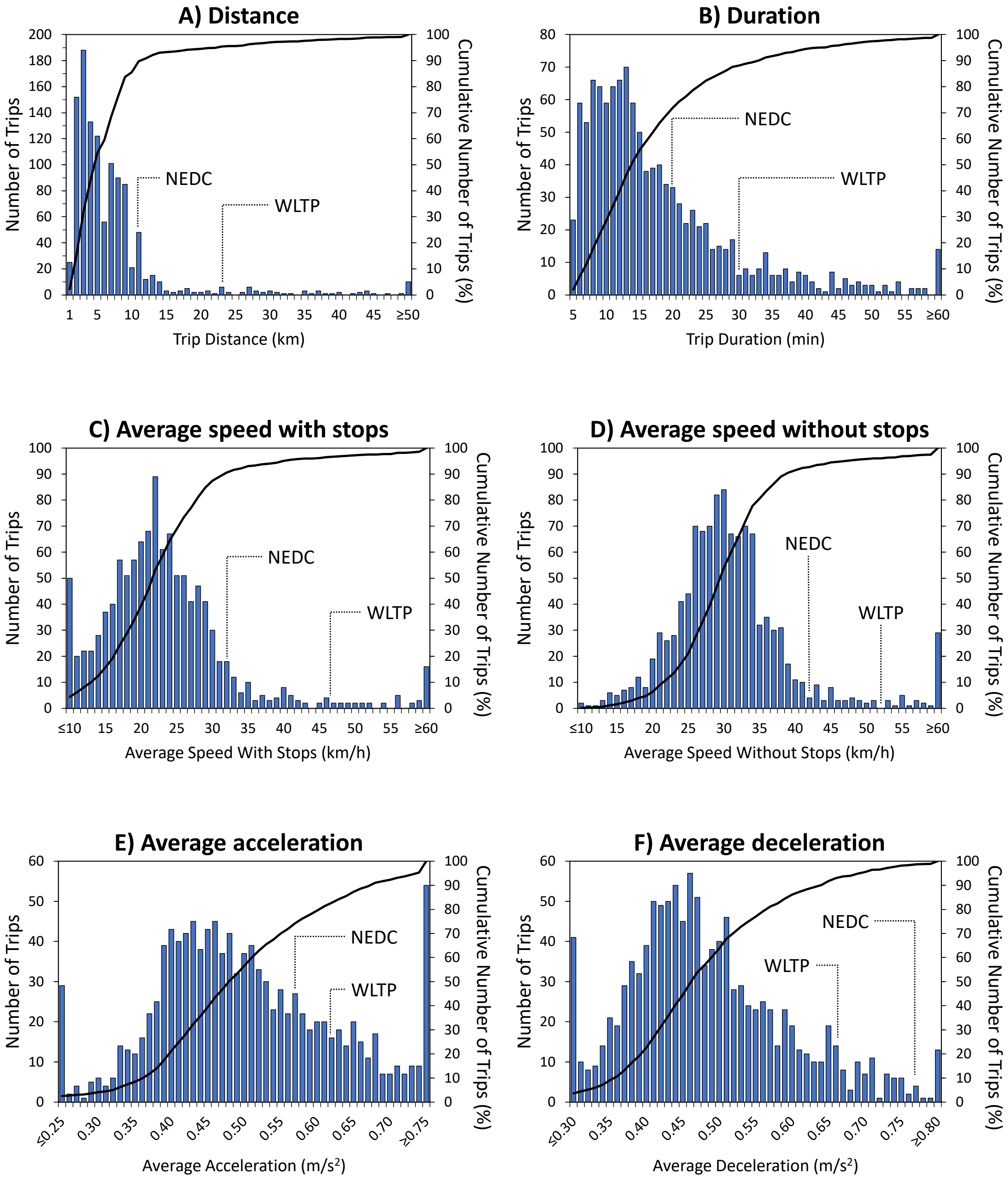

Figure 3.1: Overview of trip profiles from the real-world driving data.

3.1.3 Auxiliary Power Estimation

A method to determine the auxiliary power consumption during vehicle operation was developed, as the data logging device used to collect data was unable to record the status of the HVAC system in separate from the total power consumption. Figure 3.2 shows the vehicle speed and the total power consumption of a recorded trip randomly selected to illustrate the method applied to determine auxiliary power for all scheduled or unscheduled trips. The power consumed in the periods when the vehicle speed is zero is attributed to the auxiliary systems, following a similar assumption adopted by other authors [56]. When the vehicle is moving, there is still power consumption from the auxiliary system but it cannot be directly extracted from the data, as observed between sections 1 and 2 in the figure.

The auxiliary power is estimated using data interpolation between the last observed total power value before the vehicle starts to move and the value when the vehicle stops. This corresponds to the time range from 15 s to 81 s in the figure. The subtraction of the auxiliary power curve from the total power curve originates a new curve which positive part is the sum of drivetrain and losses power consumed from the battery, while the negative part is the regenerative power recouping back into the battery. The area integration of the power curves of auxiliaries, drivetrain and losses provides the energy consumed by each component, while the regenerated energy is given by the absolute value of the integration of the regenerative power curve.

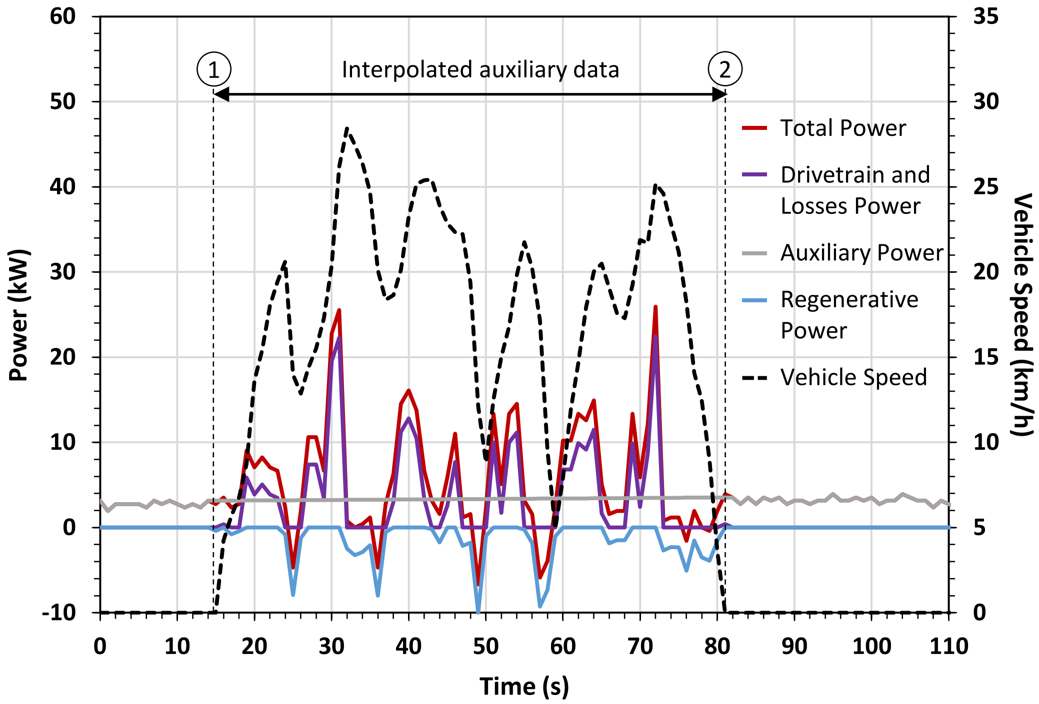

Figure 3.2: Graphical schematics of auxiliary power determination for scheduled and unscheduled trips.

3.1.4 Road Grade Determination

Changes in road grade during the trip were calculated using the collected GPS data, which included the number of satellites and elevation. Some trips showed errors in their GPS data that led to inaccurate measurements of the actual position, due to signal interference from the surrounding buildings or loss of signal, for example, when driving in a tunnel. Other situations showed unreliable data at the start of the trip due to the low number of GPS satellites to provide precise values while the data logging system was still gathering information.

GPS devices used for general commercial purposes typically have an accuracy of 3 m, and the vertical error can increase if the signal is obstructed by different objects such as building and trees [110]. This accuracy range can result in unrealistic variation in the elevation values from the GPS data with small changes in distance. To solve this problem, a data processing algorithm to accurately determine road grade was applied using a similar approach adopted by previous authors [111]. The applied method splits the trip to segments of 80 m based on travel distance and uses the elevation data at these points to calculate the road segment grade. The data processing algorithm filters the data for each trip to only consider the elevation in time steps given by 7 or more satellites to solve the issue with the low number of GPD satellites at the start of the trip. Although the method reduces the errors in calculating road grades, a maximum of 10% road grade was set to eliminate unrealistic values still presented by some segments.

3.2 Real Driving Cycle Procedure

3.2.1 Driving Cycle Description

The determination of SEC from road driving could be more easily comparable if all trips considered had similar characteristics; however, in real vehicle utilisation, a wide variety of trip lengths, stops and driving conditions are encountered. One major issue of using random trips is that it gives short trips the same weight as medium or long-distance trips on impacting the average SEC calculation, leading to widely scattered results. As a consequence, one may still lean to the use of standard laboratory driving cycles for comparison purposes.

In order to allow future correlations, the results distinguish the trips attending a real driving cycle (RDC), based on the European real-driving emissions test procedure (RDE) [112]. Although emissions measurements are not the focus of this work, the RDE cycle can conveniently be used for energy consumption evaluation and provide a firm basis for further comparisons. The RDE was introduced by the European Commission in 2019 to ensure emissions stay below regulatory limits during real traffic conditions [113-115]. The RDE test procedure has also been introduced in countries of other regions such as China, where it will be applied as part of China VI emission regulation in 2020 [116], and Korea, which has already implemented the third RDE version in 2017 [117].

The RDE has four legislative packages. The first package [118] contains several requirements and operation limits to dismiss specific types of driving and environmental condition, and the second package incorporates dynamic operation limits to exclude certain trips based on vehicle speed and acceleration [119]. The third and fourth packages [120] focus on cold start emissions, hybrid technologies and market surveillance [121]. The RDE test procedure splits the trip data into three different operation modes based on the instantaneous vehicle speed, v_i (km/h) (Table 3.3). The RDE uses dynamic operation limits to verify the trip based on the vehicle instantaneous speed and acceleration, where the maximum metric is set by the 95th percentile of the product of vehicle speed and acceleration, and the minimum is the relative positive acceleration (RPA). Both metrics are proportional to the average vehicle speed in each operation.

Table 3.3: RDC/RDE operation modes.

OPERATION MODE	VEHICLE SPEED RANGE
Urban	vi ≤ 60 km/h)
Rural	60 km/h < vi ≤ 90 km/h
Motorway	vi > 90 km/h

3.2.2 Driving Cycle Parameters

The requirements and conditions for a RDE compliant trip are summarised in Table 3.4. The RDE requirements also include a minimum of 16 km covered distance in each operation mode. In this study, the impacts on energy consumption of trips shorter than the RDE distance specification have also been evaluated. Here, a trip is considered RDC compliant if the operation mode under evaluation fully attends the RDE requirements, while the trips with operation mode shorter than 16 km but complying with all other RDE specifications are called short RDC. Partial consideration of the RDE requirements has also been used in previous studies [122, 123]. In order to evaluate the dynamic condition of the trip, the instantaneous acceleration, a_i (m/s^2), is initially calculated:

$$a_i = \frac{1}{2} \cdot (v_{i+1} - v_{i-1})/3.6 \tag{3.6}$$

The instantaneous product of vehicle speed and acceleration, $(v{\cdot}a)_i$ (m^2/s^3), is given by:

$$(v \cdot a)_i = \frac{v_i \cdot a_i}{3.6} \tag{3.7}$$

Using Eq. (3.7), the 95th percentile of the product $(v \cdot a^+)_i$ is resolved for each trip operation mode, where a^+ refers to positive accelerations only ($a_i > 0.1$ m/s^2). For a trip operation mode to be RDE compliant, the 95th percentile of $(v \cdot a^+)_i$ must be below the high dynamic limit. Above this limit, the trip is considered too aggressive.

Then, the relative positive acceleration (RPA, m/s^2) for each trip in the different operation modes – urban, rural and motorway – can be determined:

$$\mathrm{RPA} = \frac{\sum_{i=1}^{n} (v \cdot a^+)_i \cdot \Delta t}{d} \qquad i = 1,2,\ldots,n \quad (3.8)$$

where d (m) is the distance covered in each operation mode and Δt is the time step interval (s). RDE compliant trips must have the RPA above the low dynamic limit, below which the trip is considered too passive.

Table 3.4: Summary of RDC/RDE requirements.

PARAMETER	REQUIREMENTS
Ambient temperature at moderate conditions	0°C to 30°C
Average speed of evaluated trips in urban operation	15 km/h to 40 km/h
Stop percentage	Between 6% to 30% of urban time
Defining parameter of high dynamic condition	95th percentile of $v \cdot a^+$
Defining parameter of low dynamic condition	Relative positive acceleration
Use of auxiliary system	Operated as in real life use

The driving behaviour is evaluated by classifying the trip as aggressive if 95% of all calculated values of $(v \cdot a^+)_i$ (95th percentile) are in the range between the high dynamic operation limit and 75% of the high dynamic operation limit at the operation mode under consideration. Passive driving is defined if the trip RPA is between the low dynamic operation limit and 25% above the low dynamic operation limit at a given operation mode. Finally, moderate trips are those between the aggressive and passive limits. Table 3.5 summarises the driving behaviour classification.

Figure 3.3 shows the data distribution after evaluating the driving behaviour for high dynamic operation. For a trip to be valid as a short RDC or RDC compliant trip, the 95th percentile of v·apos of urban, rural or motorway operation must not exceed the high dynamic limit. Trips above the dynamic operation limit are considered too aggressive and are not used in the RDC test procedure. Similarly, data distribution after employing the low dynamic operation analysis are shown in Figure 3.4. Trips with RPA values below the low dynamic operation limit are regarded as too passive and not suited for RDC consideration. In the end, half of the RDC trips respond to moderate driving and 40% of the RDC trips are classified as passive, while aggressive driving contributes to 10% of the RDC trips.

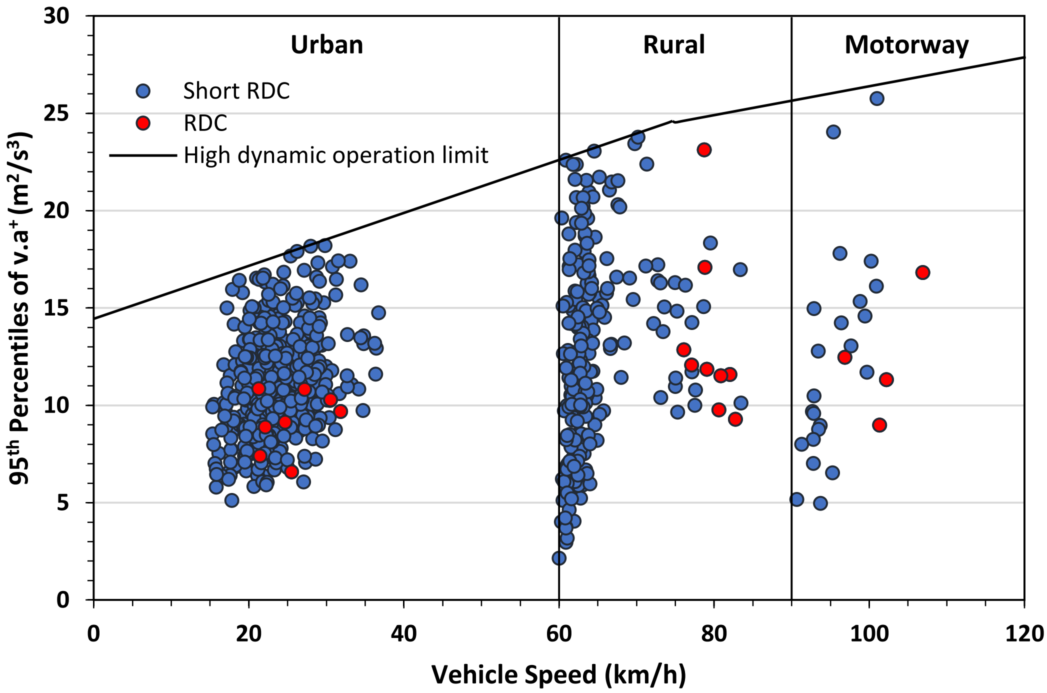

Figure 3.3: Trip distribution according to 95th percentiles of v·a^{+} in urban, rural and motorway operation.

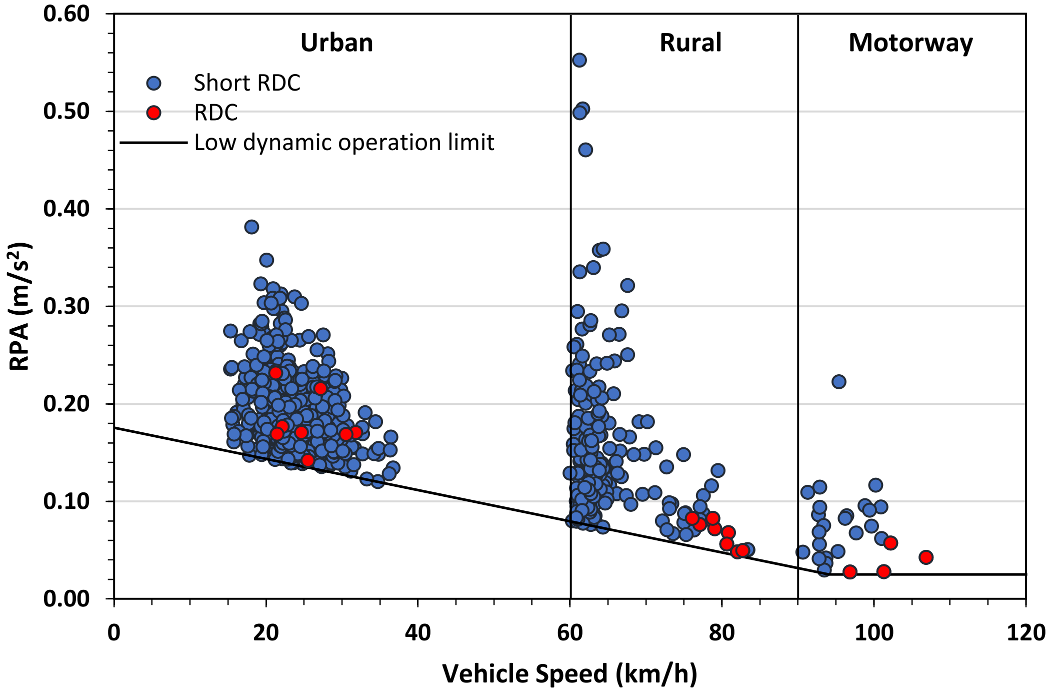

Figure 3.4: Trip distribution according to relative positive acceleration in urban, rural and motorway operation.

Table 3.5: Driving behaviour classification at an operation mode.

Driving Behaviour	Condition
Aggressive	$0.75 \cdot \mathrm{HDOL} < 95^{\mathrm{th}}$ percentile of $(\mathrm{v} \cdot \mathrm{a}^{+})_{\mathrm{i}} < 1.0 \cdot \mathrm{HDOL}$
Moderate	95^{th} percentile of $(\mathrm{v} \cdot \mathrm{a}^{+})_{\mathrm{i}} \leq 0.75 \cdot \mathrm{HDOL}$ and $\mathrm{RPA} \geq 1.25 \cdot \mathrm{LDOL}$
Passive	$1.0 \cdot \mathrm{LDOL} < \mathrm{RPA} < 1.25 \cdot \mathrm{LDOL}$

HDOL: high dynamic operation limit (see Figure 3.3).

LDOL: low dynamic operation limit (see Figure 3.4).

3.3 Carbon Emissions Model

This section describes the methodology used to predict carbon emissions of passenger vehicles fleet in Great Britain until 2050 and assess the impact of different travel demand scenarios on vehicle carbon emissions. The future travel demand projections based on vehicle usage and ownership depend on the age of the vehicles in the fleet. A complete dataset is needed to provide the number of vehicles by age for each powertrain type in any given year. Therefore, a fleet turnover model is created that can forecast vehicle uptake and split them by age in vehicle parc for each scenario.

Additionally, the share of new vehicle sales applies the ZEV mandate that is due to come into force in 2024. Furthermore, the model considers the latest government policy to end the sale of new petrol and diesel vehicles in 2030, with new hybrid vehicle sales allowed until 2035. Finally, the model differentiates between different types of ICE vehicles and electrified vehicles, as each group has its own emission characteristics and is impacted by different policies.

3.3.1 Fleet Turnover

Generally, the total number of licenced vehicles in the UK has been steadily increasing since the early 1970s with few periods of stagnation in growth. The increase is driven by population growth and rising vehicle sales. The number of vehicles registered for the first time had a stable yearly increase except during periods when the number dropped due to recessions or recently because of coronavirus measures and impact. Due to the data availability, this model uses Great Britain (GB) data. The ratio between vehicles to population numbers in GB had increased rapidly until 2005 when the rate of increase dropped initially but then increased later at a much lesser rate. This ratio is influenced by economic, social, regulatory and political factors. For the initial analysis, the ratio between the number of vehicles per capita was set to remain constant. Then, using the projected population until 2050 published by the Office for National Statistics [124], the total number of vehicles on the road can be estimated each year.

The total number of vehicles registered at a given time depends on new vehicles joining the stock and vehicles leaving the market. Maintenance and operation costs increase as vehicles age and reach a point where it is more cost-effective to replace or scrap them, and this point depends on social and economic factors [125]. Therefore, vehicle survivability with age differs between countries. The vehicle survival rate (VSR) is defined as the ratio between the number of vehicles of a specific year model still in operation corresponding to the number during the first registration for a given year. These values are extracted from historical data of licenced vehicles published by the Department of Transport (DfT) [126]. The vehicle survival rate can be determined as follow:

$$\mathrm{VSR} = \frac{\mathrm{N_{m,j}}}{\mathrm{N_{sale,m}}} \tag{3.9}$$

where $N_{m,j}$ is the number of vehicles sold in year model m that are still operating on the road in year j and $N_{sales,m}$ is the number of vehicles during first registration at year m.

Vehicle age is the most dominant factor when estimating vehicle scrappage [127]. Therefore, an age-dependent survival rate function was used in this study to estimate the number of vehicles sold in a given year that are still in operation each year until 2050. The Weibull distribution function is commonly used to determine product lifespan and is considered suitable for vehicle applications [128]. Several studies have previously used Weibull distribution to model fleet turnover to investigate future energy demand and the related emissions [129, 130]. Data obtained from Eq. (3.9) and Weibull distribution, as expressed by Eq. (3.10), were used to determine the curve of vehicle survival rate by age, VSR_α:

$$\mathrm{VSR}_\alpha = \exp\left(-\left(\frac{\alpha + \mathrm{b}}{\mathrm{L}}\right)^{\mathrm{b}}\right) \tag{3.10}$$

where α is the vehicle age (j-m), in years, b is a parameter that impacts the shape of the curve and L is the service life. The VSR curve is shown in Appendix A, Figure A 1.

The curve can be used to determine the survival probability of a vehicle at age α (SP_α) be still registered on the road:

$$SP_\alpha = \frac{VSR_\alpha}{VSR_{\alpha-1}} \tag{3.11}$$

Different powertrain configurations or vehicle segments could have different survivability with age, but determining these curves increase model complexity and highly depends on data availability which is currently not available. Therefore, this study assumed the calculated vehicle survival rate curve to be the same regardless of powertrain type. The number of vehicles of specific year model m that are still on the road in any given year can be calculated using the data of the number of vehicles for the same year model in the previous year and the following equation:

$$N_{m,j} = SP_\alpha \cdot N_{m,j-1} \tag{3.12}$$

Similarly, the number of vehicles leaving the stock of year model m in year j, $N_{scrap,m,j}$, can be determined using Eq. (3.13). Calculating and summing the number of vehicles leaving the stock for all year models gives the total number of vehicles leaving the stock each year.

$$N_{scrap,m,j} = (1 - SP_\alpha) \cdot N_{m,j-1} \tag{3.13}$$

Using the projected total number of vehicles for a given year j and the total number of vehicles from the previous year, the number of new vehicles needed in year j to meet the demand, $N_{sale,j}$, can be estimated as follow:

$$\mathrm{N}_{\mathrm{sale,j}} = \mathrm{N}_{\mathrm{j}} - \mathrm{N}_{\mathrm{j-1}} + \sum \mathrm{N}_{\mathrm{scrap,m,j}} \tag{3.14}$$

where N_j is the total number of vehicles in year j.

In normal circumstances, the vehicle survival rate is kept the same for the entire prediction period. However, the coronavirus pandemic significantly impacted vehicle sales in the UK due to lockdowns and supply chain problems, leading to vehicle component shortages [34, 36]. In addition, the decrease in new vehicle registrations and usage during the coronavirus pandemic led to an increase in the average vehicle age, as consumers keep their current vehicles longer. While the market started to recover, the ongoing component shortage, increasing costs and rising interest rates reduced demand, but recovery is expected to continue into 2023 [131]. Therefore, a dynamic vehicle survival rate was considered during the recovery period to accommodate these effects. The SMMT predicted a market recovery after 2024 [132] and, by using their forecast for vehicle sales for 2022 to 2023 [133], the vehicle survival rate was adjusted to match the number of vehicles sold during these years. This method allows for estimating the number of vehicles that remain on the road and the number of vehicles leaving the stock during the recovery period. Figure 3.5 shows the fleet turnover model procedure used in this chapter.

The fleet turnover model applies current government targets to end the sale of petrol and diesel vehicles by 2030 and hybrids by 2035 to determine the percentage of each powertrain type in the annual vehicle sales. The historical data for the number of vehicles registered for the first time, published by the DfT [22], was used to predicate the number of new vehicles added to the stock by powertrain type. Many forecast models covering the diffusion of innovation use logistic or s-shaped functions to describe innovation adoption over time [134]. Applying a logistic function to the historical data, the percentage of electrified vehicles - HEV, PHEV and BEV - was determined to the total vehicle sales until 2035.

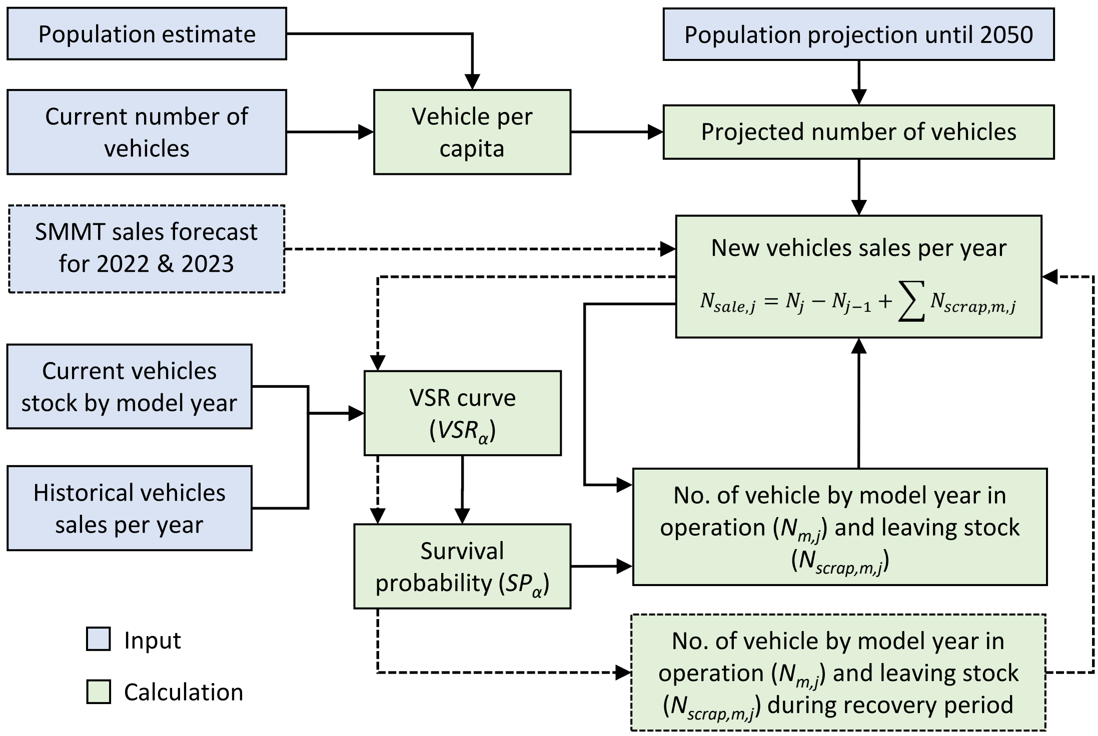

Figure 3.5: Structure of the fleet turnover model. Dashed lines show the steps taken for the recovery period calculations.

The targets from ZEV Mandate for 2024 to 2035, were used to calculate the percentage of BEV sales during the period. After 2035, all vehicle sales are considered completely BEVs. From the historical vehicle sales data, petrol vehicles dominated the market of vehicles solely propelled by ICEs with a share of nearly 83% in 2021; this percentage was set to stay the same until petrol and diesel vehicles are phased out by 2030. The predicted percentages with the total number of vehicle sales from Eq. (3.14) were used to calculate the number of vehicles sold each year by powertrain type. The historical and predicated share of new vehicle sales from the fleet turnover model are illustrated in Figure 3.6. Application of Eq. (3.12) can determine the number of vehicles of powertrain type k and model year m in a year j, Nk,m,j:

$$\mathrm{N_{k,m,j}} = \mathrm{SP_\alpha} \cdot \mathrm{N_{k,m,j-1}} \tag{3.15}$$

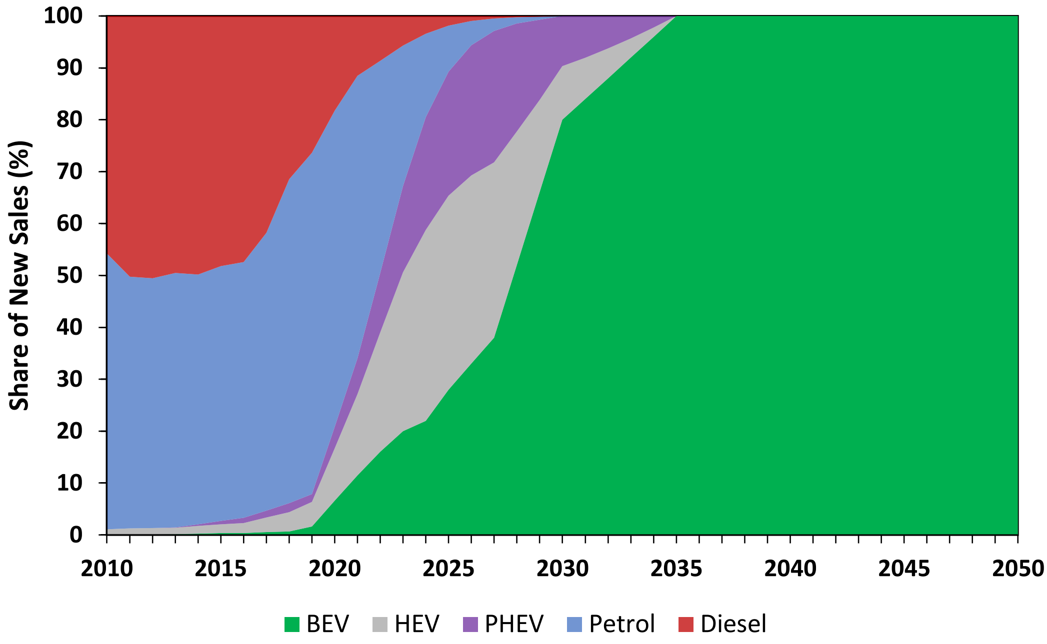

Figure 3.6: Share of new vehicle sales by powertrain type in Great Britain from 2010 to 2050.

3.3.2 Vehicle Kilometre Travel

The road traffic by all powertrain types has been growing annually in the UK at a moderate rate, with periods of minor fluctuations [135]. However, in 2020, road traffic saw a significant drop due to the coronavirus pandemic, with cars and buses being the most heavily affected, falling by nearly 25% and 32%, respectively [136].

The DfT has been monitoring the usage of transport systems during the coronavirus pandemic as it significantly impacted transportation demand and travel patterns [137]. According to the weekly published data, during the initial lockdowns in 2020, the total trips for the whole transport sector dropped significantly but gradually increased with lifting restrictions, with road transport nearly returning to the pre-pandemic level, unlike public transport. The reintroduction of restrictions in 2021 and lifting them later showed a similar pattern in transport usage to 2020 but with a lesser drop, and the road transport, including cars, appears to be returning to pre-pandemic levels in the following years. Therefore, in the initial analysis, road traffic from 2022 and onward was set to return to pre-pandemic levels by keeping the average mileage for all vehicles on the road equal to the 2019 level. The total vehicle kilometre travel for all vehicles in a year j, VKT_j (km), is measured by Eq. (3.16) from 2022 to 2050, while historical data was obtained from Road Traffic Statistics [138].

$$\mathrm{VKT_j} = \mathrm{N_j} \cdot \mathrm{D_{avg,j}} \tag{3.16}$$

where, $D_{avg,j}$ is the average vehicle mileage in year j, in km.

A study suggested EVs have lower mileage than conventional vehicles [139]. However, a recent report from an EV manufacturer showed that the mileage of their vehicles is higher than the average mileage of typical vehicles in the US [140]. In addition, data from major car manufacturers revealed that European EV drivers travel longer distances annually than their ICE counterparts [141]. A possible explanation for the conclusion in older studies is that the data was based on early adopters travel data, with limited range vehicles and the lack of public charging stations impacting how EVs are used [139]. Therefore, for simplicity, the annual travel distance was considered the same regardless of the powertrain type in this study.

The mileage of a vehicle during its life decreases with age. Craglia et al. [142] showed that vehicle mileage has a linear relationship with age, with a decay rate of 330 miles per year in the UK based on their analysis of publicly available vehicle annual roadworthiness test data. Therefore, in this study, the newest vehicles will have the highest mileage for any given year and will drop linearly with age by 330 miles per year. The mileage for a first year registration vehicle in a year j, D1st,j (km), can be calculated according to Eq. (3.17) and the vehicle mileage of age α in a year j, Dα,j (km), can be measured using Eq. (3.18):

$$\mathrm{D_{1st,j}} = \frac{\mathrm{VKT_j} + \sum_{\alpha} \varepsilon \cdot \mathrm{N_{\alpha,j}}}{\sum_{\alpha} \mathrm{N_{\alpha,j}}} \tag{3.17}$$

$$D_{\alpha,j} = D_{1st,j} - \varepsilon \cdot \alpha \tag{3.18}$$

where ε is the mileage decay rate by age equal to 531 km (330 miles), and $N_{\alpha,j}$ is the total number of vehicles of age α in a year j.

3.3.3 Carbon Emissions Calculation

This study focuses on the use phase carbon emissions aspects of different vehicle technologies, as the transport sector GHG emissions are almost entirely through carbon emissions [143]. The emissions savings from this phase could compensate for the differences in emissions generated during vehicle manufacture [144]. The use phase consists of two segments. Tailpipe emissions, also referred to as Tank-to-Wheel (TTW), are carbon emissions directly from vehicles' tailpipes with ICEs. The other segment is Well-to-Tank (WTT), which was separated into two main areas corresponding to each vehicle powertrain type: electricity production emissions from charging the batteries and emissions from the production of fuels to run ICE vehicles.

Electricity production emissions are directly related to the energy required to charge the vehicles, which is proportional to the energy consumption on the road. Battery capacity and the driving range of the top 20 generic BEV models registered for the first time until Q3 2021 [145] were used to estimate energy consumption. First, the number and exact model for the top-selling BEVs between 2014 and 2021 were identified using the database for the number of licensed vehicles per year by make and model [146]. The battery capacity and driving range of each BEV model were obtained from Vehicle Certificate Agency [147] and EV database [148]. Finally, any driving range based on NEDC was converted to WLTP value using the ratio from work carried out by the European Commission's Joint Research Centre [149]. Figure 3.7 shows the results from analysing the data for BEVs in the UK.

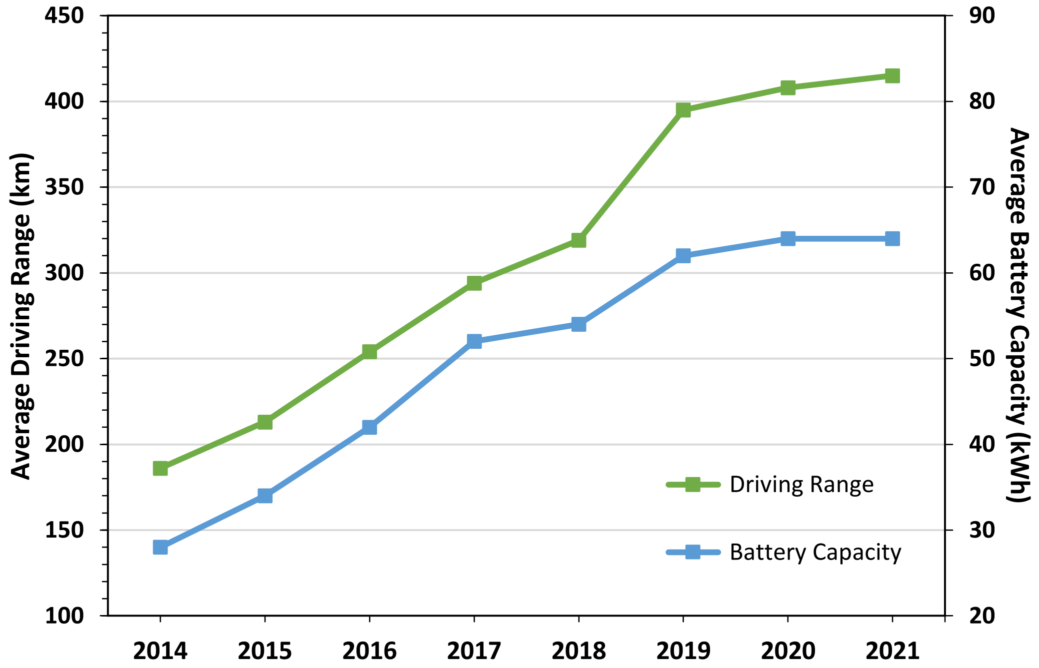

Figure 3.7: Average driving range and battery capacity of EV registered for the first time in the UK.

The SEC can be calculated using the battery capacity and driving range. The usable battery capacity was considered 90% of gross battery capacity, as 5% to 15% of gross battery capacity is unavailable to the users while driving [150]. BEVs parameters were assumed to stay at the current level. When charging a BEV, power losses occur in the vehicle, and the efficiency varies depending on the power rate and battery state of charge [151, 152]. The overall charging efficiency between 84% to 89% was measured from several vehicles tested under different charging power and climate conditions [153]. In this study, an average charger efficiency was assumed to be 90% [154] and battery efficiency of 95% [155], resulting in an overall efficiency equal to 85.5%, a similar value assumed by other authors [156]. Therefore, the energy required to charge a vehicle, EC (kWh), is calculated as follows:

$$\mathrm{EC} = \frac{\mathrm{SEC} \cdot \mathrm{D}}{\eta_{\mathrm{chg}} \cdot \eta_{\mathrm{batt}} \cdot (1 - \beta_{\mathrm{T\&D}})} \tag{3.19}$$

where D is vehicle mileage, in km, η_{chg} is the charging efficiency, η_{batt} is the battery efficiency and $\beta_{T\&D}$ is the electricity transmission and distribution losses equal to 8% [157]. The annual carbon emissions from electricity production to charge a vehicle, $c_{electricity}$ (kg), is calculated as:

$$c_{electricity} = EC \cdot CI \cdot (1 + U_{electricity}) \cdot 10^3 \tag{3.20}$$

where CI is the electricity grid carbon intensity, in g/kWh, and $U_{electricity}$ is the electricity upstream impact factor (%).

The electricity carbon intensity projections until 2050 were obtained from National Grid data, using the 'steady progression' scenario [158]. The National Grid data is considered the most realistic future projection since they are the primary owner and operator of electricity transmission networks in GB [11]. Besides the carbon emissions from electricity generation, indirect upstream emissions equal to 17% of electricity generation were added based on a five-year average [157].

Diesel engines are more fuel efficient with lower carbon emissions than their petrol equivalents [159], but further improvements in petrol engine efficiency are expected to narrow this gap [160]. However, in the UK, the average sold diesel vehicle emissions are higher than petrol ones as large size segment vehicles have a higher share of diesel engines, therefore explaining the higher average CO_2 emissions [142].

Figure 3.8 shows the historical and projected average tailpipe emissions per km of newly registered petrol, diesel and hybrid vehicles. The DfT reports the quarterly average tailpipe emissions per km for vehicles registered for the first time by powertrain type [161]. The data were analysed and a quarterly decrease in tailpipe emissions per km for new registrations was calculated for each powertrain type. The historical data was extended to predict the annual average tailpipe emissions per km of new vehicles sales until 2030 for petrol and diesel vehicles and to 2035 for HEVs using the historical quarterly decrease in tailpipe emissions per km. The fuel efficiency of ICE vehicles could improve in the future, but reduction potential seems limited even with hybrid systems [162]. Therefore, despite the projected decrease in average tailpipe emissions, ICE vehicles will not reach European emissions targets individually of 81 gCO_2/km by 2025 and 59 gCO_2/km in 2030.

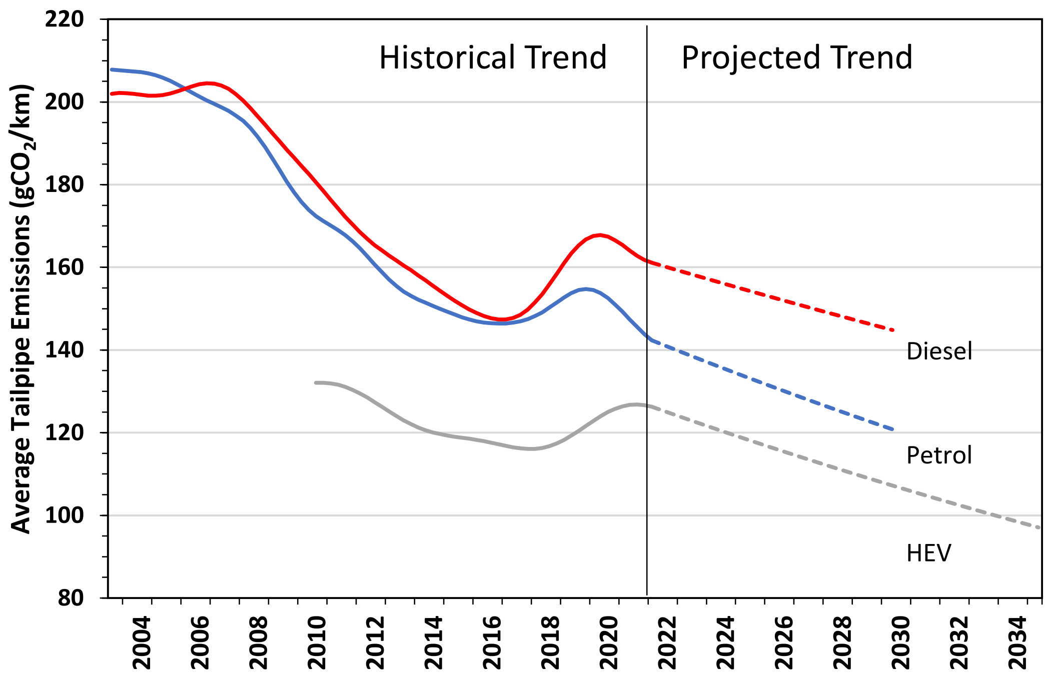

Figure 3.8: The historical and projected trends of average tailpipe emissions per km for new petrol, diesel and hybrid vehicles in Great Britain. Historical data adapted from DfT [161].

The indirect emissions of ICE vehicles are related to well-to-tank carbon emissions for producing petrol and diesel fuels, including crude oil extraction, refinery and fuel distribution [163, 164]. These processes are energy and carbon-intensive, and the ability to reduce their emissions has shown to be a challenging process [165]. Therefore, to account for fuel production, an upstream fuel production impact factor (U_{fuel}) was added to the ICE vehicle emissions, equal to 28% of tailpipe emissions of petrol vehicles, 24% for diesel vehicles, and 26% for HEVs [166]. As a result, the annual carbon emissions from an ICE vehicle or HEV, c_{ice} (kg), can be calculated as:

$$c_{ice} = c_{tailpipe} + c_{fuel} = TE \cdot D \cdot (1 + U_{fuel}) \cdot 10^{-3} \quad (3.21)$$

where $c_{tailpipe}$ is the annual carbon emissions from the tailpipe, in kg, c_{fuel} is the annual carbon emissions for fuel production, in kg, and TE is the tailpipe carbon emissions per km of an ICE vehicle, in gCO_2/km.

PHEVs can drive for a long distance under pure electric power due to their relatively large battery that can be charged from the grid. PHEV performs like BEV under charge depleting mode and operates like HEV in charge sustaining mode [167]. Assessing PHEV emissions highly depends on their utility factor (UF), defined as the share of driving done under charge depleting mode that depends on their battery size [168]. The annual carbon emissions from a PHEV vehicle, c_{phev} (kg), can be calculated as follows:

$$c_{phev} = c_{phev,cs} + c_{phev,cd} = c_{ice} \cdot (1 - UF) + c_{electricity} \cdot UF \quad (3.22)$$

where $c_{phev,cs}$ is the annual carbon emissions of a PHEV in charge sustaining mode, in kg, calculated using the parameters from Eq. (3.21). The annual carbon emissions of a PHEV in charge depleting mode, $c_{phev,cd}$ (kg), is the electricity production emissions to charge a PHEV battery using the parameters in Eq. (3.20). The tailpipe emission per km for PHEVs was set to the same value of petrol vehicles and the SEC in charge depleting mode to the same BEVs value.

The corresponding WLTP-based UF to the driving range in pure electric mode for PHEVs was obtained from [169]. Data of top selling PHEVs show that the average driving range in electric mode was 41 km in 2017, corresponding to 60% UF, increasing to nearly 60 km (80% UF) by 2021. A 90% UF was considered in 2030, as next-generation PHEVs are expected to have a more extended electric driving range; some current PHEV models already met this with a range above 100 km under WLTP driving cycle. This study refers to the tailpipe of TTW to distinguish the emission for when

PHEV is driven under charging sustaining mode and its overall WTT emissions, including fuel production and electricity grid emissions during charging.

Using Eqs. (3.20) to (3.22) the carbon emissions from each source can be measured. Combining these values gives the total carbon emissions from all vehicles in a year j, AETotal,j ($MtCO_2$), as expressed in Eq. (3.23).

$$\begin{aligned} AE_{Total,j} &= AE_{Tailpipe,j} + AE_{Fuel,j} + AE_{Electricity,j} \\ &= \sum_{m} c_{k,m,j} \cdot N_{k,m,j} \cdot 10^{-9} \end{aligned} \tag{3.23}$$

where $AE_{Tailpipe,j}$ is the total tailpipe emissions in a year j, in $MtCO_2$, $AE_{Fuel,j}$ is total fuel production emissions in a year j, in $MtCO_2$, $AE_{Electricity,j}$ is the total electricity production in a year, in $MtCO_2$, and $c_{k,m,j}$ is annual carbon emissions from a vehicle of powertrain type k and model year m in a year j, in kg.

In addition to annual carbon emissions, the cumulative emissions need to be considered as tackling climate change requires the reduction of the cumulative carbon emissions in the atmosphere once it determines the rise in global temperature. Currently, policies are focused on annual carbon emissions over a specific period. However, different emission targets can lead to different cumulative emissions over the same period, despite arriving at the same annual target at the end of the period [170]. The cumulative carbon emissions between 2020 and 2040, CE_{Total} ($MtCO_2$), can be calculated as follows:

$$CE_{Total} = \sum_{j=2020}^{2050} AE_{Tailpipe,j} + \sum_{j=2020}^{2050} AE_{Fuel,j} + \sum_{j=2020}^{2050} AE_{Electricity,j} \tag{3.24}$$

3.3.4 Real-World Correction Factor

Driving behaviour, ambient temperature and traffic conditions influence BEVs energy consumption [171]. Likewise, fuel consumption and emissions of ICE vehicles are also influenced by similar factors [172, 173]. Therefore, the influence of these factors was combined in an uplift factor that converts laboratory WLTP values to reflect real-world energy consumption and emissions.

Based on the previous analysis, the range of an EV under a RDC is 30% lower than the NEDC value, an equivalent of 15% lower than the WLTP value [174]. According to a European Commission Joint Research Centre study, the on-road vehicle CO_2 emissions measured during RDE compliant routes are 2% to 18% higher than the manufacturers declared WLTP value. [175]. Therefore, the average value of 10% was applied as a real-world correction factor to ICE vehicles. With regard to BEVs, a 15% reduction in range was considered when calculating their SEC.

For PHEV, a real-world correction factor similar to ICE vehicle was used during charge sustaining mode, and factor equal to BEV value was used in charge depleting mode. The UF of PHEV on-roads differs from expectations as it highly depends on driving and charging habits [176]. Plötz et al. [177] analysed the data from a fleet of PHEVs in Europe and constructed a UF curve based on real-world usage of PHEVs as current WLTP UF parameters are optimistic. PHEV usage and UF can be considered the same for the UK due to similarity in charging availability, driving distance and economic factors to other European countries [178]. The findings from these studies were used to modify the UF estimates in section (3.3.3) to reflect real-world behaviour.

3.3.5 Scenarios Assumptions

A baseline case was constructed to reflect the reference parameters described in previous sections. Eight alternative scenarios were defined to measure travel demand changes with road traffic impacting carbon emissions of vehicles during the use phase. The scenarios were based on changes in vehicle ownership and usage. The current study considers 2024 as the base year when the vehicle market is expected to recover and the ZEV mandate to start, and applies the scenarios projections to 2050.

Policies that aim to limit the sales of pollutant vehicles target to improve efficiency and reduce carbon emissions associated with travel, not reduction in travel or modal shift [179]. An analysis by Frost et al. [180] of Committee on Climate Change of the UK's sixth carbon budget suggests that, without additional actions being introduced, the current approaches to decarbonise the transport sector could see car ownership increase by 28% and traffic by 11% in 2050. The finding shows that the approach emphasises too much on cars without support for other means of transport such as public transport, walking and cycling. A High Ownership scenario was considered where vehicle ownership increases by 1% per year, leading to 29.5% increase in the total number of vehicles by 2050. The increase in vehicle ownership stems from EV becomes more appealing due to lower maintenance and running costs.

Awareness of the actual cost of owning a car could result in fewer vehicles on the road. Andor et al. [181] predicted 37% reduction in car ownership if drivers were aware of the true cost of owning a car, leading to increased demand for public transport and consequently increase emissions from this sector, but this impact would be minimal compared to the reduction from fewer cars. Therefore, a Low Ownership scenario was set up by assuming 1% annual decrease in vehicle ownership, leading to 26 million vehicles in 2050. Raugei et al. [84] predicted a similar projection for the total number of vehicles, where car-share and ride-share schemes become mainstream.

The Balanced Net Zero Pathway by CCC [182] targets 17% reduction in car travel by 2050. The fall in car miles is driven by shifting to walking, cycling and public transport or an increase in average car occupancy and reduced commute due to an increase in working from home. Therefore, a Low Usage scenario was considered based on 17% reduction in vehicle mileage by 2050. However, vehicle electrification and autonomy could potentially increase vehicle utilisation [183]. Therefore, in a High Usage scenario, vehicle mileage was assumed to increase by 17% in 2050. While this value is above the 11% previously suggested, the assumption would put the projected road traffic to a similar forecast by the DfT [184] before accounting for decarbonising transport and infrastructure plans to reduce car dependency.

Four other scenarios were considered that combine the upper and lower limits of car ownership and usage. These scenarios cover a High Ownership + High Usage scenario in which car ownership increases and government fails to meet targets to increase the appeal of public transport and move commuters to other alternative transport modes. In the High Ownership + Low Usage scenario, owning a car is still appealing to the general public, but public transport, cycling or walking become the first choice of travel. For Low Ownership + High Usage, owning a car becomes unnecessary but remains the choice of travel due to an increase in ride hailing services, leading to an increase in traffic but lower overall vehicle number. Finally, Low Ownership + Low Usage scenarios increase car occupancy, and government targets are met in moving more people to use public transport, particularly short trips done by cycling or walking. Table 3.6 summarise the scenarios used in the study. A flowchart for the carbon emissions prediction model summarising the procedure used in this chapter with sample calculation is shown in Appendix A, Figure A 2.

Table 3.6: Summary of the scenarios.

SCENARIOS	DESCRIPTION
High ownership	Vehicle per capita increases by 1% annually
Low ownership	Vehicle per capita decreases by 1% annually
High usage	Average mileage increases to 17% by 2050
Low usage	Average mileage decreases to 17% by 2050
High ownership + High usage	Vehicle per capita increases by 1% annually and average mileage increases to 17% by 2050
High ownership + Low usage	Vehicle per capita increase by 1% annually and average mileage decreases to 17% by 2050
Low ownership + High usage	Vehicle per capita decreases by 1% annually and average mileage increases to 17% by 2050
Low ownership + Low usage	Vehicle per capita decreases by 1% annually and average mileage decreases to 17% by 2050

3.4 Charging Scenarios

This section describes the model created to investigate the differences in associated carbon emissions from EV charging using uncontrolled, delayed or optimised charging under two schedules – routine and minimal – in each region of Great Britain. The developed model considers the regional differences in road traffic, ambient temperature and electricity grid profile. The impact of delayed charging on carbon emissions is based on the new government Smart Charge Points regulations that shift the charging outside peak hours. The optimised charging moves the charging window to times with grid carbon intensity to minimise carbon emissions when charging.

3.4.1 Charging Schedules Description

The majority of EV charging is expected to occur at home [185] due to the convenience of home charging since it is the most common location for vehicles, and the preferred scenario by EV users to charge at home in the evening [186]. Current estimates suggest that 75% of EV charging will be residential charging [187]. According to a UK dataset of residential charging events, the most popular time for plugging in EV is between 5 pm and 7 pm, with an average total plug-in duration of 12 hours and 41 minutes [188].

Two charging schedules were considered – routine and minimal – based on the work presented by Dixon et al. [189]. A routine charging schedule describes a case in which drivers view charging to carry negligible inconvenience and turn into a routine, where users plug in their EVs every time they arrive home regardless of the battery SOC [189]. The minimal charging schedule represents a case where drivers see charging as inconvenient and aim to have fewer times to plug in their EVs.

For both charging schedules, the duration and energy requirement for every charging event is a function of the EV energy consumption, depending on the travel demand. While the energy requirement might differ daily in the routine schedule, the monthly energy consumption was converted to an everyday demand, assuming 30 days each month. Charging frequency is a factor to be considered in the minimal schedule that depends on the battery capacity and SOC for which the EV should be charged. The model assumes the driver to plug in the EV once the battery SOC drops to 15%, as the minimum allowed SOC for emergencies [190], and charge the battery until 90% SOC, a suggested value by vehicle manufacturers to maintain the best battery performance [191].

3.4.2 Uncontrolled and Smart Charging

Uncontrolled Charging

The initial model analysis measures the impact of uncontrolled charging on carbon emissions under the two schedules – routine and minimal – considering the plug-in time starts at 6 pm and ends at 7 am to reflect the home charging situation. Home charging power of 7 kW was used in this study, as most chargers are likely to be rated at that power due to no difference in price compared to slower 3.5 kW chargers and since all new generation EVs are capable of charging at 7 kW power [192, 193]. Also, current regulation requires new homes with associated parking to have charge points installed with a minimum rated output of 7 kW [194].

Delayed Smart Charging

In a response to the smart charging policy consultation in 2021, the government highlighted the intention to mandate for smart chargers to have the capability to offer users a charging schedule with a default setting that prevents EVs from charging at specified peak hours [195]. In May 2022, the UK government announced that the Electric Vehicle (Smart Charge Points) Regulation would come into force at the end of June 2022 [196]. The regulations state that new private charge points must be pre-set to not charge during peak hours between 8 am to 11 am and 4 pm to 10 pm. The model was extended to evaluate the impact of delayed smart charging on carbon emissions. In these scenarios, the charging events were delayed to start after 10 pm to reflect the new regulations requirements.

Optimised Smart Charging

An optimisation charging model was created to provide an optimal schedule for charging an EV to minimise the carbon emissions while considering the constraints on the charging window between 6 pm and 7 am and meet the required energy demand. First, the model measures the total charging duration to determine the number of charging events for both routine and minimal schedules. Then, based on the number of charging events, the model identifies the times when the electricity grid has the lowest carbon intensity. Finally, the model calculates the carbon emissions using the required energy demand.

Figure 3.9 demonstrates the general behaviour of uncontrolled, delayed, and optimised charging for routine and delayed schedules. The park time refers to the total duration when the vehicle was plugged in from 6 pm until 7 am, charging times are the periods when the vehicle is charged from the grid and idle times are the hours when the vehicle is plugged in but not charging.

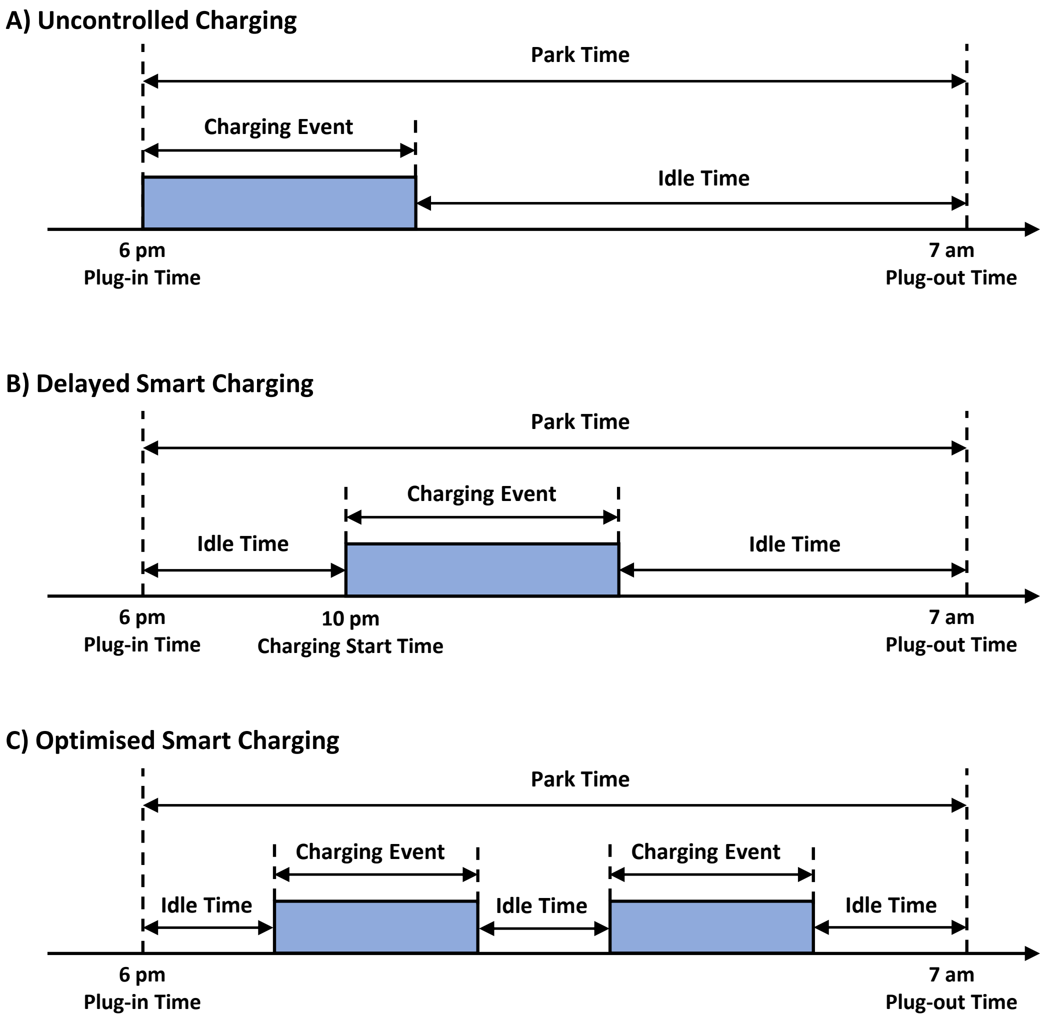

Figure 3.9: General presentation for uncontrolled, delayed and optimised charging for routine and minimal schedules.

3.4.3 Road Traffic

The DfT does not provide separate data for car traffic in each region divided by road class; therefore, it had to be determined using the currently available data. In this section, vehicle type covers all road vehicles, including cars, light commercial vehicles, heavy goods vehicles, and all other road vehicles. In the first step, the model takes the data of road traffic by vehicle type and road class in GB [197], extracts the car traffic for each road class and measures the percentage of road traffic covered by cars to the total road traffic by road class. Then, the obtained percentages combined with the data for road traffic by road class and region provided by the DfT [198] were used to calculate the car traffic in each region divided by road class.

The annual distance travel per car, or mileage, in each region was determined using car traffic by region data [199] and the total number of cars in each region. Then, the distance covered for each road class was determined using the mileage in every region and multiplied by the percentage of car traffic by road class calculated from the previous step in each region.

Monthly traffic flow varies between all road vehicle types and road classes. For example, August has the highest traffic flow for motorway roads, while for urban and rural roads, June has the highest traffic flow. In comparison, January has the lowest traffic flow for all road classes [200]. The monthly traffic flow by vehicle type and road class data was applied to all regions, obtained from [201], to calculate the monthly distance covered by road class per car for each region. Road traffic flow varies daily and hourly, but to avoid complexity in the model, the analysis in this study was based on the monthly changes in road traffic, energy consumption and electricity grid carbon intensity. This study uses 2019 data for travel demand and electricity grid profile to calculate the carbon emissions under different charging scenarios in each region.

3.4.4 Temperature and SEC Data

Changes in ambient temperature highly influence the SEC and differs when driving under different road classes, as previously discussed. Therefore, each region's monthly ambient temperature variation was determined using Met Office [202] data, averaging five-year temperature data for each month to account for variation in ambient temperature impact on SEC. Met Office provides separated temperature data for Scotland and Wales but splits England data into two parts, north and south. Therefore, in this study, North East, North West, and Yorkshire and the Humber temperature reading were taken as Met Office north England data, while the remaining England regions were assumed to equal Met Office south England temperature data.

The model uses the specifications for the average new registered EV, which are 64 kWh battery capacity and 415 km driving range based on the WLTP driving cycle, determined from several sources [145-148], as previously explained in Section 3.3. A ratio of 90% was applied to account for usable battery capacity. The relation between ambient temperature and specific energy consumption under different road classes was adjusted to reflect real-world driving based on RDC from Section 3.2. While the average new registered EV has different battery capacity and range from the EV studied in Section 3.1, the analysis is applicable, as C-segment vehicles, including compact cars and compact crossovers, account for over 30% of newly registered vehicles. Also, Koncar et al. [203] showed that ambient temperatures impact different EV models similarly, showing a u-shape relation with specific energy consumption. A 90% charging efficiency and 95% battery efficiency were applied to calculate the annual carbon emissions.

3.4.5 Regional Grid Carbon Intensity

Data for the electricity grid carbon intensity was obtained from the National Grid Carbon Intensity API website [204]. The Carbon Intensity API provides a historical regional breakdown of carbon intensity with 30 min resolution. The Carbon Intensity API estimates the carbon intensity of the electricity consumed in each region using a reduced GB network model for modelling the power flows between importing and exporting regions, and the carbon intensity of those power flows [205].

The model in this work extracts the half-hourly data from the Carbon Intensity API for each day in the studied period and produces monthly carbon intensity profiles for each region. The Carbon Intensity API divides South East region data into two parts, which average carbon intensity was considered in this study. Figure 3.10 and Figure 3.11 show an example of electricity grid profile for each region in February and August, respectively, built from Carbon Intensity API data. Figure 3.12 summarises the procedure used in this chapter to find the carbon emissions of charging an EV under different scenarios in each region.

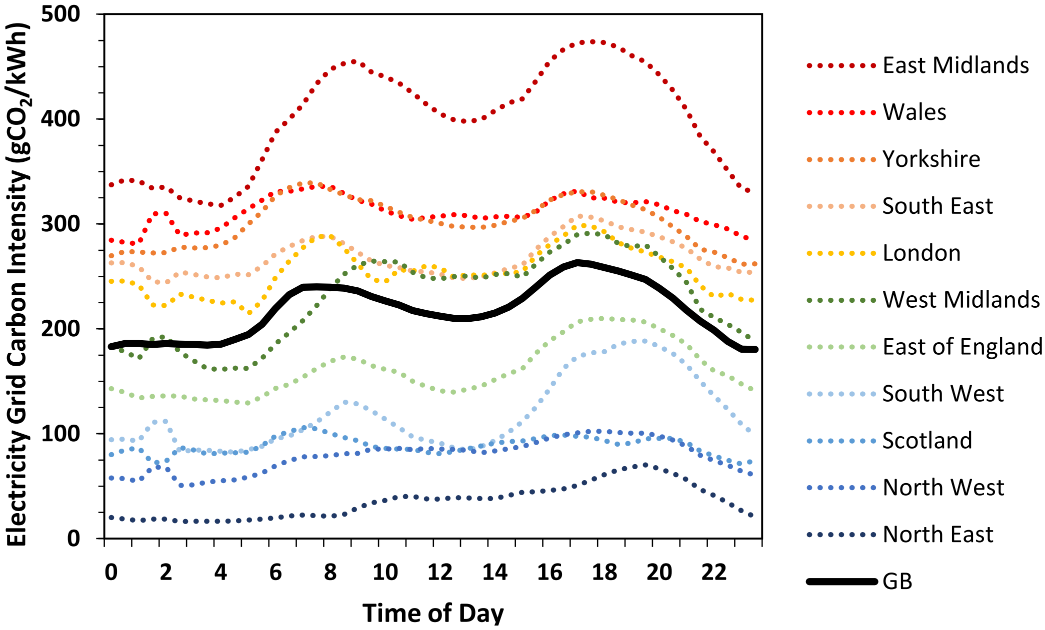

Figure 3.10: The hourly electricity grid carbon intensity for each region in February 2019, extracted from Carbon Intensity API [204].

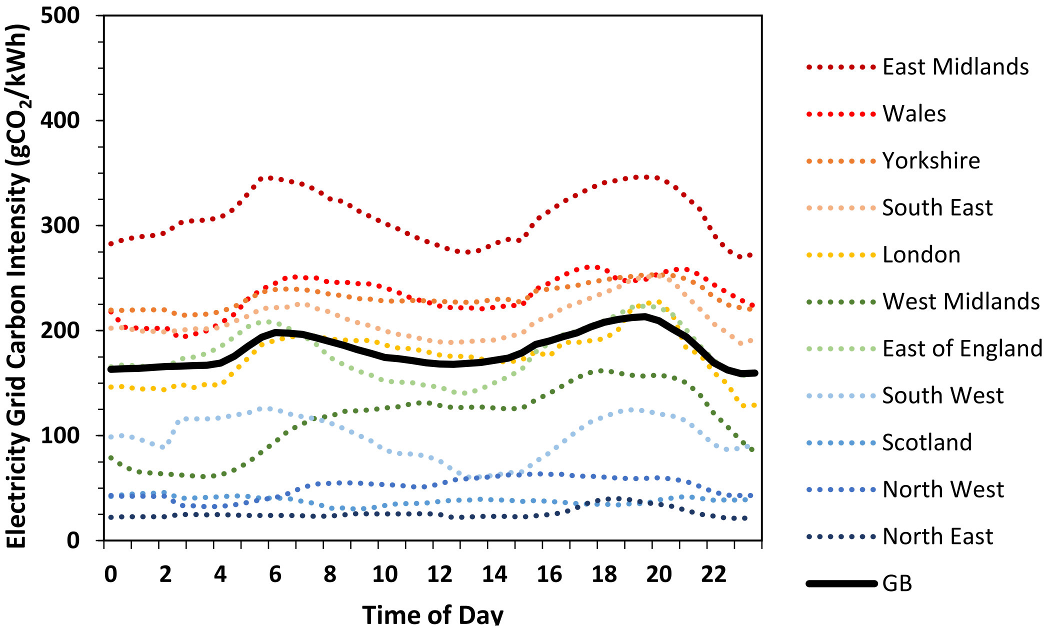

Figure 3.11: The hourly electricity grid carbon intensity for each region in August 2019, extracted from Carbon Intensity API [204].

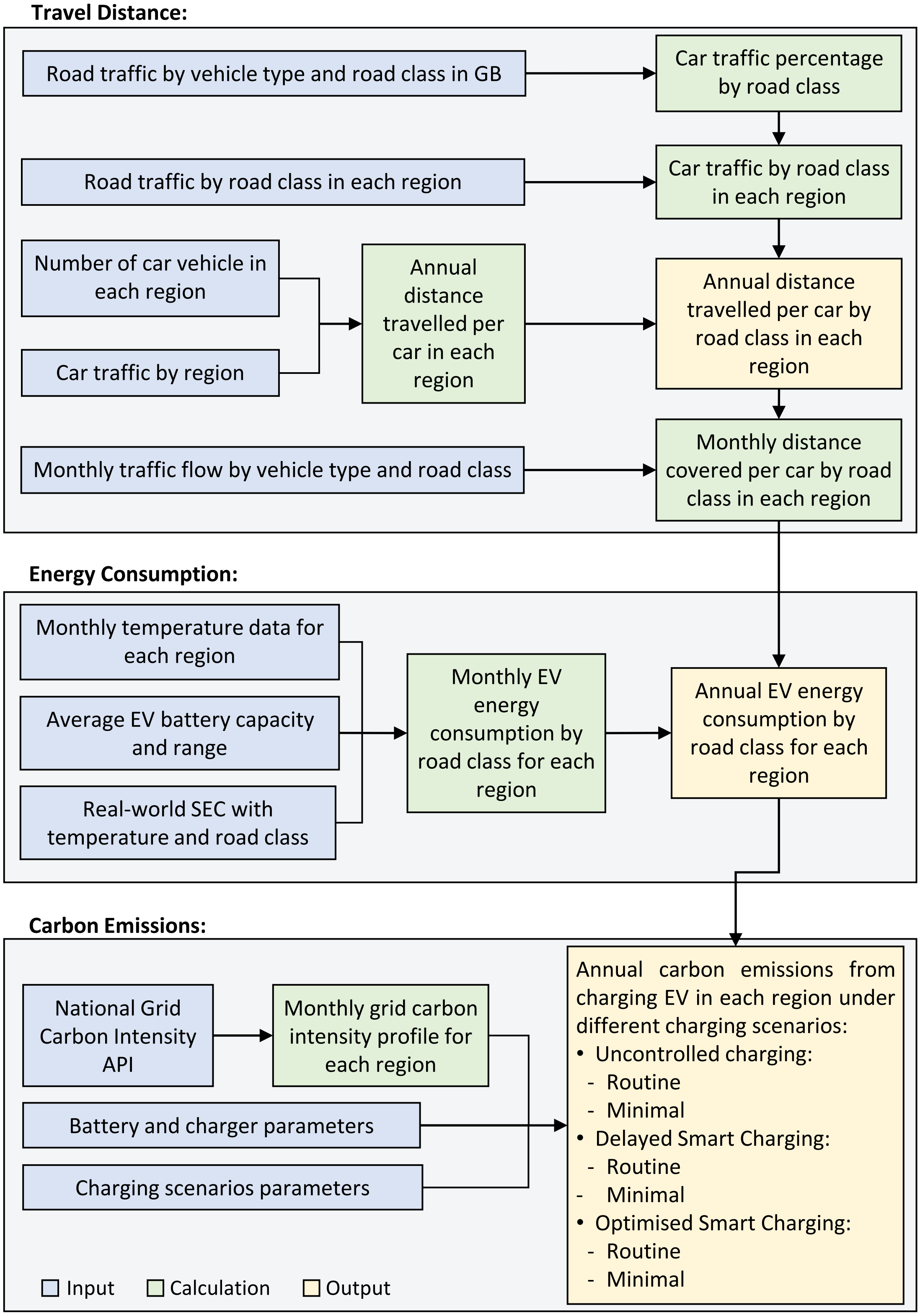

Figure 3.12: Overview illustration of modelling the impact of different charging scenarios on carbon emissions in each region.

Chapter 4

Results and Discussion

4.1 Evaluating Electric Vehicle Energy Consumption

4.1.1 Results Overview

Figure 4.1 presents the SEC results of all EV trips divided into bins of 0.05 kWh/km, showing the number of occurrences in the dataset for each bin and the cumulative percentage. This result was obtained using data from a set of trips with a large coverage of routes, distances, and travel conditions. Nearly 70% of the trips presented SEC between 0.10 kWh/km and 0.20 kWh/km, with less than 5% of the trips showing SEC lower than 0.10 kWh/km and about 25% displaying SEC higher than 0.20 kWh/km.

Figure 4.2 shows the variation of SEC with the travelled distance. The majority of the trips were performed over short distances. Up to 47% of the trips had a distance of 5 km or shorter, and less than 1% of the trips had a travel distance of 50 km or longer. A high variation in SEC was observed with relatively short distance trips.

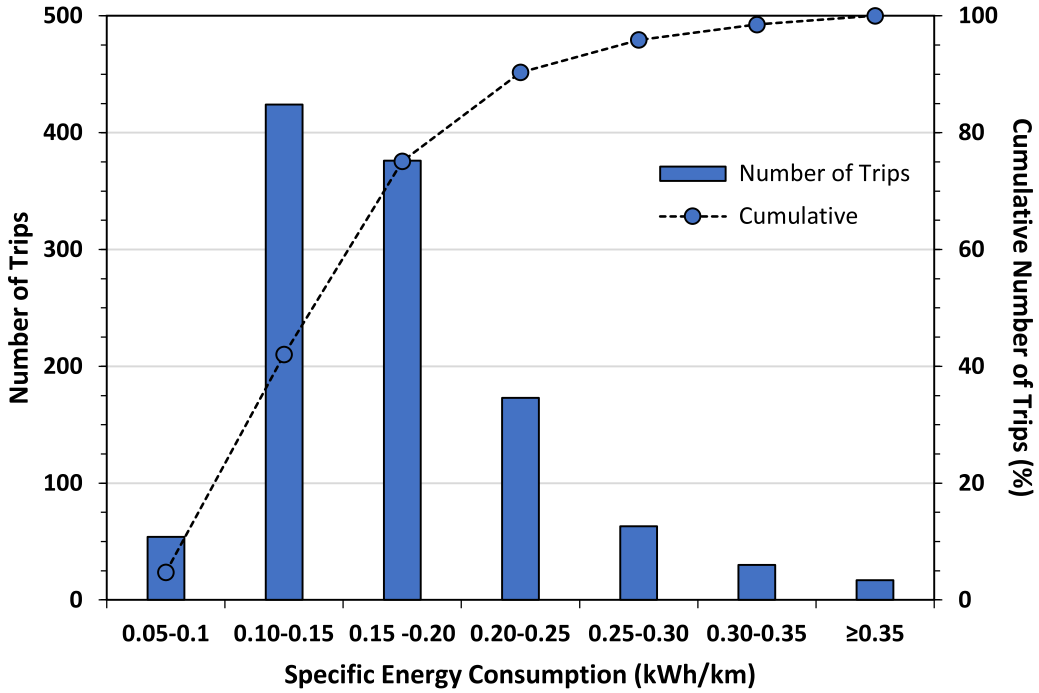

Figure 4.1: Distribution of trips specific energy consumption.

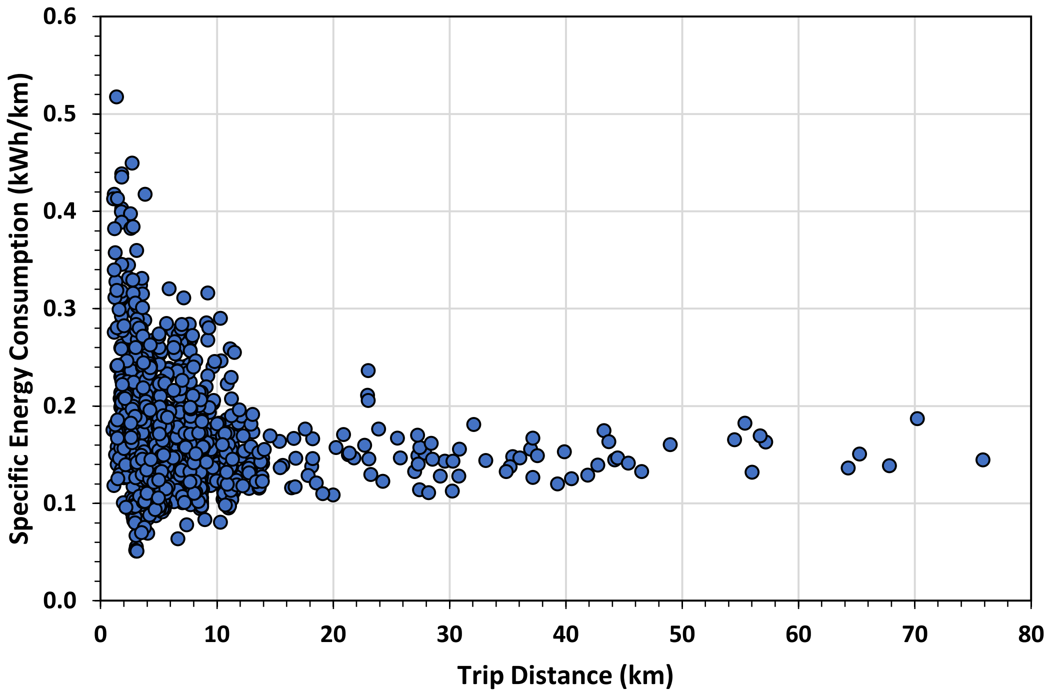

Figure 4.2: Variation of EV specific energy consumption with trip distance.

Driving time

This section discusses the effects of driving time on energy consumption based on a comparison between weekdays and weekend results. Figure 4.3 shows the percentage of the trips driven around a specific time of the day, divided into weekday and weekend trips, and the average SEC for each bin. Only trips between 6:00 to 23:59 are shown, as this is the period when the vehicle was used, with nearly 80% of the trips recorded during the weekdays. During weekdays, trips are divided into two periods, from 8:00 to 10:59 and from 15:00 to 19:59, while on the weekends, most trips occurred from 9:00 to 10:59 and from 13:00 to 16:59. The obtained data reflects typical driving in the UK as it displays similar patterns to car road traffic in UK [200]. The average SEC for weekday trips stays nearly constant from 10:00 to 16:59, with the highest value occurring around 6:00. After 17:00, the SEC rises and then drops sharply at about 23:00.

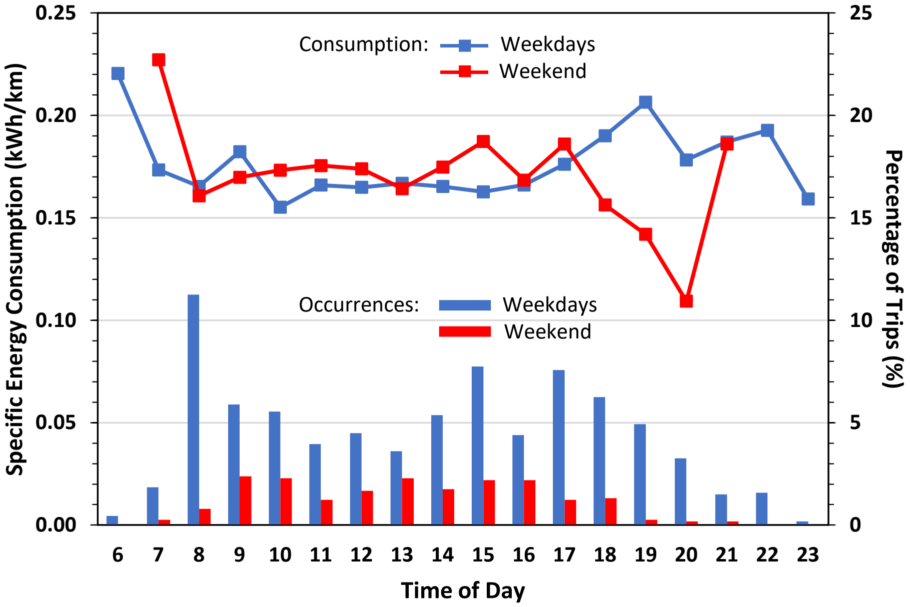

Figure 4.3: Variation in specific energy consumption and distribution of trips based on weekdays and weekends.

Similarly, for the weekend trips, the highest SEC is recorded early in the day, at 7:00, and a relatively small variation in the SEC values can be observed between 8:00 to 17:00. Opposite to weekdays, the weekend trips show a reduction in SEC from 17:00

until 20:59, when it shows a high jump in value. A possible explanation for the high SEC in the morning (6:00-7:00) and the sudden change at night (after 21:00) is due to the small number of trips recorded around these periods of the day, as they account for less than 9.5% of total trips.

Figure 4.4 presents the results of SEC, average vehicle speed and number of stops per km along the day, excluding the periods with a low number of data (6:00-7:59 and 20:00-23:59) for both weekday and weekend trips. The difference between weekdays and weekends in SEC for the same time during the day is relatively small until 17:00 (Figure 4.4a). After that, both show opposite behaviour to each other, as during weekdays the SEC increases by an average of 15% while it decreases on weekend trips. The SEC increases by an average of 20% on weekdays compared to the weekend after 17:00. Figure 4.4b shows that, for weekend trips, the average vehicle speed remains close to around 22 km/h for the majority of the day, below the average recorded for weekday trips from 9:00 to 16:59. On weekdays the average speed reaches highs of 27 km/h around 10:00 and 14:59. This is probably because people tend to drive more relaxed in urban areas on weekends, while the weekday commitments push people to drive quicker. Weekday driving presents lower average speeds than weekend driving from 17:00 because of intensified traffic by people driving back from work to home on weekdays. Before 9:00, driving on weekdays is slower than on weekends, as people move from home to work intensifies the traffic.

Figure 4.4c shows the average number of stops per km recorded along the day. A rise in the number of stops is observed from 15:00 to 17:59 for weekday trips, then drops. On weekends, the number of stops gradually increases, reaching a peak by 16:00, then falls but rises again at 19:00. Furthermore, the rise in the number of stops due to frequent start and stop situations in heavy traffic directly affects the average speed as observed during weekdays between 16:00 to 18:59, where an increase in the number of stops leads to a decrease in average vehicle speed. The number of stops seems to have a larger effect on the SEC (Figure 4.4a) than the average speed (Figure 4.4b). This result is explained by the auxiliary devices still consuming power when the vehicle is not moving. These findings indicate that short distance trips with a high number of stops will have high SEC depending on the use of the auxiliaries.

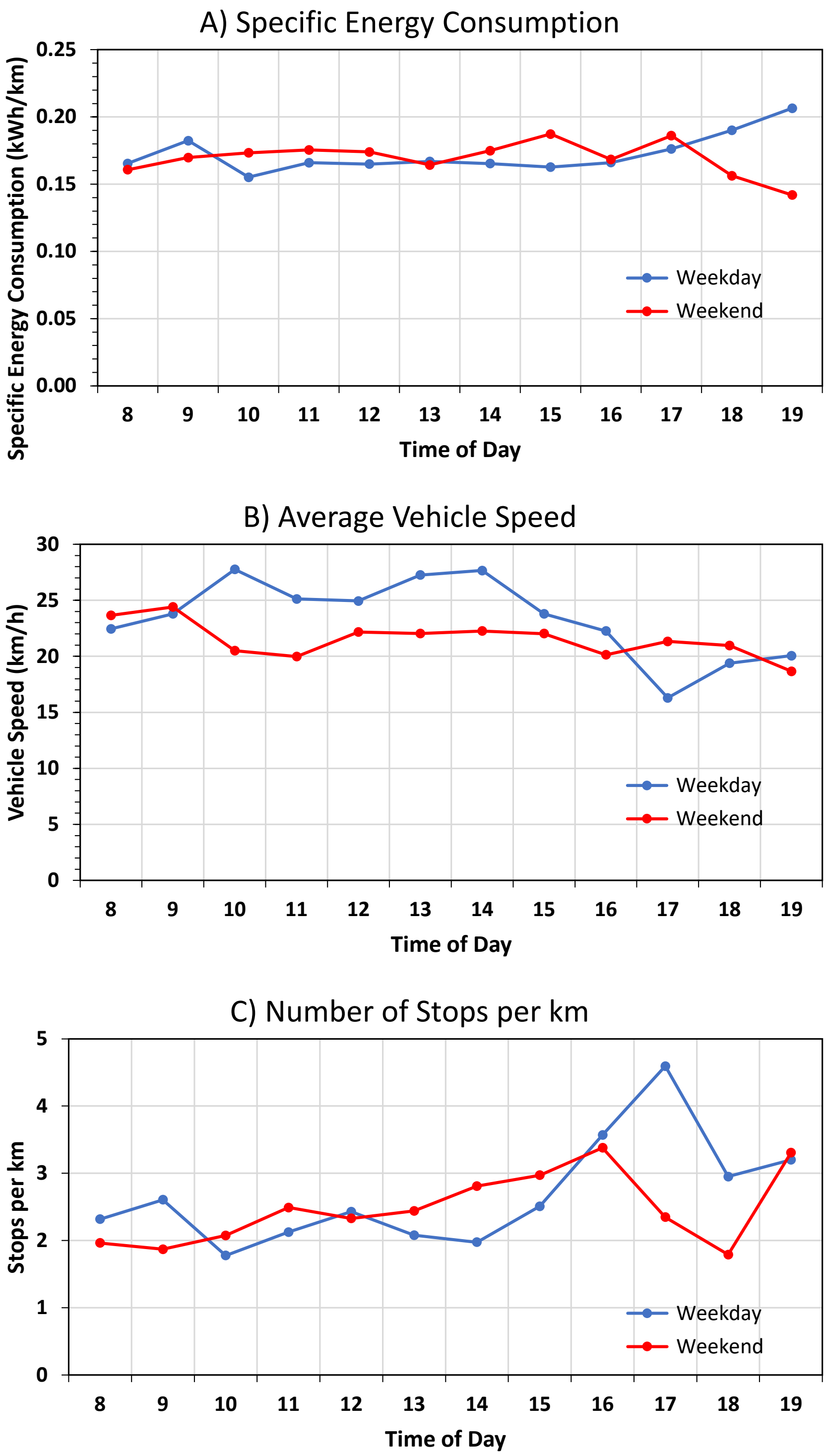

Figure 4.4: Variation of A) Specific energy consumption, B) Average vehicle speed, and C) Number of stops per km for weekdays and weekends.

Driving mode

The driving mode is evaluated by investigating how idling, cruising, acceleration and deceleration impact the SEC. Figure 4.5 shows the occurrences of the data for the percentage of the trip of the four driving modes with their average SEC. Figure 4.5a shows that as the idling state takes most of the trip, the energy consumption increases. The opposite occurs with cruising, as trips with a longer cruising state present lower SEC until above 40% (Figure 4.5b). These results can also be related to the travel distance (see Figure 4.2), a higher number of cruising events normally occur in long trips, the reason why the SEC is reduced and then stabilised at higher percentages of cruising driving (see Figure 4.2). On the other hand, a higher number of idling events tend to occur in short trips and, therefore, the SEC is increased (see Figure 4.2). For more than 35% of the trips, idling state happens from 20-30% of an individual trip, similar to cruising, while 32% of trips had an idling state below 20% compared to 56% for cruising (Figure 4.5a and Figure 4.5b).

The SEC gradually decreases with an increase in the percentage of both acceleration and deceleration states (Figure 4.5c and Figure 4.5d). In more than 73% of the trips, acceleration occurred along 20-30% of an individual trip with none above 40% (Figure 4.5c). In deceleration, 60% of trips occurred for the same bin with a small percentage between 40-50% and none above 50% (Figure 4.5d). The decrease of SEC with a higher percentage of acceleration state in a trip (Figure 4.5c) is further explained by Figure 4.6, which shows the variation of idling, deceleration and cruise states relative to the acceleration state. The percentage of the idling state is dramatically increased with lower percentages of the acceleration state (Figure 4.6), consequently increasing the SEC (see Figure 4.5a). The percentage of deceleration state increases with increasing participation of acceleration state in the trip (Figure 4.6), the reason why they show similar trends for the SEC (see Figure 4.5c and Figure 4.5d).

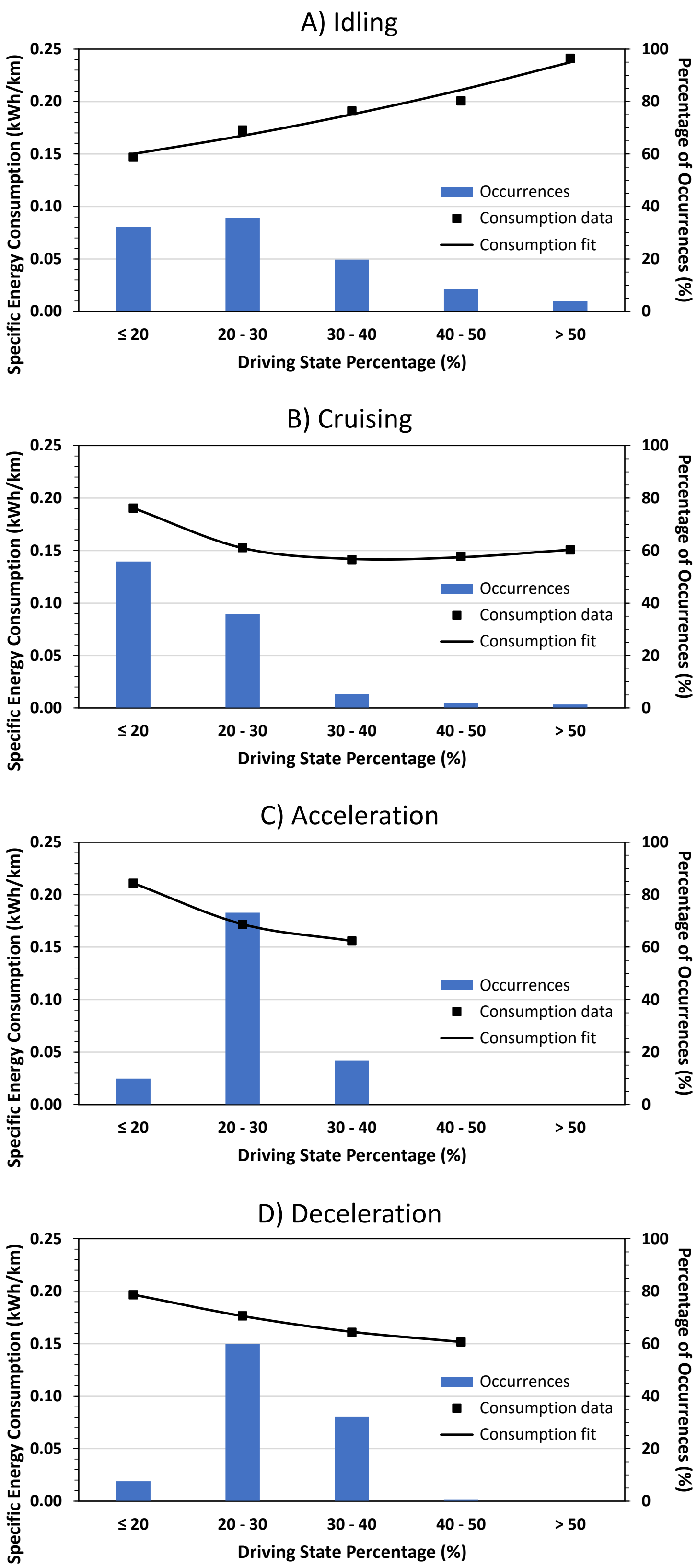

Figure 4.5: Variation of specific energy consumption and distribution of trips based on A) Idling, B) Cruising, C) Acceleration and D) Deceleration states.

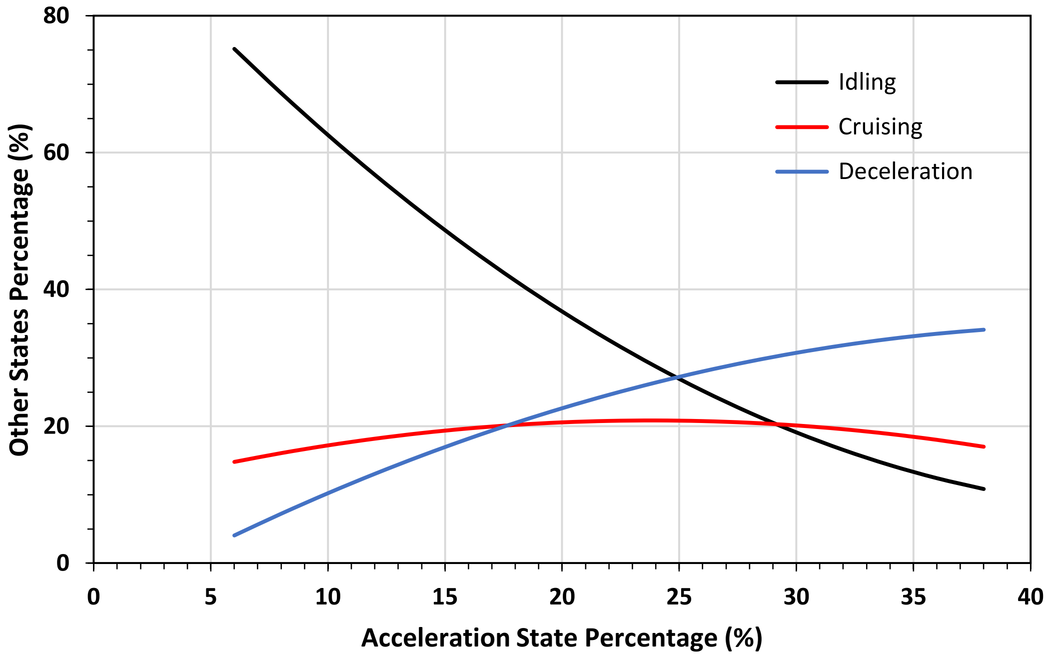

Figure 4.6: Changes in idling, cruising and deceleration states relative to acceleration state.

Ambient temperature

Figure 4.7 shows the number of occurrences for each group and the recorded average SEC variation with the ambient temperature outside. As the temperature gets below 15°C, the SEC is increased. At moderate temperatures around 15-20°C and 20-25°C, the SEC drops to low values, thus, driving the EV during those ambient temperatures will achieve the highest driving range. With the ambient temperature above 25°C, the SEC rises again. The relationship between ambient temperature and energy consumption of EVs is affected by changes in powertrain and battery efficiency and the use of auxiliary systems, particularly the ones related to cabin comfort, as EVs use DC-to-DC converters to transfer energy from the high-voltage battery to run the auxiliary systems [206]. The heating and cooling systems for passenger comfort are the primary auxiliaries that can influence the SEC. The load from these systems reaches 6kW driving in hot or cold conditions, significantly impacting the driving range [207]. The above analysis shows that ambient temperature outside and trips with a large share of idling events have a high impact on the SEC. The influence of ambient temperature on SEC is further discussed in Section 4.1.2.

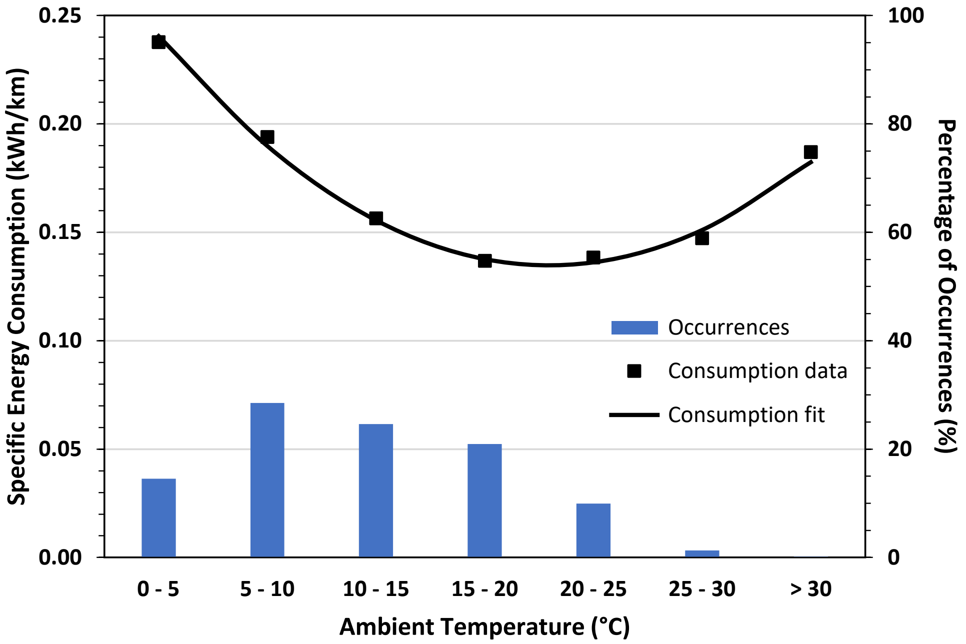

Figure 4.7: Variation in specific energy consumption distribution of trips based on ambient temperature.

4.1.2 Effects of Ambient Temperature

Figure 4.8 shows the changes in SEC and ambient temperature based on monthly average and across different seasons. The lowest SEC values are obtained between June and July, when the ambient temperature reaches its peak. For the other months, as the temperature drops, the SEC is increased. The highest energy consumption is recorded between December and January. The increase in energy consumption from the lowest average values at summer months to the highest average values in the cold months is of 69.5%.

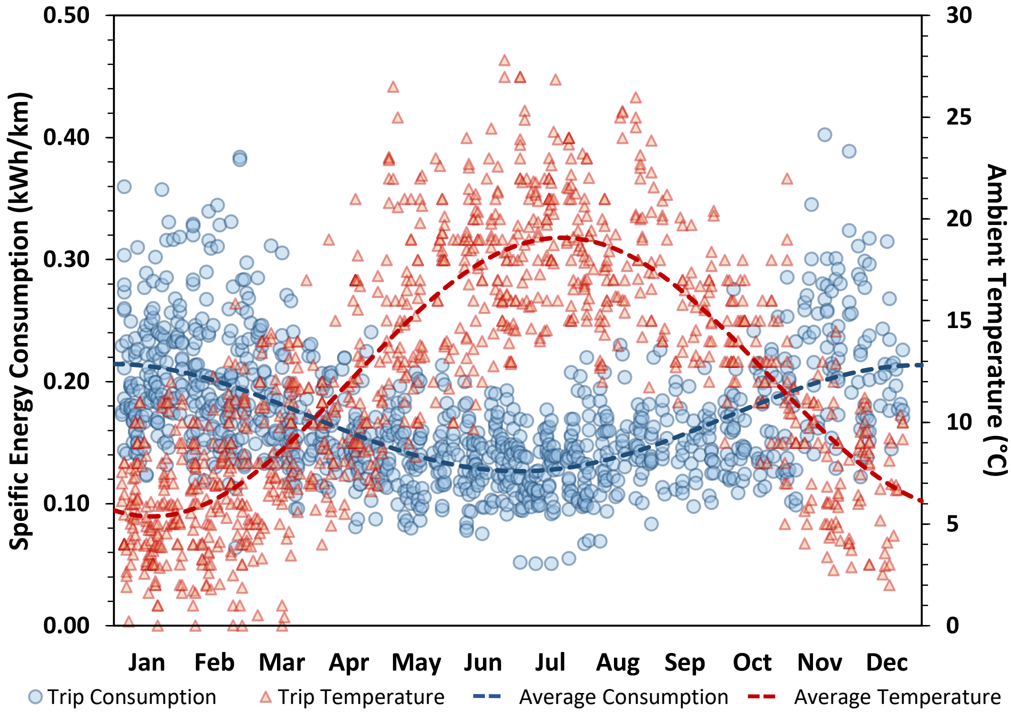

Figure 4.8: Monthly change in specific energy consumption and ambient temperature.

Figure 4.9 shows the SEC and the average ambient temperature for each trip. It can be noticed that data dispersion is higher at lower temperatures. The relationship between the ambient temperature and the SEC has a non-linear u-shape trend, with the dashed line representing the best fit to the data average, in agreement with previous observation by other authors [15]. In general, it is observed decreasing SEC with increased temperature from cold weather condition until reaching a minimum value at around 21°C. Similar findings are reported by other authors [51], who also found that the energy consumption decreases with an increase in temperature. With further increase of ambient temperature, the SEC rises again. The temperature where the lowest energy consumption was here achieved is close to the range found elsewhere [62], between 21.8°C and 25.2°C.

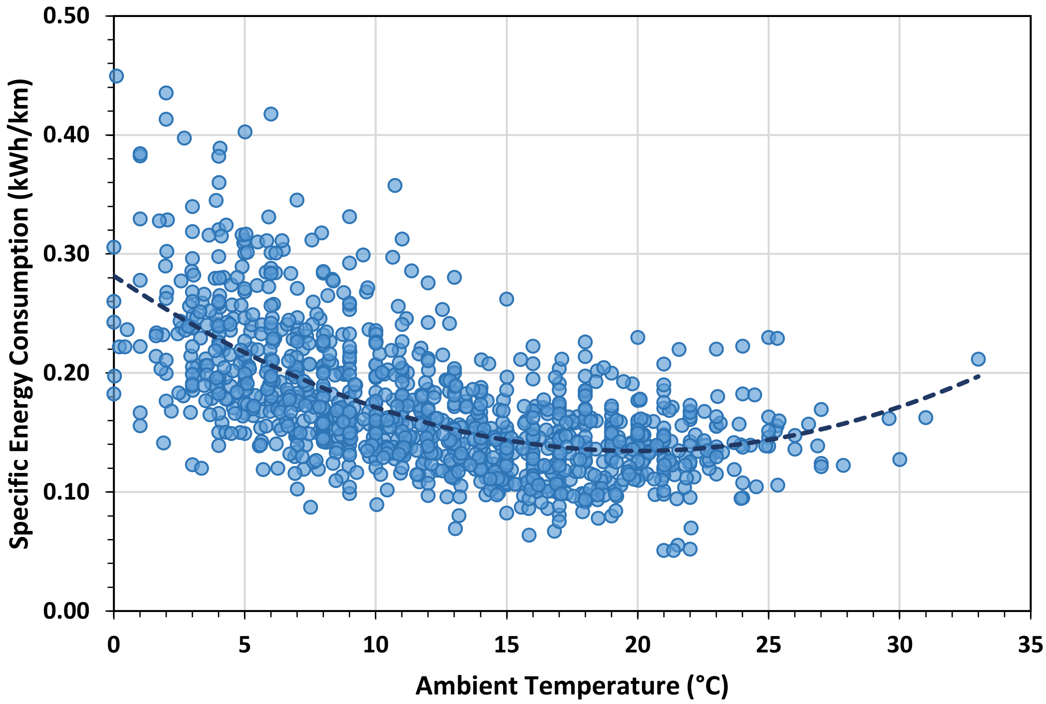

Figure 4.9: Variation of EV specific energy consumption with ambient temperature.

Similar to conventional ICE vehicles, EVs have several auxiliary devices to improve the driver experience and comfort. Generally, in any EV, three sources are attributed to the total energy consumed by the auxiliaries. Firstly, the HVAC system to keep the occupants at comfort levels. Secondly, the battery thermal management (BTM) system, which purpose is to maintain the optimal battery operating condition [208]. Lastly, other auxiliary devices such as lighting, entertainment system, navigation system and any other optional comfort systems. These other auxiliary devices have a relatively low impact on power consumption [60, 209], accounting for just around 50-70 W, and, thus, can be neglected [210].

The battery pack in the EV here utilised is sealed, and the BTM can be classified as a passive air-cooled system, as it depends directly on the natural airflow around the pack [211]. The Nissan Leaf has four temperature sensors in the battery pack to monitor the temperature of four different modules. The average reading of the four sensors shows the linear relationship between the battery temperature and ambient temperature with a Pearson correlation coefficient of 0.93, as shown in Figure 4.10. Therefore, the ambient temperature can be used to represent the battery temperature. The vehicle contains an electrical battery heater that turns on at -17°C to heat the battery and switches off at -10°C [212]. As the ambient temperature during the data collecting period did not reach these extreme cold conditions, no power was consumed from the battery heater. Therefore, the energy consumed by the auxiliaries is primarily attributed to the HVAC system.

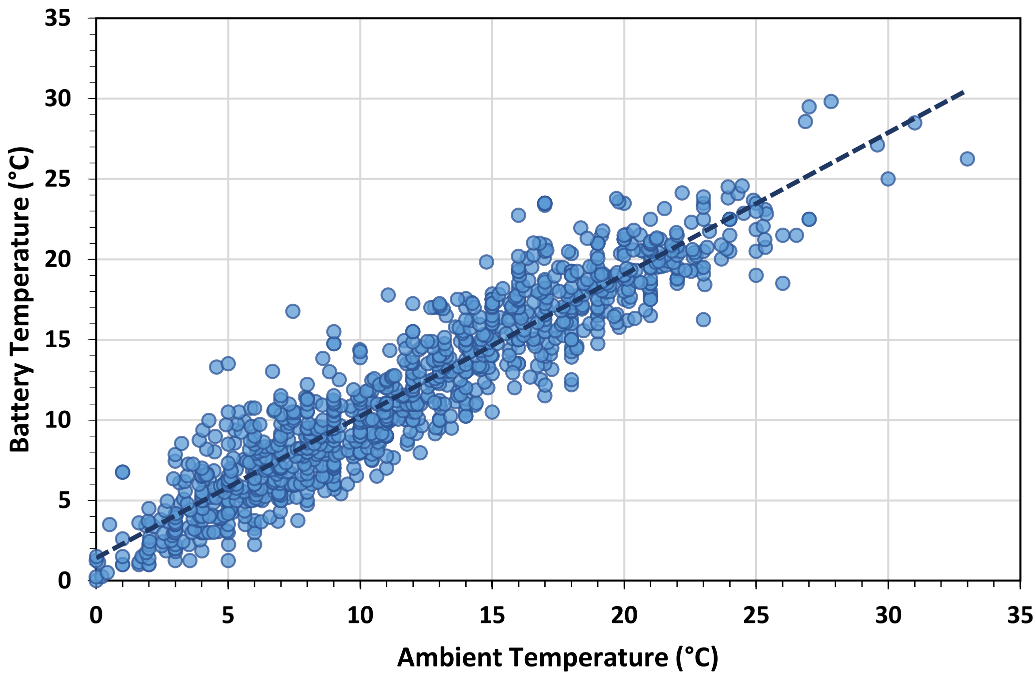

Figure 4.10: Variation of battery temperature with ambient temperature.

Figure 4.11 shows the variation of the energy consumed by the auxiliaries with changing ambient temperature outside. The auxiliary SEC reaches a minimum at around 18°C, increasing for trips outside the moderate temperature range. A higher variation in the auxiliary SEC is observed at temperatures below 10°C, compared to the rise at warmer conditions. The higher impact of heating systems among EV auxiliary devices was also reported by other authors [45]. Higher energy consumption at low temperatures outside is attributed to air warming inside the vehicle for cabin comfort or window defrosting [66]. Therefore, the larger spread noticed when more heating is required depends on several factors but also reflects the driver reaction to reach a temperature inside that provides the desired comfort level. For similar ambient temperature outside, the thermal sensation to the driver may change from different trips and affects heating demand. The high spread of the auxiliary SEC data at low temperatures affects the span of the EV specific energy consumption in the same range (Figure 4.9).

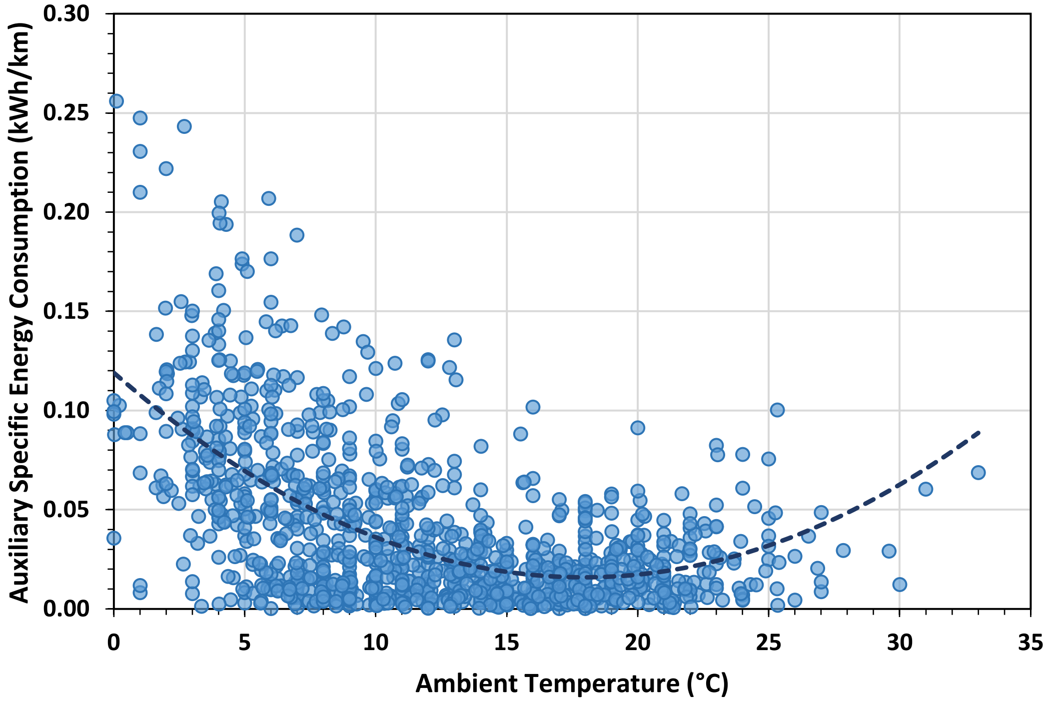

Figure 4.11: Variation of auxiliary specific energy consumption with ambient temperature.

The crucial data obtained from the CAN bus to calculate vehicle and auxiliary power consumption and SEC (Eqs. (3.1) to (3.5)) are battery voltage and current, and vehicle speed (time and distance), together with ambient temperature as the main independent variable in this evaluation. A sensitivity analysis of the battery parameters has been carried out through the variation of SEC with ambient temperature, as shown by Figure 4.12. The accuracies of battery voltage and electric current measurements are $\delta V = \pm 0.01$ V and $\delta I = \pm 1$ A. The sensitivity of vehicle and auxiliary SEC to the measured battery voltage is negligible, therefore it is not represented in the figure. The sensitivity of vehicle and auxiliary SEC to battery current measurements varies from 0.02 kW.h/km to 0.03 kW.h/km and from 0.01 kW.h/km to 0.02 kW.h/km, respectively, in the whole range of ambient temperature investigated.

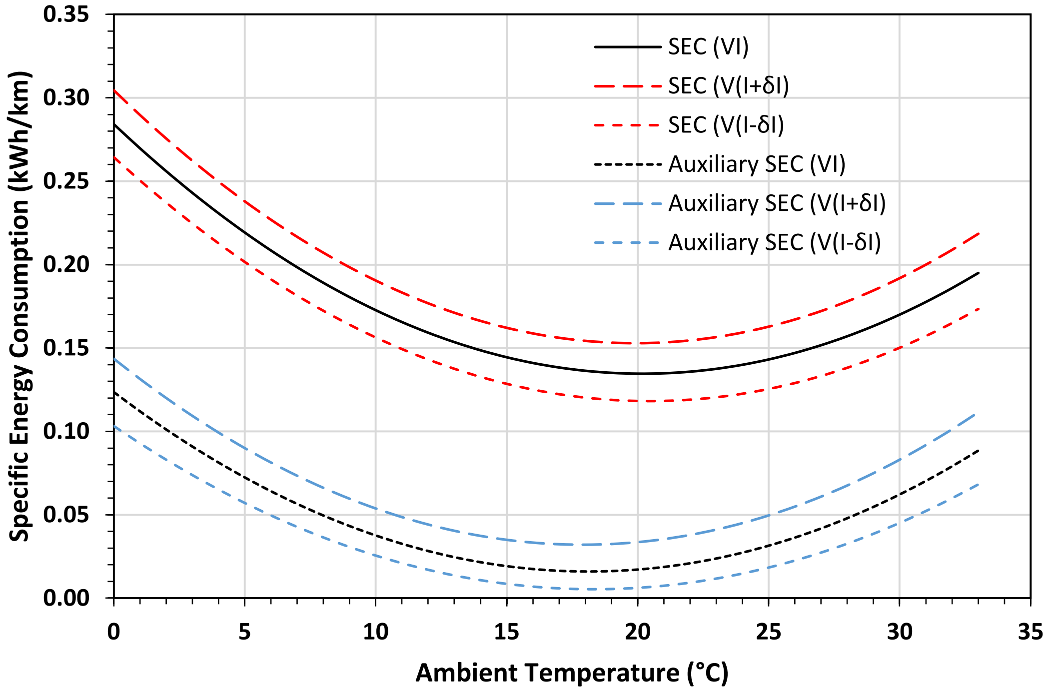

Figure 4.12: Sensitivity analysis of battery current in the calculation of specific energy consumption and auxiliary specific energy consumption with varying ambient temperature.

The rise of energy consumption when the vehicle operates outside moderate temperatures about 21°C, under colder or hotter weather conditions, can be directly linked to the added consumed energy used to run the auxiliary devices. Figure 4.13 shows the relationship between the energy consumption of the auxiliary systems and the vehicle SEC. Despite the scattered data, a highly linear correlation is obtained as indicated by the calculated Pearson correlation coefficient of 0.87. This behaviour of increased SEC with increasing load from the auxiliary systems is due to the energy used to run auxiliary devices being drawn from the EV battery. Therefore, any rise in power required from the auxiliaries leads to a direct impact on the EV specific energy consumption.

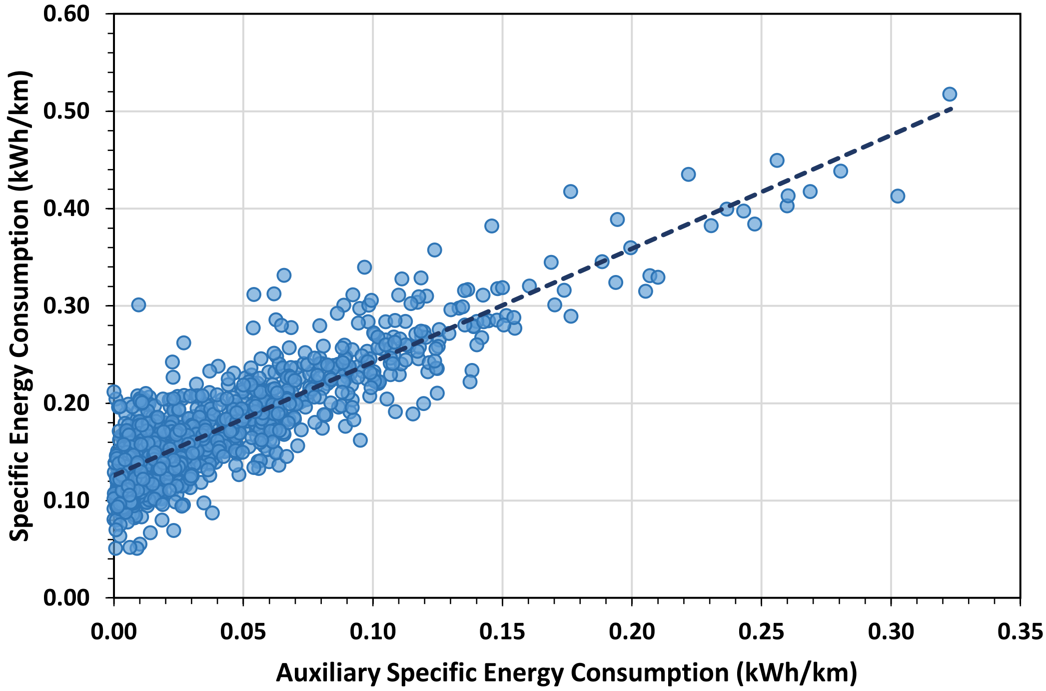

Figure 4.13: Variation of EV specific energy consumption with auxiliary system specific energy consumption.

Figure 4.14 presents the ratios of the consumed energy by the auxiliary devices (E_{aux}) and the recovered energy from the regenerative braking system (E_{reg}) to the net consumed energy by the EV (E_{cons}). At moderate conditions, with temperatures between 14°C and 22°C, the energy consumed by the auxiliary accounts for less than 10% of the net EV energy consumption. However, at extreme conditions, with temperatures below 4°C or above 32°C, the energy drawn by the auxiliaries reaches 25% and up to 38% of the net consumed energy by the EV. The difference in energy consumption between cold, moderate and warm conditions is also affected by the changes in regenerative braking efficiency. According to the literature, the capability to charge the battery is affected by driving behaviour or drop in battery performance with ambient temperature changes. The exact portion of these factors that affect regenerative braking efficiency is suggested as a subject of future research. The recovered energy by the regenerative braking system reaches highs of 30% to 32% of the net consumed energy at temperatures between 15°C and 30°C. At the lowest temperature in the range studied, of 0°C, a minimum energy recovery of 14% of the net consumed energy is achieved.

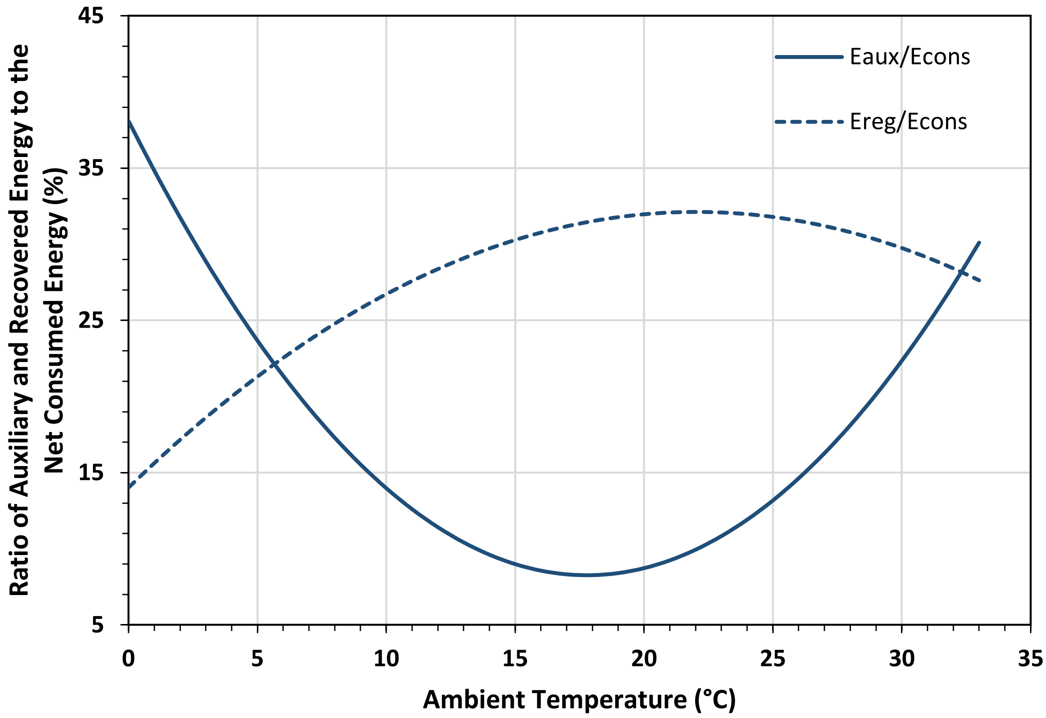

Figure 4.14: Percentage variation of auxiliary and recovered energy to the net consumed energy with ambient temperature.

Trip characteristics have significant impact on EV specific energy consumption. Figure 4.15 shows the typical profile of auxiliary power consumption of a random trip taken in a fairly flat road with the outside temperature at 5°C, recorded in the first 1600 s after start. The figure also includes the vehicle speed, trip distance and inside temperature profiles. The auxiliary power peaks soon after the start of the trip and it stays high until about 3 km, when it drops to about half of the peak value. This behaviour is because the heating system operates at maximum power at the start of the trip to reach the desired temperature as quickly as possible, thus requiring extra power. With an increase in distance, the auxiliary power tapers to lower values, as the inside temperature reaches comfortable levels for the driver and heating requirements are reduced. This illustrates how cold weather and short trips are critical conditions to increase auxiliary power consumption, leading to high scattering in the SEC (see Figure 4.11).

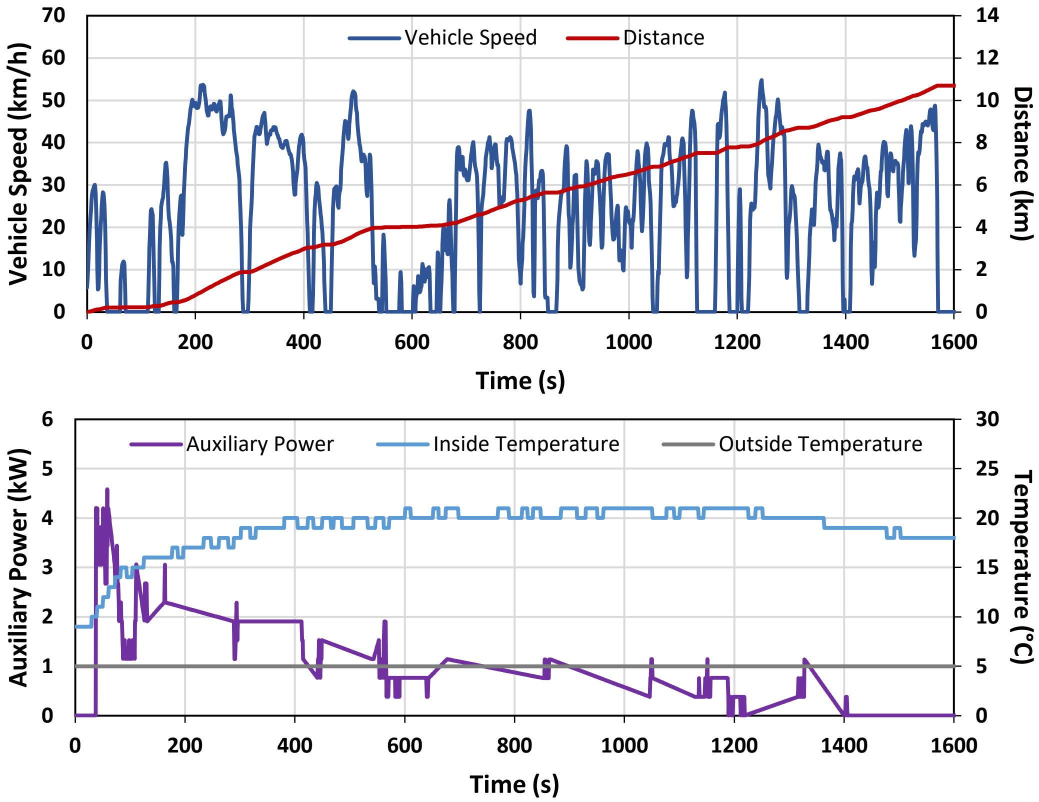

Figure 4.15: Typical profiles of auxiliary power consumption, vehicle speed, distance and inside temperature for a random urban trip at flat road from cold start at 5°C outside temperature.

Another parameter that can significantly impact the EV energy consumption is the stop percentage of the trip time, which must be separated from the temperature effects. Figure 4.16 highlights different stops for a 6-min section of a typical trip profile occurred during cold conditions in urban driving, at 3°C. The results reveal that, during the stops, when the EV normally has zero tractive power values, there is still power consumption from the use of auxiliaries. Therefore, with increased number of stops an increase in SEC is expected. The longer the percentage of stop time in a trip, the higher the SEC, as the cumulative auxiliary energy consumption is increased. The impact of stops is due to high auxiliary power demand at the start of the trip, as mentioned previously. At the start of the trip and before the vehicle starts to move there is high auxiliary power consumption, which is amplified during winter due to the use of heating systems such as windows defrost [213]. Therefore, an increase in the stop time percentage directly translates into a rise of the SEC. The combination of long stop time and colder temperatures has the largest impact on increasing the SEC, as demonstrated by Figure 4.17.

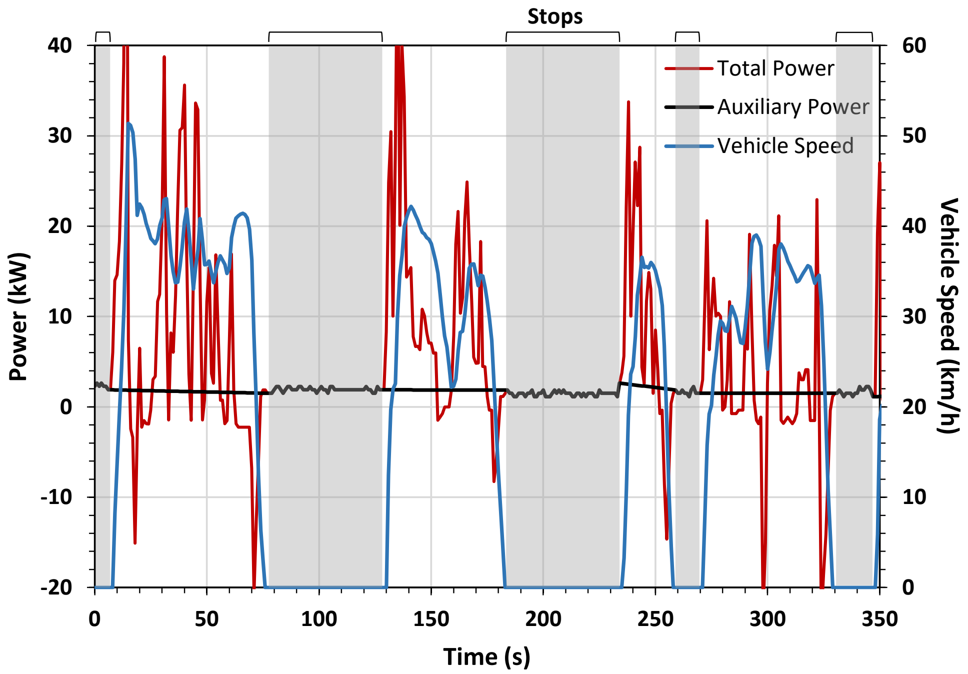

Figure 4.16: Auxiliary power consumption during stops.

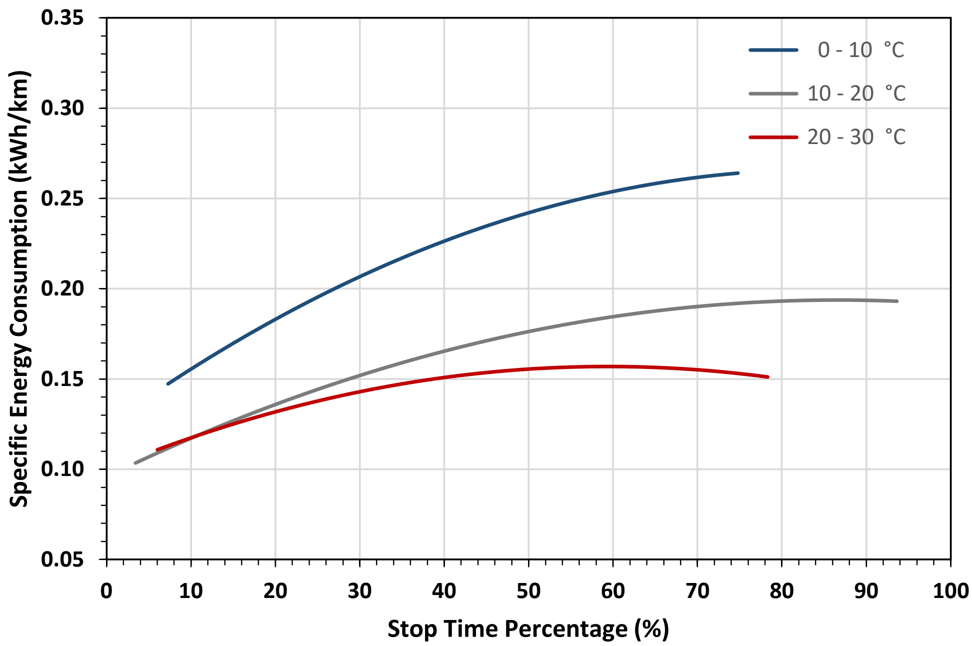

Figure 4.17: Variation of specific energy consumption with stop time percentage.

4.2 Real Driving Cycle

4.2.1 General Results

The distribution and the cumulative percentage of all trips fully attending the RDC conditions and the short RDC trips, as discussed before, are show by Figure 4.18 according to SEC bins of 0.05 kWh/km in the measured range. More than three-quarters of all short RDC trips presented SEC between 0.10 kWh/km and 0.20 kWh/km, with less than 6% of the trips showing SEC lower than 0.10 kWh/km and about 17% displaying SEC higher than 0.20 kWh/km. A total of 20 trips fully met the RDC conditions, with up to 60% of these trips having SEC between 0.10 kWh/km to 0.15 kWh/km, while 40% of the RDC trips showed SEC above 0.15 kWh/km.

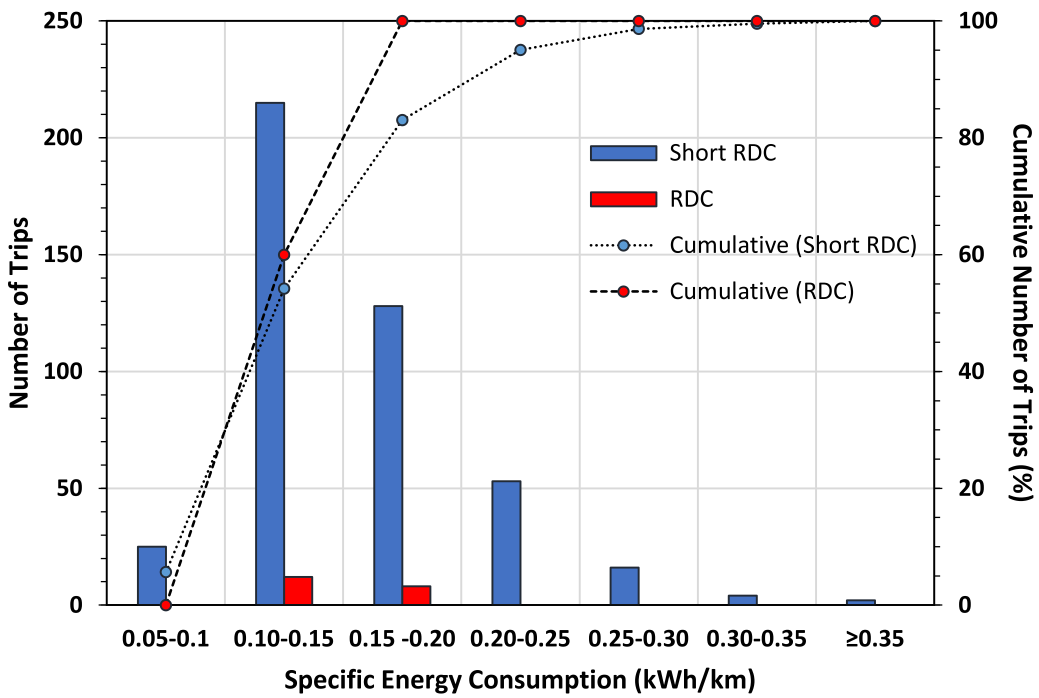

Figure 4.18: Distribution of trips with specific energy consumption ranges.

4.2.2 Driving Behaviour

Short RDC trips present higher SEC than fully compliant RDC trips in all operation modes, as shown by Figure 4.19. The total average SEC considering all operation modes is 0.158 kWh/km for the short RDC trips and 0.144 kWh/km for the RDC compliant trips, meaning an increase of 9.7% in energy consumption for the trips shorter than 16 km. Aggressive driving in full RDC trips increases SEC by 9.1% in comparison with passive driving, and by 8.4% compared with moderate driving. For short RDC trips, aggressive driving increases the energy consumption by 16.3% and 7.1% in comparison with passive and moderate driving, respectively. Aggressive driving has the potential to increase the amount of recovered energy during braking as a result of hard deceleration, however, the high energy consumed in acceleration events produces a net impact of reduced EV energy efficiency [214]. A significant percentage of braking energy is lost as a result of unnecessary over acceleration that, added to the limitations of the regeneration system, reduce the amount of recovered energy below the available potential [215].

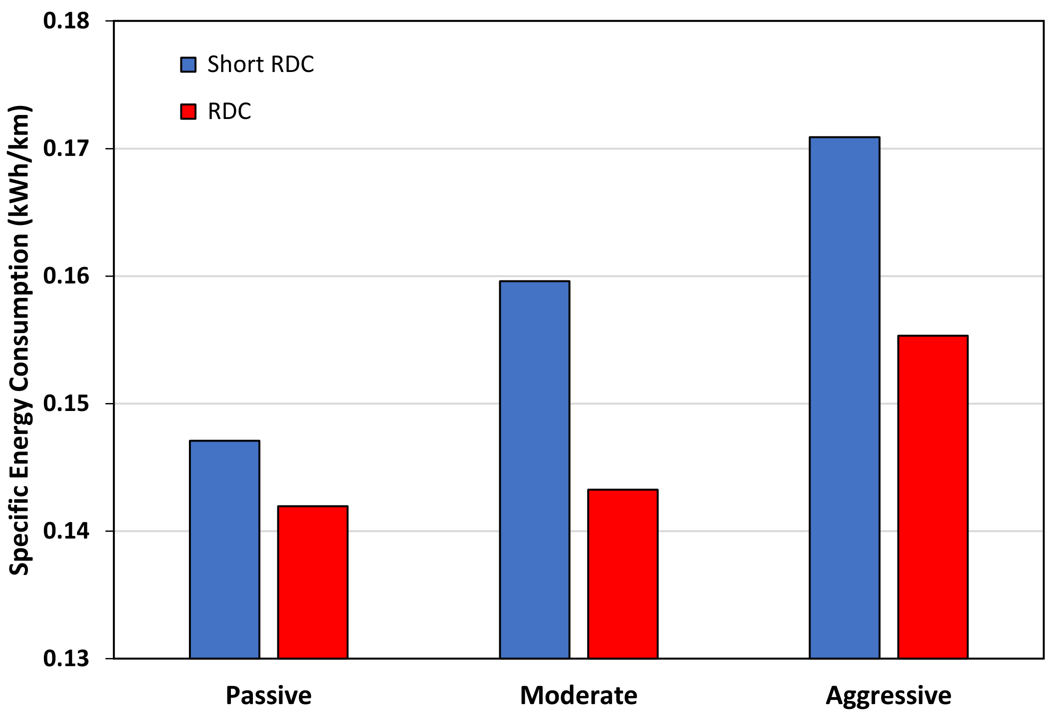

Figure 4.19: Variation of specific energy consumption with driving behaviour.

4.2.3 Trip Distance

Figure 4.20 presents the variation in SEC with trip distance including both short RDC and fully compliant RDC trips. From the 20 RDC trips shown, all of them attend the full specifications in urban operation, 19 in rural and 14 in motorway mode, as represented in Figure 3.3 and Figure 3.4. The short RDC trips show a high SEC scatter, ranging from 0.07 kWh/km to five times higher values (Figure 4.20). RDC compliant trips show less variation, with the minimum SEC of 0.109 kWh/km and the maximum of 0.181 kWh/km. Similar findings have been reported by other authors [51], where high variation was noticed at short trips and, with increased trip distances, the average SEC remained constant while the variation was reduced.

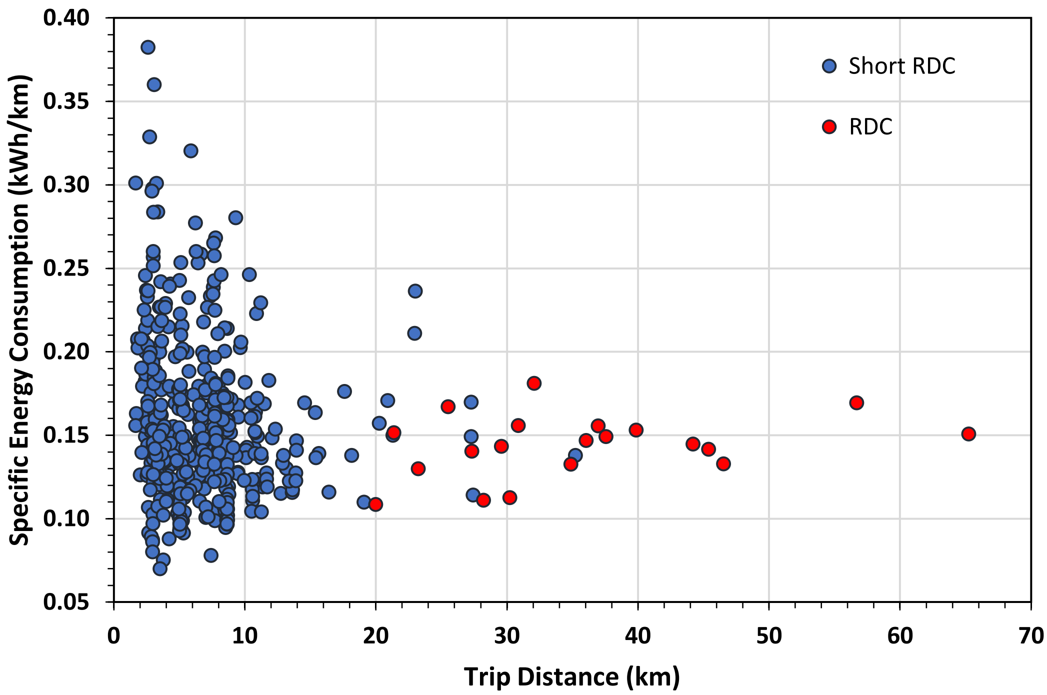

Figure 4.20: Variation of specific energy consumption with full trip distance.

The impact of travel distance on the average SEC in urban, rural and motorway operation modes is shown by Figure 4.21. Short RDC was divided into very short trips, with distances below 4 km, and trips with distance between 4 km and 16 km to further highlight the impact of short trips on SEC. For all operation modes, short distance driving less than 4 km always present the highest average SEC, ranging from 0.157 kWh/km in rural operation up to 0.225 kWh/km in motorway. The difference to short RDC of less than 4 km and RDC trips ranges from 14.9% to 29.2% and is more prominent in motorway operation, because the additional energy required to accelerate to motorway speeds has a higher impact in short trips. In any RDC trip distance range, motorway operation always presents the highest SEC, while the lowest levels are generally observed at rural operation. The lowest average SEC, of 0.136 kWh/km, is recorded for RDC trips at rural condition. This operation mode generally avoids the extra energy consumption from higher stop percentage due to heavy traffic typical from urban driving and requires less energy than that required to overcome the air resistance at high-speed motorways.

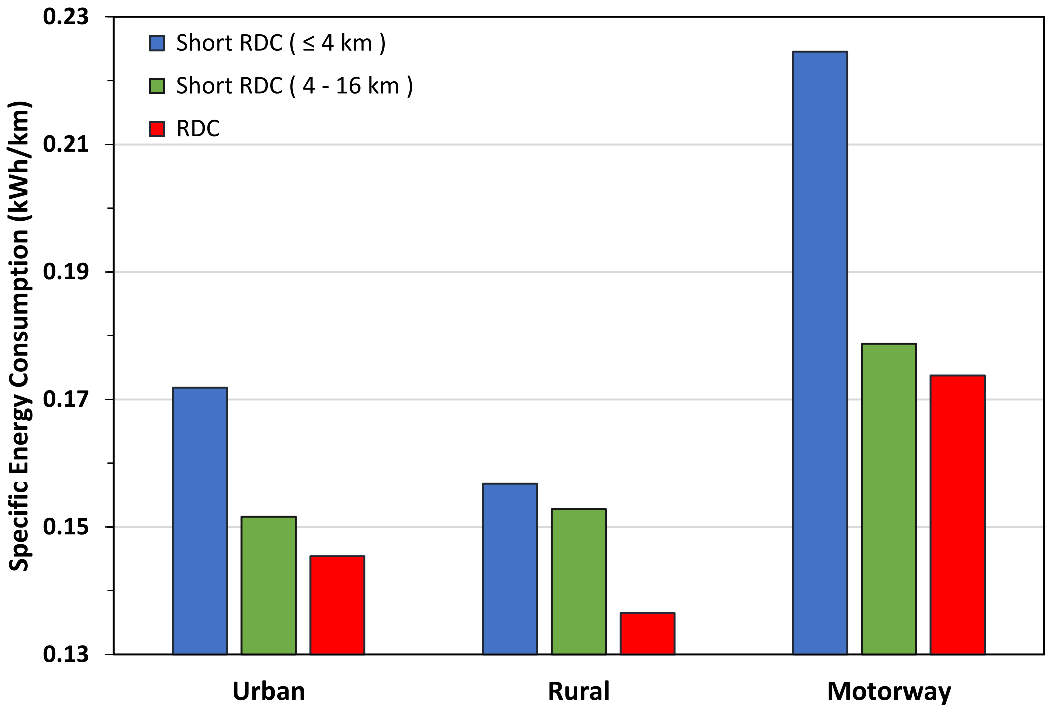

Figure 4.21: Variation of specific energy consumption with trip distance ranges in urban, rural, motorway and full RDC operation.

Figure 4.22 shows the vehicle cumulative SEC and speed profile of a recorded trip. The trip covered the three operation modes – urban, rural and motorway – along a total distance of 30 km. At the beginning of the trip, in the first 1 km and just over, the

SEC shows much higher values than in the remaining of the trip. Only after about 16 km the SEC reaches and approximately stabilises to a minimum level around 0.14 kWh/km. Therefore, trip sections shorter than 16 km show higher SEC values and with large variability. The first 5 km or so presents the largest cumulative SEC variability and trends seemingly difficult to predict. These results explain why full RDC trips, which require distances longer than 16 km for each driving mode, have lower SEC than short trips. Though RDC trips are good representatives of real world driving in many situations and serve well for comparison purposes in similar conditions, they do not adequately represent short trips common in urban areas.

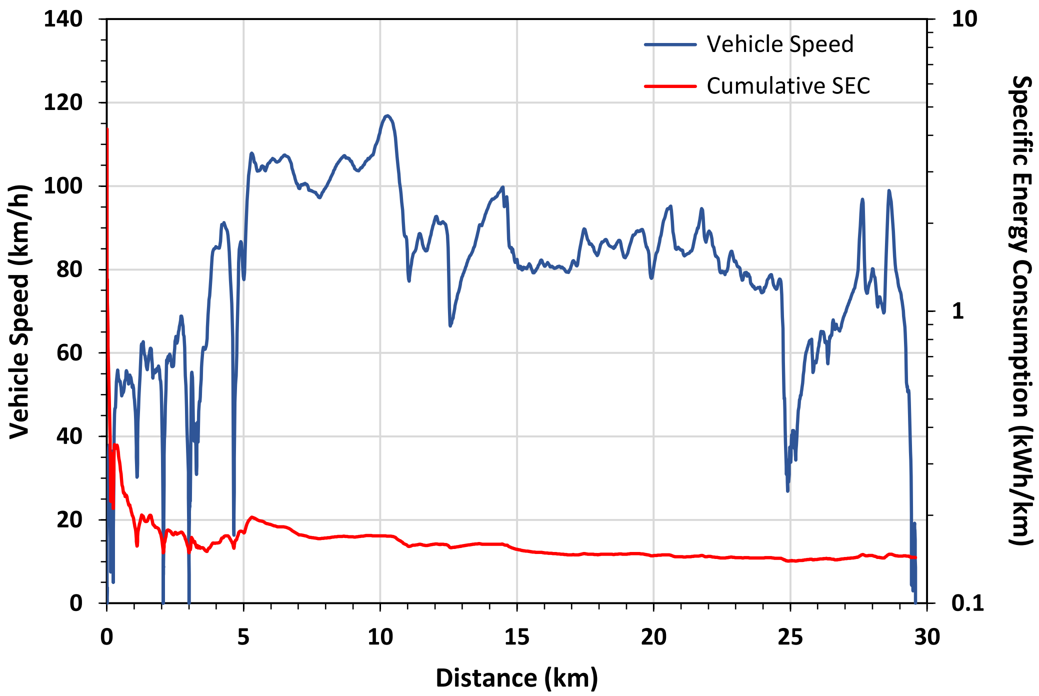

Figure 4.22: Typical trip speed and cumulative specific energy consumption profile.

4.2.4 Ambient Temperature

The variation of SEC with the recorded ambient temperature outside for short RDC trips and RDC compliant ones is shown by Figure 4.23. The general data exhibit a high dispersion but there is a trend to attain minimum SEC values at around 18°C to 20°C, indicating that the EV reaches the highest energy efficiency in the moderate temperature range. A similar behaviour was found by other authors [55], where the minimum specific energy consumption was found around 17°C to 18°C. Decreasing temperatures below 10°C show the highest SEC levels, above the one obtained at 30°C. There are several possible explanations for this behaviour, which include a possible reduction of regenerative braking efficiency with low temperatures and increased demand of auxiliary systems. The regenerative braking system efficiency has been reported to decrease significantly in cold weather [216]. Moreover, to prevent lithium plating, regenerative braking is restricted from recharging lithium-ion batteries at low temperatures, thus contributing to the drop in EV range in cold climate [217]. As the powertrain efficiency of an EV has a uniform behaviour and approaches to a constant value [18], regenerative braking and the auxiliary systems are here assumed to have a larger impact on the SEC with changes in ambient temperature.

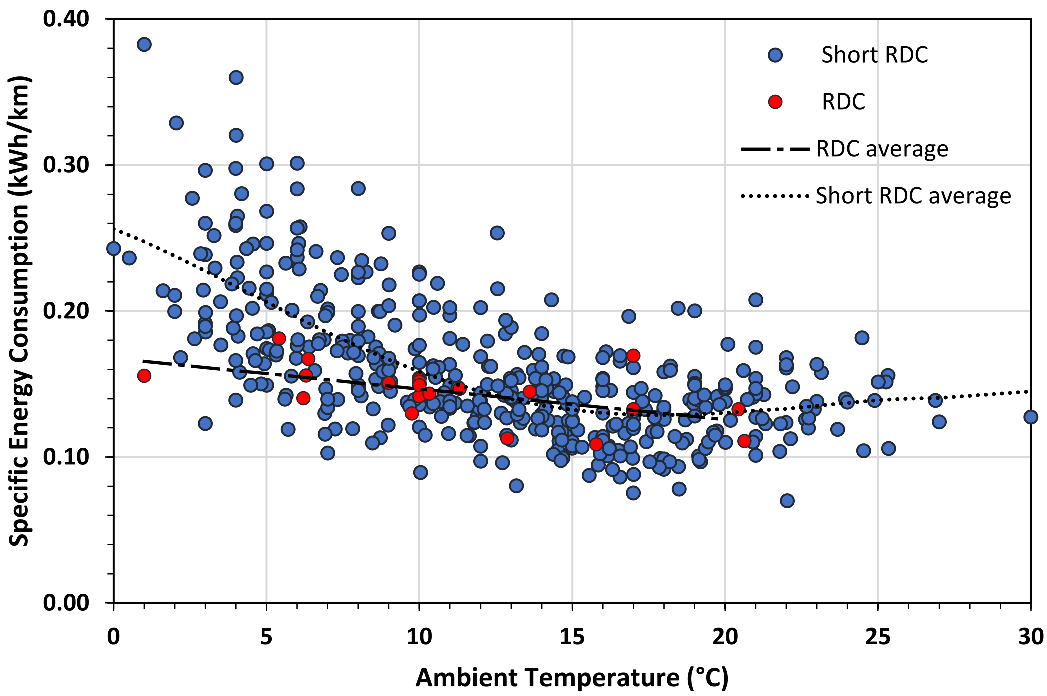

Figure 4.23: Variation in specific energy consumption with ambient temperature.

The main EV auxiliary that affects SEC is the HVAC system. The HVAC system increases SEC at low temperatures due to the increased load from the heating system and, at high temperatures, the SEC rise is attributed to the use of air conditioning

(Figure 4.23). The impact of auxiliaries significantly increases during heavy traffic and longer idling periods [218], reducing the range of PHEV in EV mode between 16% to 29% [219]. Auxiliary power consumption was reported to peak at the first portion of a trip [213], as heating and cooling requirements are higher at the beginning of the journey to bring the cabin to comfort temperature [220], thus increasing SEC in short trips. An improvement to the overall EV efficiency can be achieved from the use of more efficient HVAC systems, cabin preconditioning and better insulation of the vehicle interior.

4.2.5 Traffic Conditions

The impacts of traffic conditions on SEC are evaluated based on changes in EV average speed and stop time percentage in urban operation. Figure 4.24 shows the variation of SEC with vehicle speed bins in urban operation for both short RDC and full RDC compliant trips. The general trend shows a consistent increase of SEC with decreasing average speeds, rising by as much as 19% in short RDC and 15% in RDC trips. In urban driving, lower average speeds are directly related to larger stop time percentages. The auxiliary system continuously demand energy during the stops, being the reason for the overall increase of SEC as the stop time percentage is increased.

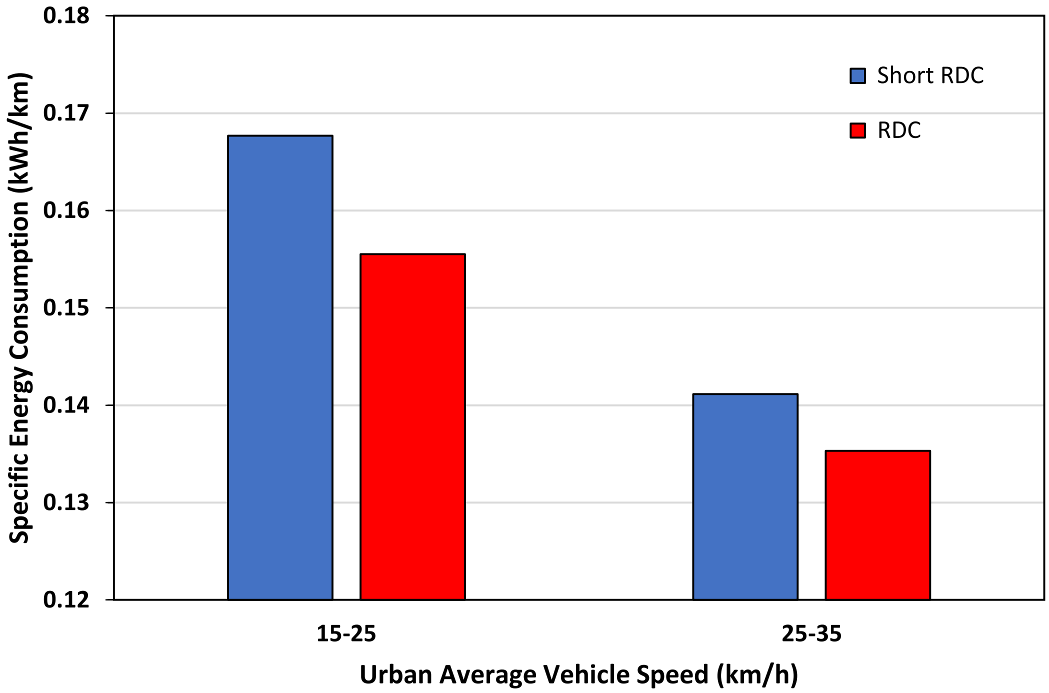

Figure 4.24: Variation of specific energy consumption with average vehicle speed in urban operation.

Figure 4.25 shows how SEC in urban EV operation is affected by stop time percentage, distributed in bins from 6% to 30%, according to RDC requirements. The SEC consistently increases with larger stop time percentages for both short RDC trips and fully compliant RDC one. For the RDC trips, the SEC increases by around 20% from the stop time percentage range 12-18% to the range 24-30% and, for short RDC trips, the SEC increases by around 40% from the stop time percentage interval 6-12% to the bin 24-30%. The primary reason for this behaviour is the power required by the auxiliary systems even if the vehicle is not in movement [221]. The impacts are magnified at very low ambient temperature conditions, due to higher heating power demand, and short trips, as the stop time percentage is increased.

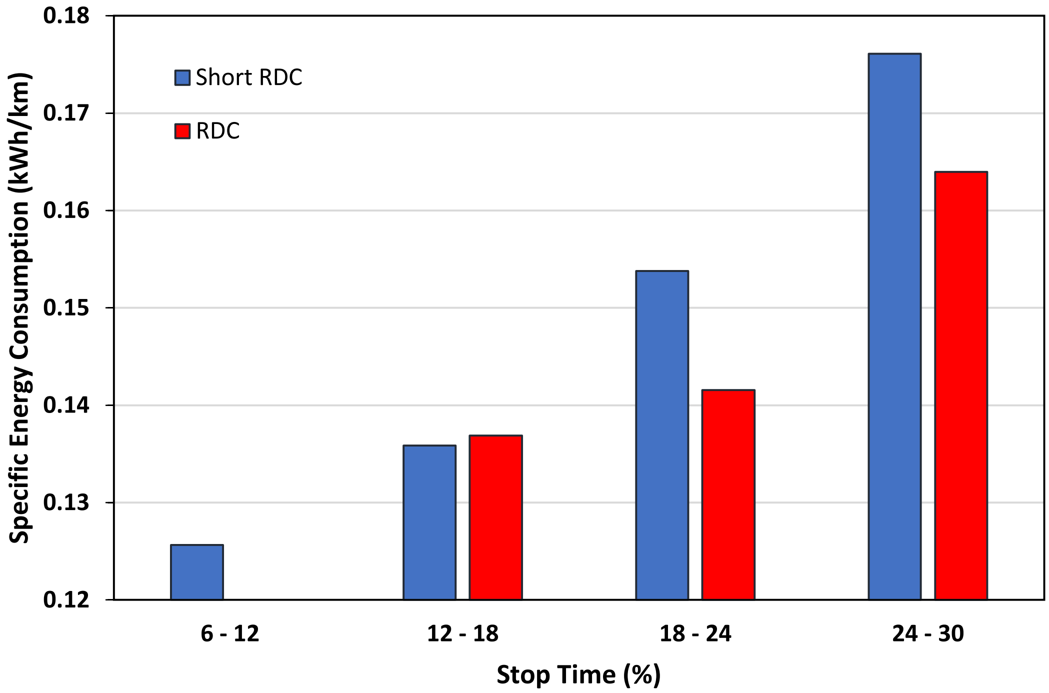

Figure 4.25: Variation of specific energy consumption with stop time percentage in urban operation.

According to the National Travel Survey [222], 78% of trips driven by passenger vehicles in the UK were below 10 miles, of which 31% were below 2 miles. These statistics highlight the importance of understanding the impact of short trips on EV energy consumption under different traffic conditions and its relation to ambient temperature. Repeated short trips driving with long park duration between them, allowing the cabinet temperature to cool down during winter, will further increase the total energy consumption, as previously discussed. Consequently, it leads to a shorter driving range and more frequent charging, which results in rising energy demand from the grid and could increase carbon emissions during EV charging. Therefore, local authorities should incentivise and promote a shift to walking or cycling as an alternative if applicable or use cabinet preconditioning and, if possible, reduce the demand for heating during short trips.

While the results here used a single EV data, the analysis can be applied to other EVs. As previously discussed, ambient temperature highly influences the variation of

SEC, and the relationship of ambient temperature and SEC of different EVs shown by Koncar et al. [203] have a u-shape similar to the one in this work. Therefore, while the SEC quantifications can vary for other EV types, the general behaviour of the different factors influencing SEC here investigated are expected to be similar for EV models of the same car segment operating at low road grades, as changes in vehicle weight up to about 12% and operation at non hilly conditions do not significantly affect SEC [56]. The results should also be unaffected by the use of different BTM system in other EV models, especially considering that most of the tests were performed at low and moderate temperatures [59].

4.2.6 Road Grade

In order to isolate the road grade impact on EV energy consumption from the other highly influential parameters, only selected trips in specific temperature, distance and stop percentage ranges were analysed. To minimise the temperature effects, only trips with ambient temperatures above 10°C were considered. Short RDC trips were excluded to eliminate the variation of short distance, and trips with high stop percentage from 24% to 30% were rejected with the aim to reduce the effects of this parameter. The filtering process resulted in selecting six RDC compliant trips for the evaluation of road grade impact.

Figure 4.26 shows the changes in the SEC with road grade. The data binning was performed by rounding the road grade to the nearest integer in each trip, where negative values refer to descending parts of the trip, and positive values mean ascending parts. The SEC increases consistently with increasing road grade. Ascending roads with 3% road grade increases SEC by 50%, while descending roads with -3% road grade decreases SEC by 80%, in comparison with flat road trips. This is because increasingly ascending trips impose higher loads on the powertrain system, thus demanding larger amounts of energy. On the other hand, there is a rising amount of recovered energy by the regenerative braking system during downhill driving.

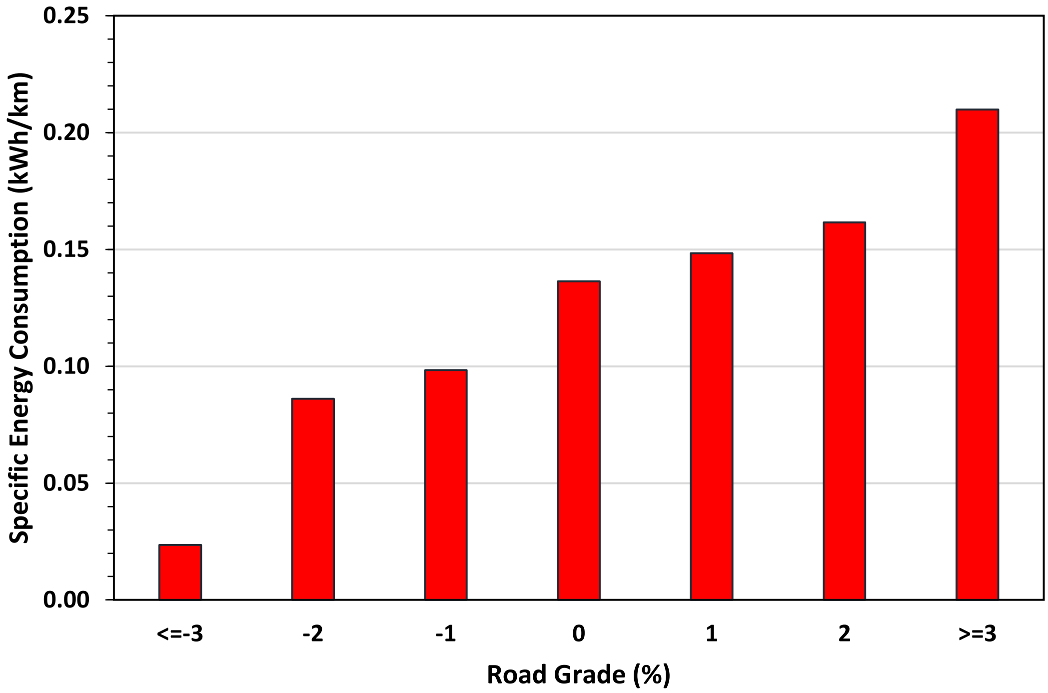

Figure 4.26: Variation of energy consumption with road grade in RDC trips.

4.2.7 Breakdown of Specific Energy Consumption and Regeneration

High auxiliary power demand at the start of the trip has less impact on the EV specific energy consumption in long trips, which, thus, tend to produce better estimates of actual energy consumption than short trips. A comparison of the average values of EV SEC and the auxiliary SEC between all random trips and the combination of the selected sections that met the RDE criteria is presented by Figure 4.27. At cold temperatures, the SEC of the RDE-compliant sections is significantly lower than the SEC of data, dropping about 30% at 1°C. This is mainly due to the removal of the short-distance (< 16 km) and large stop percentage (> 30%) trips from the RDE selected ones, as those types of trips present higher energy consumption by the auxiliaries. This can be also observed from the similar drop of SEC presented by the auxiliaries at colder temperatures, when comparing the RDE-compliant sections against all trips. At moderate temperatures, from around 17°C to 22°C, the SEC of all trips had similar values as the SEC of the RDE-compliant ones. In this temperature range, the auxiliary

SEC reaches minimum values, being slightly lower for the RDE-compliant trips in comparison with all trips.

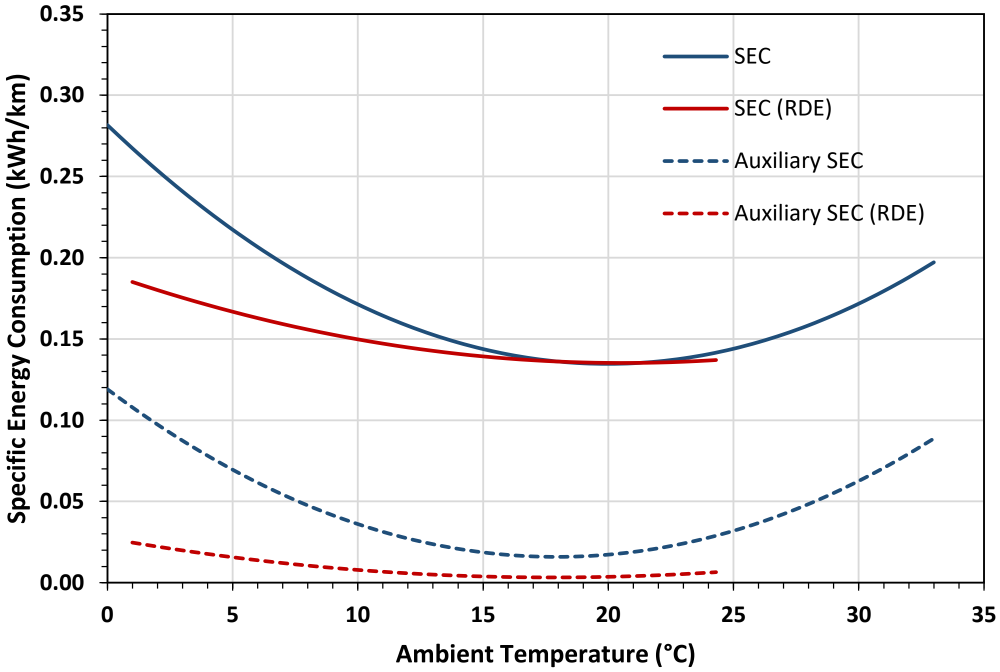

Figure 4.27: Comparison of average EV SEC and auxiliary SEC variation with ambient temperature for all random trips and RDE sections.

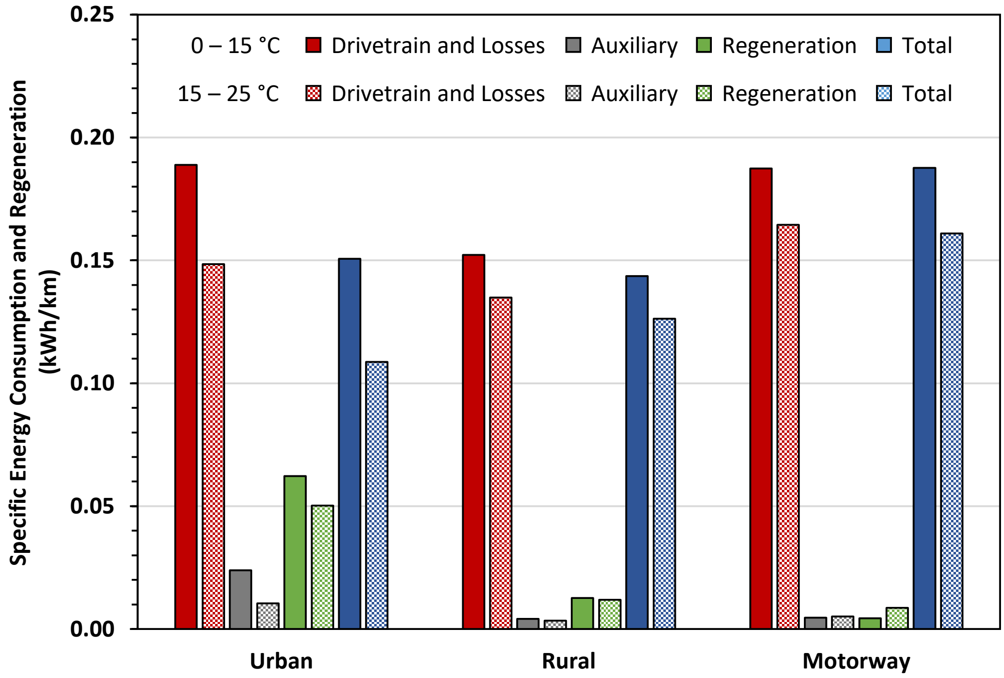

Figure 4.28: Breakdown of specific energy consumption and regeneration in urban, rural and motorway operation of RDE sections at cold and moderate temperature ranges.

Figure 4.28 shows a breakdown of specific energy consumption and regeneration for the RDE sections under urban, rural and motorway operation in the temperature ranges from 0°C to 15°C and 15°C to 25°C. In general, the energy required for drivetrain operation plus losses are from 14% to 27% higher in the low temperature range for all RDE operation modes. The stop-go situations in urban driving that are normally followed by acceleration events require extra power to move the vehicle from standing still, being the reason for the higher energy consumption by the drivetrain and losses at these operating conditions. Furthermore, the efficiency of electric motors is decreased under low speed and power operation, thus increasing energy consumption in urban driving [221]. For rural and motorway operation the vehicle travels at higher speeds, with higher air resistance decreasing its efficiency [56] as more power is needed to overcome the aerodynamic drag, thus increasing the specific energy consumption. The energy required by the auxiliaries is more than twice higher in the low temperature range under urban operation, keeping similar levels for the two temperature ranges under rural and motorway operation modes.

While the drivetrain energy consumption plus losses is close for urban and motorway operation at both temperature ranges, the total EV energy consumption is from 20% to 32% lower in urban driving in comparison with motorway driving (Figure 4.28). This is because energy regeneration is 6 to 14 times higher during urban driving, even with 2 to 5 times higher energy demand by the auxiliaries. The relatively small energy regeneration for both rural and motorway operation denotes that regenerative braking is less actuated in these driving modes, which present more cruising speeds, in comparison with urban driving. In contrast, frequent deceleration events and repeated stops in urban driving make the most of regenerative braking. These results show that EVs operate more efficiently under urban and rural conditions than in motorways, backing the initiatives to promote a rapid deployment of EVs in largely populated zones.

Considering that the EV model used in this investigation has an average SEC of 0.15 kWh/km for the combined RDE sections (Figure 4.28), the real-world driving range of the EV calculated using Eq. (3.3) is 140 km. This is about 30% lower than the official range published by the manufacturer based on NEDC laboratory testing, of 199 km [13]. If the vehicle is primarily used in urban trips, and considering the calculated average SEC of 0.11 kWh/km at moderate temperatures from 15°C to 25°C (Figure 4.28), it will attain maximum range of 193 km. This calculation reveals a drop of 28% in range for urban operation in the cold temperature range, from 0°C to 15°C, which has the same SEC as the overall RDE section. Following similar analysis for motorway operation, the range will drop 14% from 130 km to 112 km under moderate and cold temperatures, respectively.

Figure 4.29 shows the relationship between SEC and average vehicle speed at the temperature ranges of 0°C to 15°C and 15°C to 25°C in urban, rural and motorway operation of RDC sections. In general, the energy consumption is higher in the lower temperature range regardless of the average speed. In the temperature range from 15°C to 25°C a minimum SEC is achieved at an average speed of 45 km/h and, in the range from 0°C to 15°C, the minimum SEC occurs at 55km/h, both under urban operation. The prominent SEC increase at lower speeds in the low temperature range has the energy consumed by the auxiliary systems as the dominant factor. Also, trips with low average vehicle speed have large stop time percentage, as discussed previously, leading to high SEC. Similar behaviour of SEC variation with vehicle speed was found by other authors [15], where the maximum efficiency occurs at a driving range between 45 km/h and 56 km/h. In the domain of rural and motorway operation, the SEC increases with increasing average vehicle speed in both low and moderate temperature ranges.

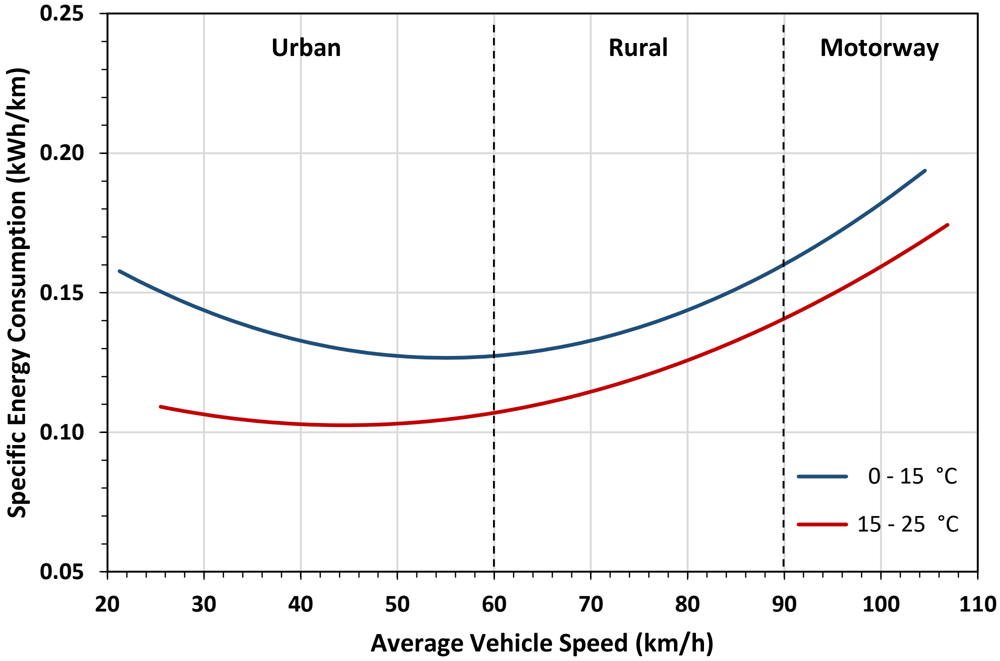

Figure 4.29: Variation of specific energy consumption with average vehicle speed at cold and moderate temperature ranges in urban, rural and motorway operation of RDE sections.

4.3 Carbon Emissions Projection

4.3.1 Vehicles Outlook

Figure 4.30 shows the historical number of vehicles and the projected results of the fleet turnover model up to 2050, when the numbers are expected to reach 33.8 million. Historically, petrol vehicles dominated GB market with above 87% share of vehicles fleet by 2000. However, the demand for diesel vehicle kept increasing until 2015, driven by its cost efficiency than petrol vehicles [223] and improved fuel economy supported by favourable regulations in Europe that demanded manufacturers to meet fleet average carbon emissions [224]. While diesel typically emits less carbon than petrol for similar-sized vehicles, the larger average engine capacity of diesel vehicles [225] and their increased popularity in larger vehicles lead to the difference in fleet average carbon emissions between diesel and petrol vehicles being significant [226].

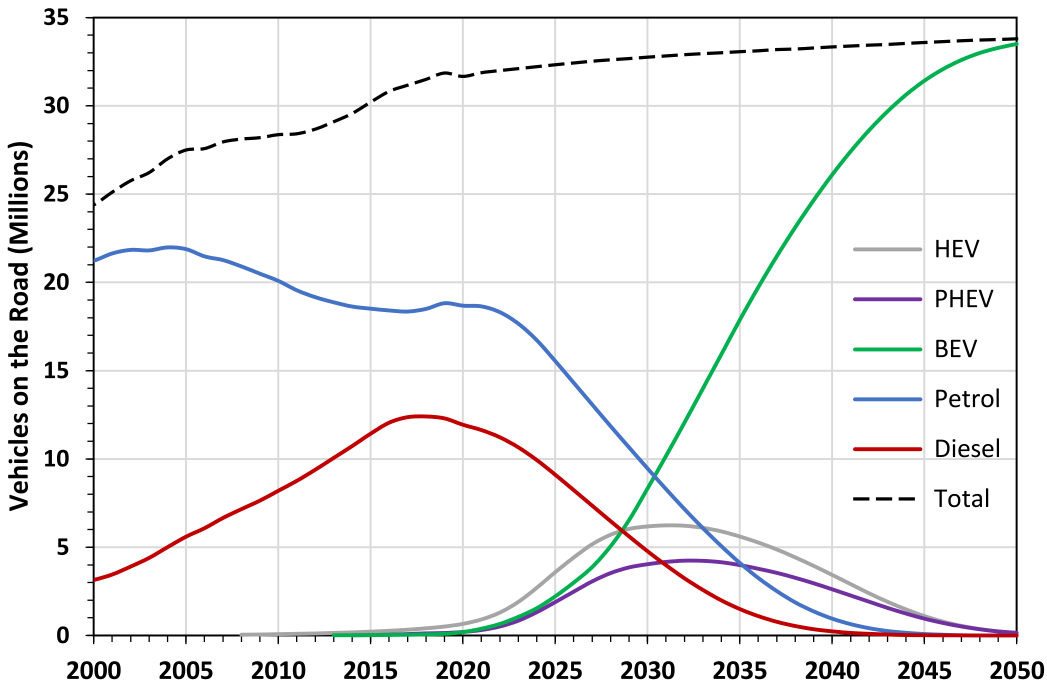

Figure 4.30: Vehicle parc between 2000 and 2050 in Great Britain.

In 2016, the number of new diesel vehicles sold started to drop, leading to a continuous decline in diesel vehicle numbers on the road. This decline in sales happened right after when EPA found a major car manufacturer had been intentionally manipulating diesel vehicle emissions, also referred to as “dieselgate” scandal [227]. This change shows the importance and the awareness of air pollution to consumers with the ability to switch to alternative options that offer better emissions reduction.

In 2020, the total number of vehicles on the road dropped for the first time compared to the previous year. The figures improved in the year after but were still below the 2019 level. There were already more BEVs on the road in 2021 than PHEVs and, with the current projections, BEVs number will pass diesel vehicles and HEVs before 2030 (Figure 4.30). While petrol vehicles will continue to decline, they will remain dominant in the market share until 2031. Electrified vehicles will reach 50% of the vehicle stock by the end of this decade, and BEVs will account for most of these vehicles. By 2035, BEVs will contribute to more than half of the vehicle stock and nearly all vehicles in 2050 (Figure 4.30). While there are still a few thousands of vehicles with ICEs in 2050, mainly HEVs and PHEVs, fossil fuel production has to decline rapidly by 2050 to meet the internationally agreed climate goals [228]. If BEVs become the primary choice of travel, the number of vehicles with ICEs could be lower than anticipated, as refilling these vehicles become unfeasible because of the scarcity and economic uncertainty of fossil fuels. While the number seem to show extreme outcomes over a short period, the results align with the UK government strategies [229].

4.3.2 Annual Carbon Emissions

The predicted annual carbon emissions from passenger vehicles by source ─ tailpipe, fuel production and electricity production ─ in Great Britain under the baseline case are shown in Figure 4.31. In 2020 carbon emissions dropped to 75 $MtCO_2$ emitted during the use phase, a 26.5% drop from 2019 based on this study model, as result of coronavirus measures. Once coronavirus restrictions were eased in 2021, allowing people to travel more freely, carbon emissions increased to 79.5 $MtCO_2$, 5.9% rise from 2020, but still 22% below 2019 level. Carbon emissions are expected to rise in 2022, reaching 95.8 $MtCO_2$ but decreasing to 30.6 $MtCO_2$ by the end of the transitioning period in 2035, 70% drop from 2019 and 59.3% from 2020. The continuous yearly drop in carbon emissions is driven by phasing out petrol and diesel vehicles, increase share of electrified vehicles, improved overall powertrain efficiency and cleaner electricity grid mix. The decline will reach 1.9 $MtCO_2$ in 2050, 93.8% decrease from 2035, 97.5% from 2020 and 98.1% from 2019.

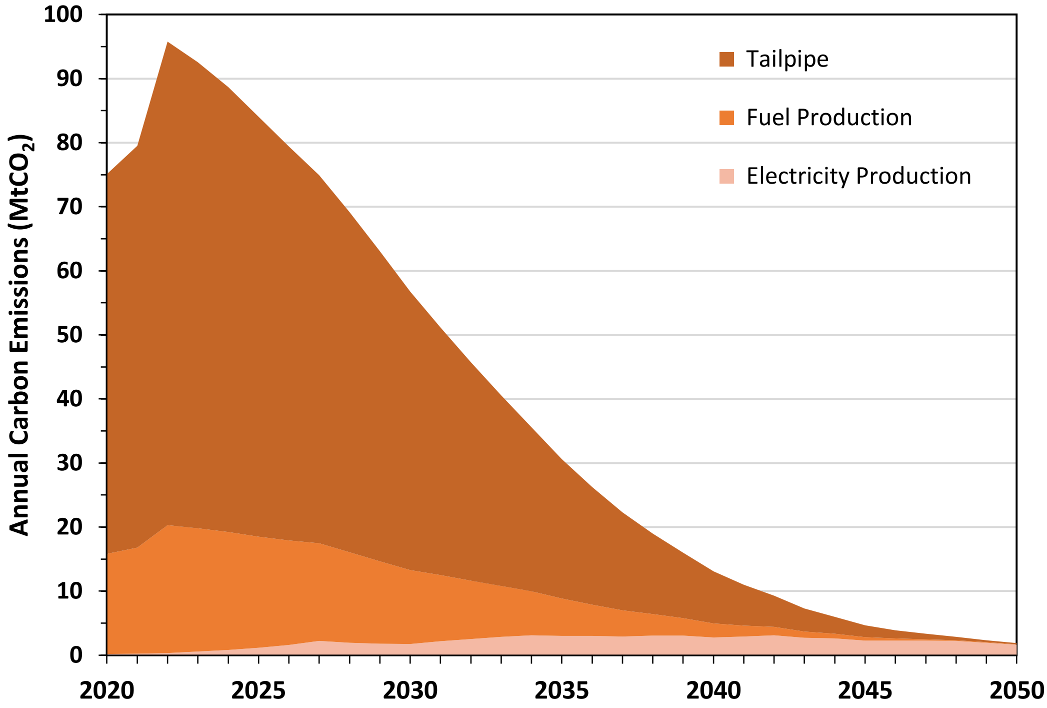

Figure 4.31: Annual carbon emissions of passenger vehicles during the use-phase in Great Britain between 2020 and 2050.

Tailpipe emissions contribute to the majority of annual carbon emissions, 79% in 2020 and only drop below 50% in 2043, even with the current targets to end the sale of ICE vehicles. Emissions from fuel production are typically overlooked [230], yet, they account for 20.9% of total annual emissions in 2020. While the percentage continues to drop over time, reaching 17% in 2039, fuel production emissions remain above electricity production emissions.

Emission from charging BEVs and PHEVs have minimal contributions compared to tailpipe emissions. In 2020, a total of 0.15 $MtCO_2$ carbon emissions were produced to charge these vehicles, accounting for 0.20% of the total emission. This low percentage is mainly due to the small number of BEVs currently on the road. However, by 2030, where BEVs and PHEVs are predicted to account for over 50% of the fleet, electricity production emissions are expected to be 1.73 $MtCO_2$, 3% of total emissions, and 3.01 $MtCO_2$, by 2035, 9.8% of total emissions. The low carbon emissions are due to the cleaner electricity grid projected in the future due to an increase in renewables share. By 2045, carbon emissions from charge BEVs and PHEs will overtake tailpipe emissions and become the largest contributor to use phase carbon emissions.

4.3.3 Cumulative Carbon Emissions

Figure 4.32 shows the carbon emissions accumulated from 2020 to 2050 for each powertrain type, including the source of these emissions, tailpipe, fuel production and electricity production. While carbon emissions added from driving petrol vehicles remain low after 2040, when most of these vehicles would be phased out, they will still be responsible for 44.8% of 1211.7 $MtCO_2$ total cumulative carbon emissions by 2050, followed by diesel vehicles with 24.3%. HEVs and PHEVs contribution to total cumulative carbon emissions will continue to rise, reaching 18.8% and 7.3%, respectively. Cumulative carbon emissions from charging BEVs show a continuous increase as they become the majority of vehicles on the road over time, contributing to 4.8% of total cumulative emissions. Unlike ICE vehicles, BEVs have the potential to reduce their carbon emissions with age due to decreasing in electricity carbon intensity as the grid mix becomes increasingly cleaner. Figure 4.32 also shows that tailpipe emissions account for 74.8% of the total cumulative carbon emissions with 906.3 $MtCO_2$. Fuel production emissions will contribute to 240.6 $MtCO_2$ cumulative carbon emissions by 2050, accounting for 19.9% of total cumulative carbon emissions, demonstrating the impact of fuel production. In comparison, cumulative carbon emissions from electricity production to charge BEVs and PHEVs result in 64.7 $MtCO_2$, 5.3% of the total.

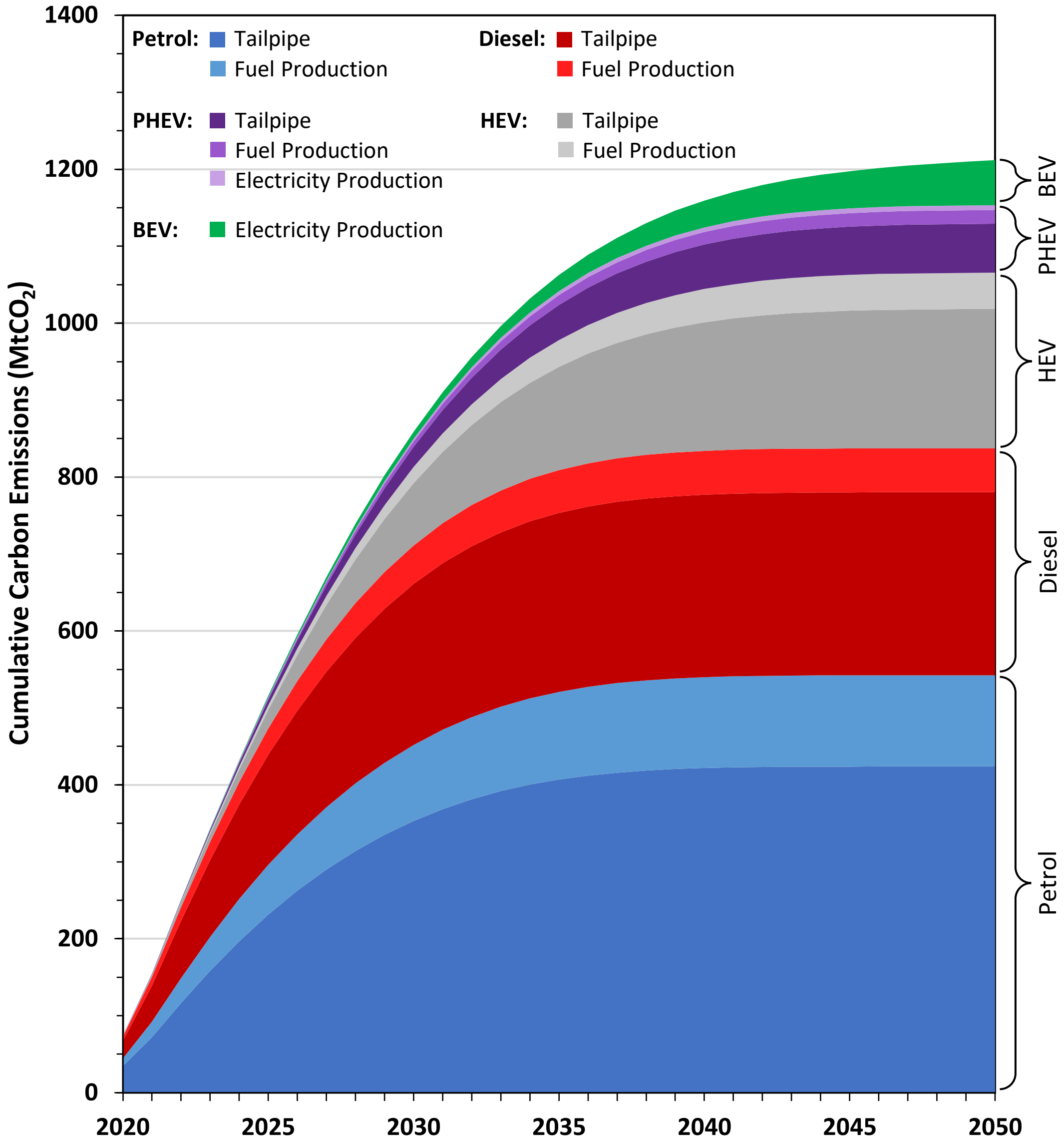

Figure 4.32: Cumulative carbon emissions from passenger vehicles during the use phase in Great Britain from 2020 to 2050.

The electricity grid data used in this study only considered metered generators [231]. An off-grid solar system for charging BEVs will not be visible to the grid but will further reduce carbon emissions. Access to solar-powered charging systems reduces ownership costs over time and significantly reduces GHG emissions [232]. Many rapid charging forecourts are expected to spread across the country in the following decades. The UK first solar-powered forecourt operates with its battery energy storage system (BESS), which aims to demonstrate the forecourt economic, social, and environmental benefits [233]. Integrating BESS with solar for charging stations reduces the dependence on the grid, offsetting electricity demand [234]. An increasing number of charging stations coupled with a solar farm will further reduce BEVs carbon emissions.

The UK government policies to decarbonise the transport sector are technology neutral. However, this work sets the transition for passenger vehicles to shift entirely to BEVs. Fuel cell electric vehicles, have not been considered due to several setbacks withheld their mass adoption, including lack of availability, infrastructure and difficulty in hydrogen transport, distribution and storage. According to IEA, most of the 94 Mt hydrogen global demand is produced from fossil fuels, while low emissions hydrogen contributes to no more than 1 Mt of the total production in 2021 [235]. Water electrolysis accounts for less than 0.1% of hydrogen production, with a fraction of this powered by renewable energy [236]. The heavy reliance on fossil fuels to produce hydrogen defies the target to decarbonise passenger vehicles and reduce the reliance on fossil fuels. A similar argument can be made about using hydrogen in ICEs, and the lower ICE efficiency would amplify hydrogen drawbacks. The energy-intensive production of e-fuel from hydrogen and captured CO_2 requires a significant amount of renewable energy, making e-fuel difficult to scale and economically inviable for passenger vehicles. The losses in each step of e-fuel from electricity to useful energy result in an efficiency of 10%, leading to the use of e-fuels in an ICE vehicle requiring at least five times more electricity than directly using electricity in BEV [237].

4.3.4 Scenarios Results

Figure 4.33 shows the change in the accumulated carbon emissions in 2050 for each scenario compared to the baseline and sources of these changes. In general, higher vehicle usage scenarios lead to a higher increase in total cumulative carbon emissions and lower usage reduces the emissions. The highest increase of 78.9 $MtCO_2$ will be achieved in the High Ownership + High Usage scenario, where BEVs are responsible for 20.9% of that increase as their emissions increase by 16.5 $MtCO_2$, 28.3% increase from the baseline. The most significant decrease equals 70.1 $MtCO_2$ saved in the Low Ownership + Low Usage scenario, where BEVs emissions decrease by 22.1%. In either High Ownership or High Usage scenarios, total cumulative carbon emissions are expected to increase by 33.6 $MtCO_2$ and 42.1 $MtCO_2$, respectively. For the Low Ownership scenario, a reduction of 30.9 $MtCO_2$ occurs similarly to the Low Usage scenario with a 42.1 $MtCO_2$ drop in total cumulative carbon emissions.

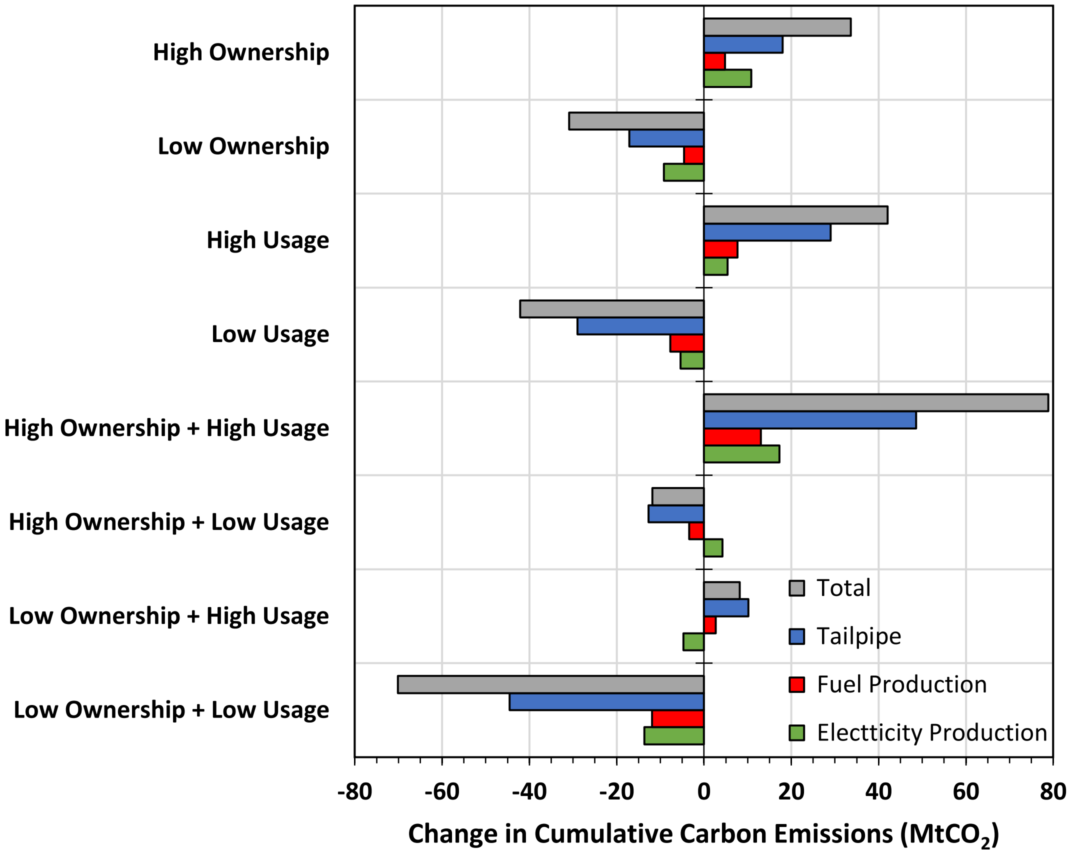

Figure 4.33: The changes in cumulative carbon emission for each scenario by 2050 compared to the baseline.

Both tailpipe and fuel production accumulated carbon emissions follow the pattern of total cumulative emissions in all the scenarios. For electricity production, the cumulative carbon emissions show an increase in the High Ownership + Low Usage scenario and a decrease in Low Ownership + High Usage, and the opposite behaviour compared to the tailpipe and fuel production. The main reason for the difference can be traced to the projected road traffic and the number of each type of vehicle still in operation for each scenario.

Figure 4.34 shows the projected road traffic in 2035 and 2050 for all scenarios, including baseline and the historical values in 2019 and 2020 added for comparison. Higher Ownership, High Usage and Higher Ownership + High Usage scenarios will see increasing road traffic until 2050. In contrast, a Low Ownership scenario, Low Usage and Low Ownership + Low Usage scenarios will have declining road traffic over time, reaching below the 2019 level in 2050 and in the extreme case of Low Ownership + Low Usage to be below 2020 road traffic level. For High Ownership + Low Usage, road traffic will increase from 2035 to 2050. During that period, most road traffic will be covered by BEVs and all new vehicles will be BEVs, thus increasing electricity production cumulative carbon emissions (Figure 4.32). For the same scenario, other vehicles with direct emissions from the tailpipe will decrease in number and usage, leading to a decrease in their cumulative carbon emissions by 2050 compared to the baseline. In the Low Ownership + High Usage scenario, road traffic and the number of new vehicles will decrease with time, decreasing cumulative electricity production carbon emissions for charging BEVs compared to the baseline (Figure 4.33). However, for ICE vehicles for the same scenario, while their number will decrease, their usage would be higher than the baseline, leading to an increase in tailpipe and fuel production cumulative carbon emissions (Figure 4.33) since their emissions do not improve with age, as previously discussed.

These findings show that an increase in ride hailing services could reduce carbon emissions even with higher vehicle usage if overall vehicle ownership is reduced and BEVs cover driving. Also, the above analysis reveals that a change in travel demand will have a larger impact on road traffic than cumulative carbon emissions, as the road traffic in the best-case scenario is 31% and 58% lower in 2035 and 2050, respectively, compared to the worst case of high ownership with high usage. The difference between the best and worst-case scenarios in terms of cumulative carbon emissions is only an 11% reduction. The main reason is the low carbon emissions of future vehicles, resulting from a cleaner electricity grid and highly efficient powertrain, as reported by other authors with similar findings [81].

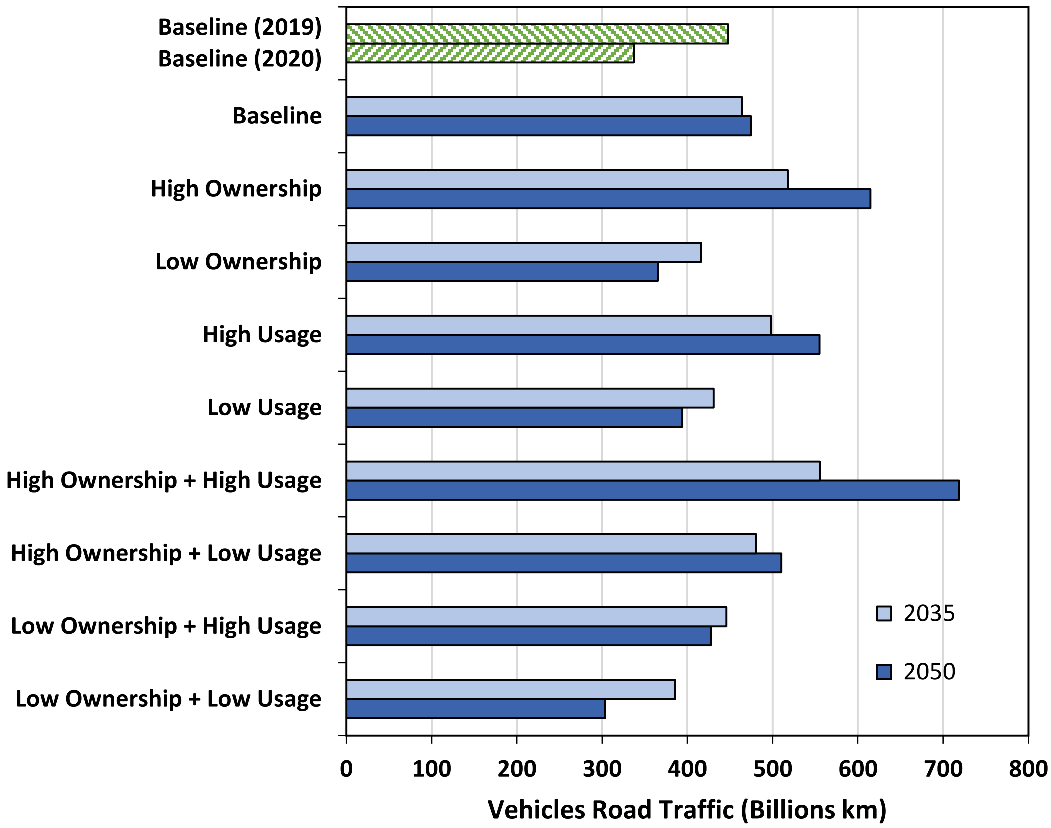

Figure 4.34: Road traffic projecting in 2035 and 2050 for each scenario.

The benefits of reducing vehicle ownerships can be extended to include carbon emissions associated with the manufacturing phase of vehicles. Nearly 3.6 $kgCO_2/kg$ is emitted during the production of one vehicle [81]. Thus, a significant reduction in carbon emissions can be achieved with fewer vehicles being sold. In the case of BEVs, a lower number of vehicles needed in the future reduces battery production emissions, which is shown to be an energy-intensive process. According to a recent report by IVL [238], 60-106 $kgCO_2$ are produced for every kWh of battery capacity. Based on current estimates, the UK will need 52 GWh of battery capacity in 2025, increasing to a yearly average of 144 GWh battery capacity from 2035 to meet the local demand for new vehicles sales.

Figure 4.35 shows that battery production cumulative carbon emissions under different scenarios of ownership. Battery projection for new HEVs, PHEVs and BEVs will lead to 77.7 $MtCO_2$ cumulative carbon emissions by 2050 for the baseline scenario, using current and future projections of battery production carbon emissions per kWh from Ricardo [239]. A High Ownership scenario would lead to a 15.6 $MtCO_2$ increase in cumulative carbon emission from battery production by 2050 or, in the case of a Low Ownership scenario, a reduction by 12.9 $MtCO_2$. However, battery recycling might reduce carbon emissions produced during manufacturing as using recovered material from recycled batteries is less energy-intensive than producing batteries from virgin ones [240].

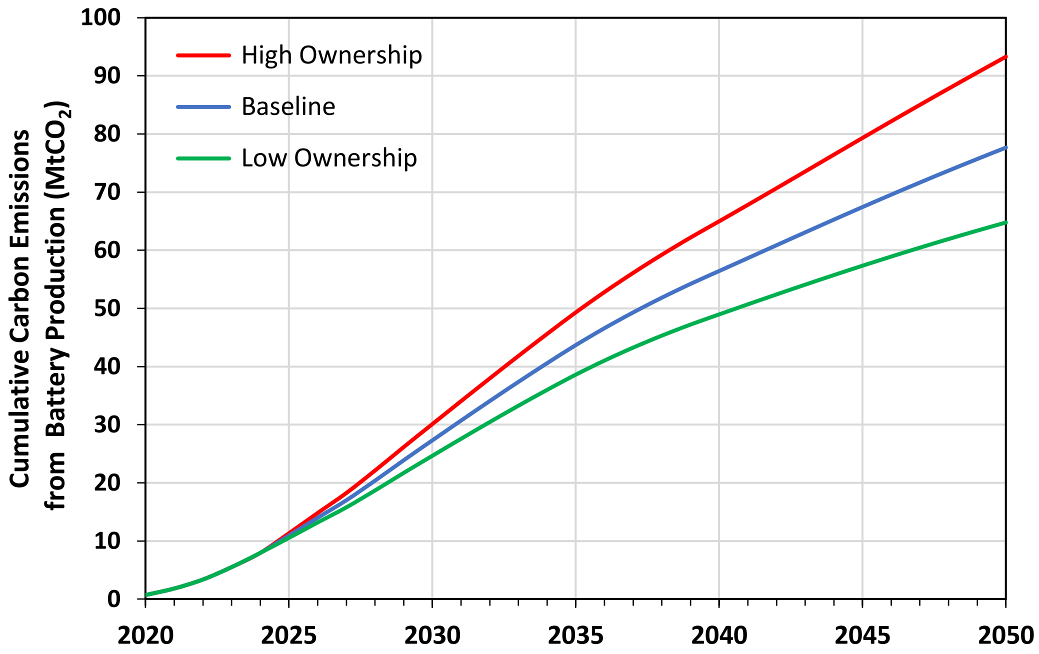

Figure 4.35: Cumulative carbon emissions from battery production of new HEVs, PHEVs and BEVs in Great Britain from 2020 to 2050.

ULEZs and CAZs aim to charge petrol and diesel vehicles that exceed Euro emissions standards to enter certain areas to reduce the usage of pollutant vehicles

[241]. Introducing these schemes can drop vehicle usage, leading to reduced road traffic [29]. If similar policies were widely adopted in the UK aiming to drop road traffic, and assuming these plans were able to reduce the usage of petrol and diesel vehicles by 17% in 2040, it would lead to a reduction of cumulative carbon emission by 30 $MtCO_2$ in 2050. If the schemes expand to include HEVs, the reduction in cumulative carbon emissions will increase to 51.5 $MtCO_2$ by 2050. A further reduction of 45% can be achieved by moving the target to reduce road traffic to 2035. While CAZ regulations have the potential to improve air quality, particularly in urban areas, they still risk the possibility of people with cleaner vehicles being reluctant to use public transport or shift to active modes [242].

The change in travel demand through vehicle ownership or usage can go beyond the impact on carbon emissions. Figure 4.36 shows the annual electrical energy demand for each scenario, with the majority of demand due to charging BEVs. In the baseline, electricity demand will keep increasing and peak at 98 TWh in 2050 due to increased BEVs numbers. Any scenario that sees an increase in vehicle ownership will lead to an increase in electrical energy demand compared to the baseline. In the High Ownership scenario, the demand will reach 127 TWh in 2050 and 149 TWh for the High Ownership + High Usage scenario, 52% increase from the baseline. A decrease in vehicle ownership will cause a reduction in electrical energy demand. In the Low Ownership + Low Usage scenario, energy demand will peak in 2044 (66.3 TWh) and decline to 62.7 TWh in 2050, a 36% reduction from the baseline.

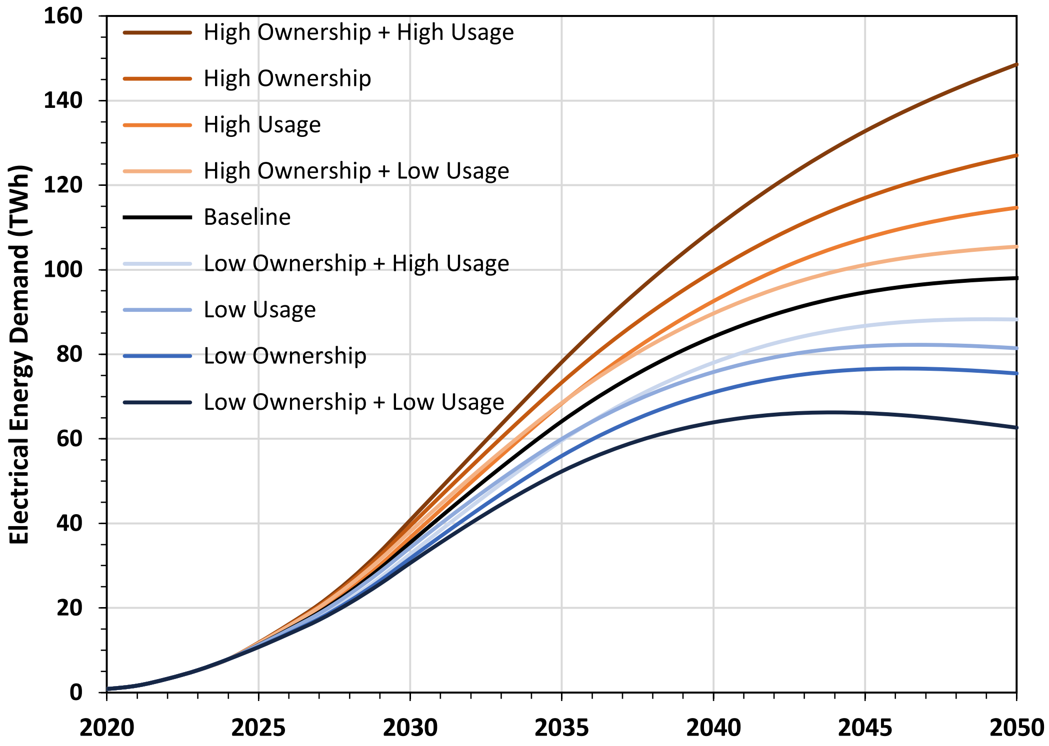

Figure 4.36: Annual electrical energy demand to charge BEVs and PHEVs for each scenario from 2020 to 2050.

4.3.5 Sensitivity Analysis

Sensitivity analysis has been carried out to test the impacts on cumulative carbon emissions from several key variables such as vehicle efficiency, electricity grid carbon intensity and the year to end sale of HEVs. The rapid growth in BEVs globally could result in the efficiency and performance of ICE vehicles remaining unchanged as more resources are allocated to developing BEVs [243]. One major car manufacturer will end the investment in new engines for all its major markets, justifying the decision due to the rising cost of developing new ICEs [244]. Other manufacturers are also considering similar decisions due to challenges in meeting the expected stricter emissions regulations [245]. Some authors suggested that the diversification of technologies in the transport sector is the solution to mitigate carbon emissions, and there is still significant potential to improve ICEs [246]. Major manufacturers are introducing larger and more powerful, and the social pressure to increase BEV size leads to an increase in energy consumption [247]. While increased experience in designing BEVs leads to reduced transmission losses, aerodynamics improvement, lower weight and reduced rolling resistance [248]. However, larger EVs with bigger batteries diminish any improvement in electric powertrain overall efficiency. Therefore, the simulation model has been adjusted to conduct different cases of yearly efficiency improvement in new vehicles for ICE and electric powertrain until 2035 and their impact on cumulative carbon emissions.

Figure 4.37 presents the change in cumulative carbon emissions in 2050 compared to the baseline impacted by changes in new vehicle efficiency improvement. Improving new diesel and petrol vehicles efficiency will have a modest positive impact on changing cumulative carbon emissions and a similar negative impact with no further efficiency improvements to current levels, as most of these vehicles have already been registered. For HEVs, if new vehicles efficiency remains at the current level without improving, there is a risk of cumulative carbon emissions increasing by 20.8 $MtCO_2$, while the opposite occurs if the rate of improvement doubles in the following years, as a high percentage of HEVs that would remain on the roads are set to be sold in the following years. Increasing new BEVs efficiency to match the ICE vehicle value of nearly 2% yearly improvement would reduce cumulative carbon emissions by 10.6 $MtCO_2$. In comparison, a yearly decrease of 2% in new BEV efficiency would increase cumulative carbon emissions by 13.1 $MtCO_2$. These findings highlight the need for future vehicles with ICEs to be highly efficient, particularly HEV, which can be achieved with stricter emissions standards and ensuring any improvement under laboratory tests can be translated to the real world.

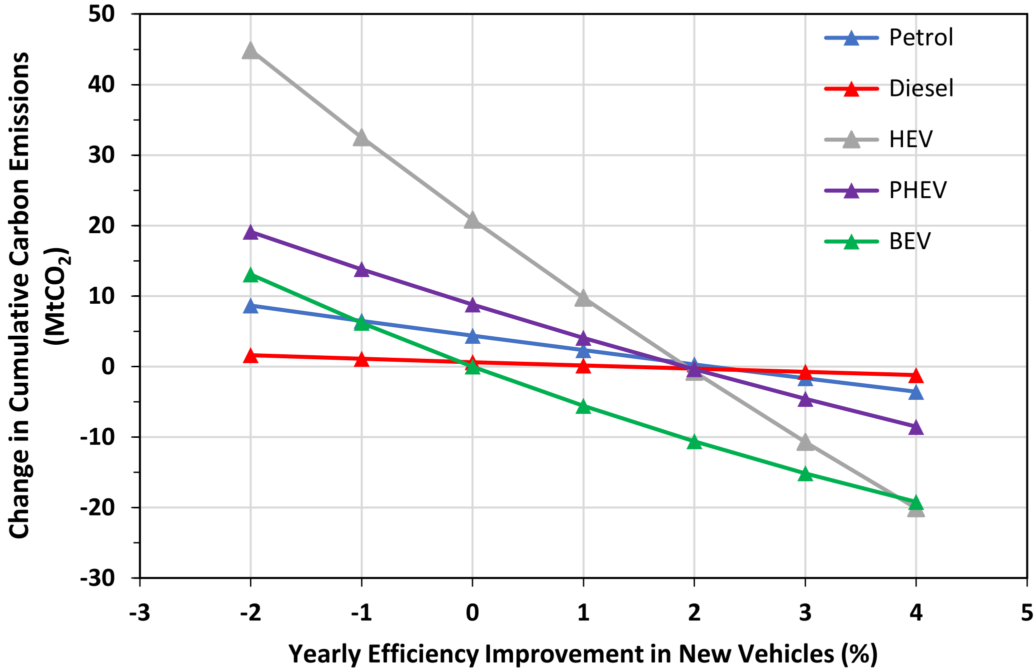

Figure 4.37: Changes in cumulative carbon emission by 2050 compared to baseline due to changes in new vehicles efficiency for each powertrain type.

The previous results used the National Grid steady progression scenario for the electricity generation mix. The National Grid provides additional pathways for accelerating the decarbonisation of electricity supply, while the assumptions are more ambitious yet credible from the CCC [158]. In the high ambition case, the government's commitment for offshore wind to reach 40 GW by 2030 is met and has a stronger push to develop new projects earlier for increasing generation from renewables, including solar, with additional 17 GW by 2050. Electricity generation carbon intensity for the Leading the Way scenario was used for the high ambition case and to measure the impact on cumulative carbon emissions. Another case was considered where the transition is slower to decarbonise the electricity grid. In the low ambition case, government policies are pushed back to their original targets, for example removing coal from the electricity mix by 2025 instead of the new target in 2024 and minimum offshore wind to be 25 GW by 2030 compared to 31 GW. For this case, electricity generation carbon intensity from older National Grid FES was considered [249]. The electricity grid carbon intensity for each case is shown in Appendix A, Figure A 3.

The results of different cases of electricity grid mix impact on electricity production carbon emissions to charge BEVs and PHEVs are shown in Figure 4.38. Annual carbon emission from electricity production peaks in 2032 and 2034 for the high ambition and steady progress, respectively, compared to 2043 for the low ambition peak due to the increasing number of BEVs and carbon intensity showing a low declining rate. In the high ambition to decarbonise the electricity grid, cumulative carbon emissions in 2050 from electricity production to charge BEVs and PHEVs will equal 27.9 $MtCO_2$, lower by 36.8 $MtCO_2$ from steady progress or 43% of the original value of steady progress of 64.7 $MtCO_2$. In the low ambition case, the progress in decarbonising the electricity slowed from current targets would lead to additional 115 $MtCO_2$ in electricity production cumulative carbon emissions compare to steady progress. These demonstrate the strong influence of the electricity generation mix and the importance of maintaining current targets to decarbonise the grid.

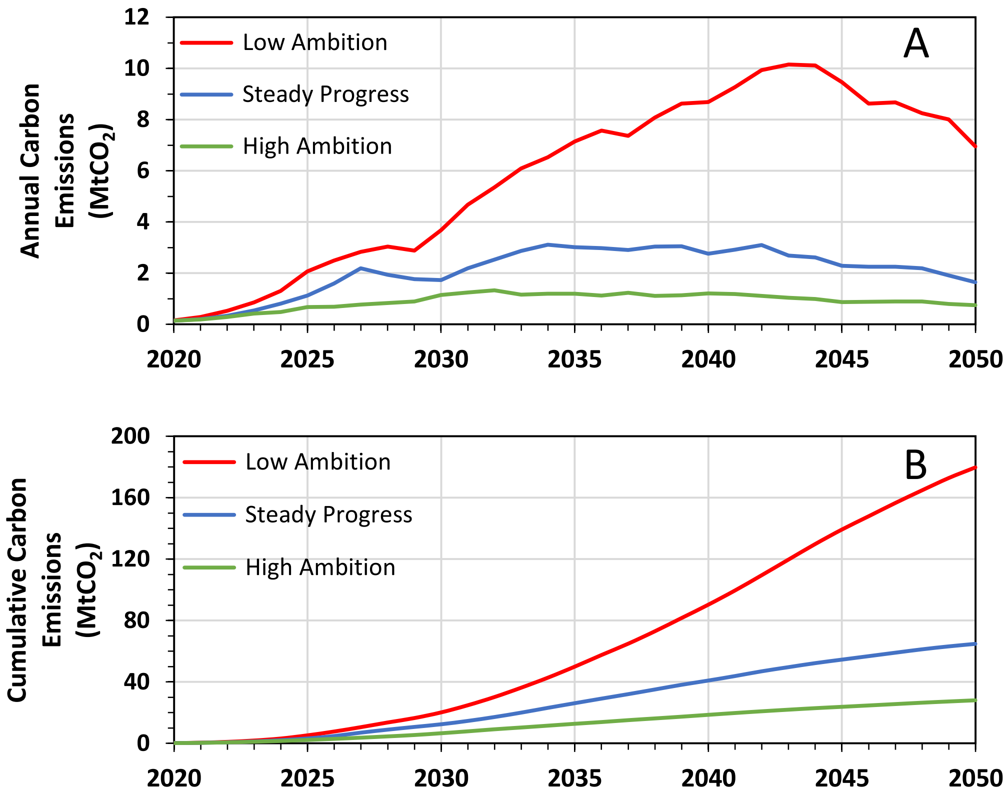

Figure 4.38: Sensitivity analysis results for the electricity grid. A) Annual carbon emissions from electricity production to charge BEVs and PHEVs and B) Cumulative carbon emissions to charge BEVs and PHEVs from 2020 until 2050.

The UK government plans to end the sale of diesel and petrol vehicles by 2030 and set a target that all vehicles sold between 2030 and 2035 must be able to drive a significant distance with zero tailpipe emissions. However, the value of this range has not been defined yet. Therefore, including HEVs in the 2030 ban remains uncertain. Recent government response to the green paper mentioned a distance between 8.4 miles to 150 miles [7]. The model has been adjusted to consider the sale of HEVs to end by 2030. Two cases were modelled: in one case, the portion of new vehicles initially set to be HEVs from 2030 to 2035 was assumed to shift to BEV, resulting in a reduction of 18.7 $MtCO_2$ in cumulative carbon emissions in 2050. Another case was simulated where the shift goes to PHEVs, resulting in a lower reduction of 10.1 $MtCO_2$. The results show that while considering HEVs in the sale ban by 2030 reduces cumulative carbon emissions, as previously mentioned, ensuring highly efficient HEVs above current efficiency improvement to be sold until 2035 would bring greater benefits.

4.4 Regional Comparison

4.4.1 Travel Distance

Figure 4.39 shows the average vehicle mileage for each region divided by road class. Except for London, the average annual distance travelled per vehicle in all regions ranges from 14000 to 16000 km, with Wales having the highest mileage. The relatively low vehicle mileage in London, around 10600km, can be attributed to the overall decline in vehicle usage as population density increases and key investment decisions to expand rail transport rather than increase road capacity for vehicle traffic [250].

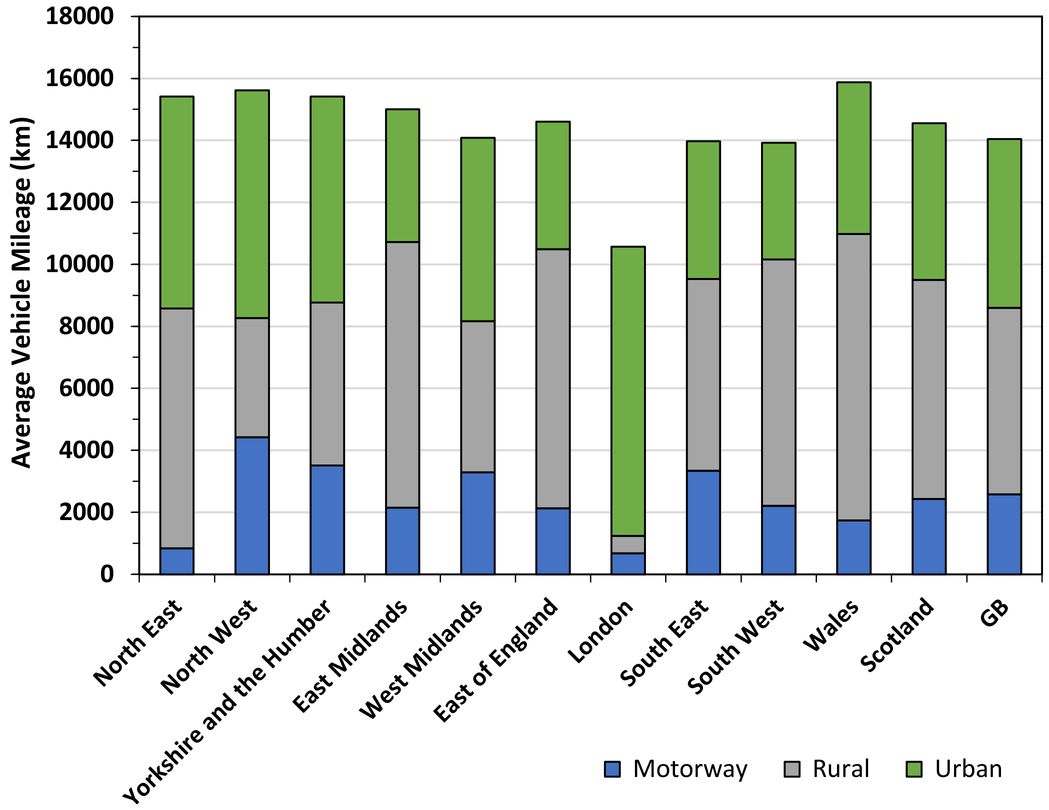

Figure 4.39: Average vehicle mileage by road class in each region.

Driving in North East, East Midlands, East of England, South West and Wales mainly consists of rural driving with over 50% of annual distance travelled. Besides London, North West has the lowest rural driving, below 25% of the overall distance, but relatively high motorway and urban driving, around 28% and 47%, respectively. West Midlands and Scotland have similar mileage to the national average, with slightly higher motorway driving in West Midlands and higher rural driving for Scotland. Urban driving in West Midlands has a close percentage and distance travelled value to the national average. This observation suggests driving in the West Midlands to be a good representative of driving in the UK, especially for EVs, due to similar urban driving patterns.

4.4.2 EV Energy Consumption

Figure 4.40 shows the annual energy an EV will consume when driving in each region divided by road class. The results highlight the variation in energy consumption when considering the difference in mileage, road class and ambient temperature between the regions. The energy consumption in London has the lowest value because of the low mileage. The low temperatures in northern regions influence the increase in energy consumption, especially in Scotland and North West. While North East and North West regions have similar mileage, driving in North East has lower energy consumption due to the higher portion of rural driving, which is less affected by temperature variation. Both East of England and West Midlands have nearly equal energy consumption to the national average, but West Midlands has much closer value for urban driving.

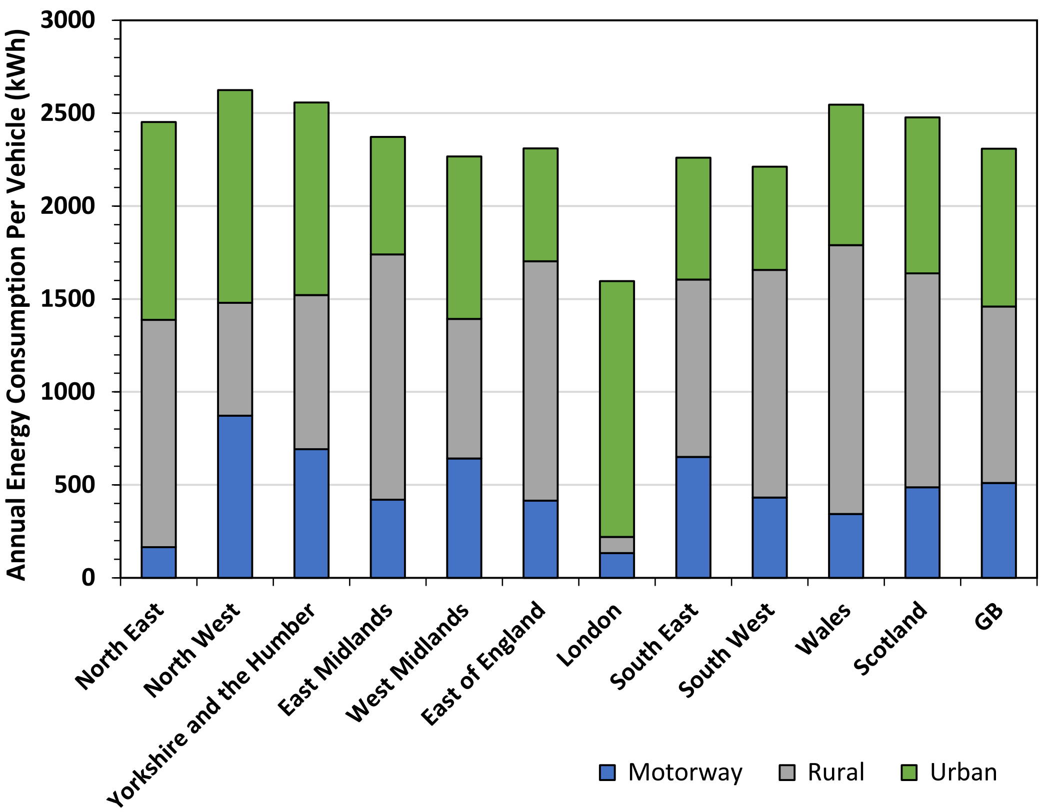

Figure 4.40: Annual EV energy consumption by road class in each region.

The appropriate planning for charging infrastructure should consider the energy consumption of EVs, the behaviour patterns of EVs users and the environment where chargers are deployed. [251, 252]. The real-world energy consumption results (Figure 4.40), combined with the data for the number of EVs in each region, would provide useful information for charging network operators and local authorities to optimise the charging infrastructure [253] regarding the charger location, numbers and size [254].

The mileage and energy consumption results of each region show that the real-world driving range of an EV will have the highest drop from the advertised WLTP range in Scotland, followed by North West with 18% and 17%, respectively. Conversely, driving in London will have the lowest impact on dropping the EV range by an 8%, compared to the national average of 15%.

4.4.3 Uncontrolled and Smart Charging Scenarios

Uncontrolled charging

The impact of routine and minimal schedules on annual carbon emissions using uncontrolled charging for each region is shown in Figure 4.41. For all regions, routinely charging an EV regardless of the battery SOC could result in higher carbon emissions than charging the vehicle once the battery drops to a specific SOC, 14.6% increase based on national average. Battery capacity and energy consumption are some of the factors affecting the charging frequency of an EV [255]. The average EV with 64 kWh battery capacity needs to be charged once a week if only charged when the SOC drops to 15%, similar behaviour reported by research covering the needs and preferences of EV drivers in the UK [256]. For London, the charging frequency decreased to every 10 days due to the lower vehicle usage and thus lower energy demand. During winter, the frequency of charging an EV will rise due to an increase in energy consumption impacted by lower ambient temperatures. For example, in North West, the vehicle needs to be charged every 5 days in winter compared to 6 days in summer.

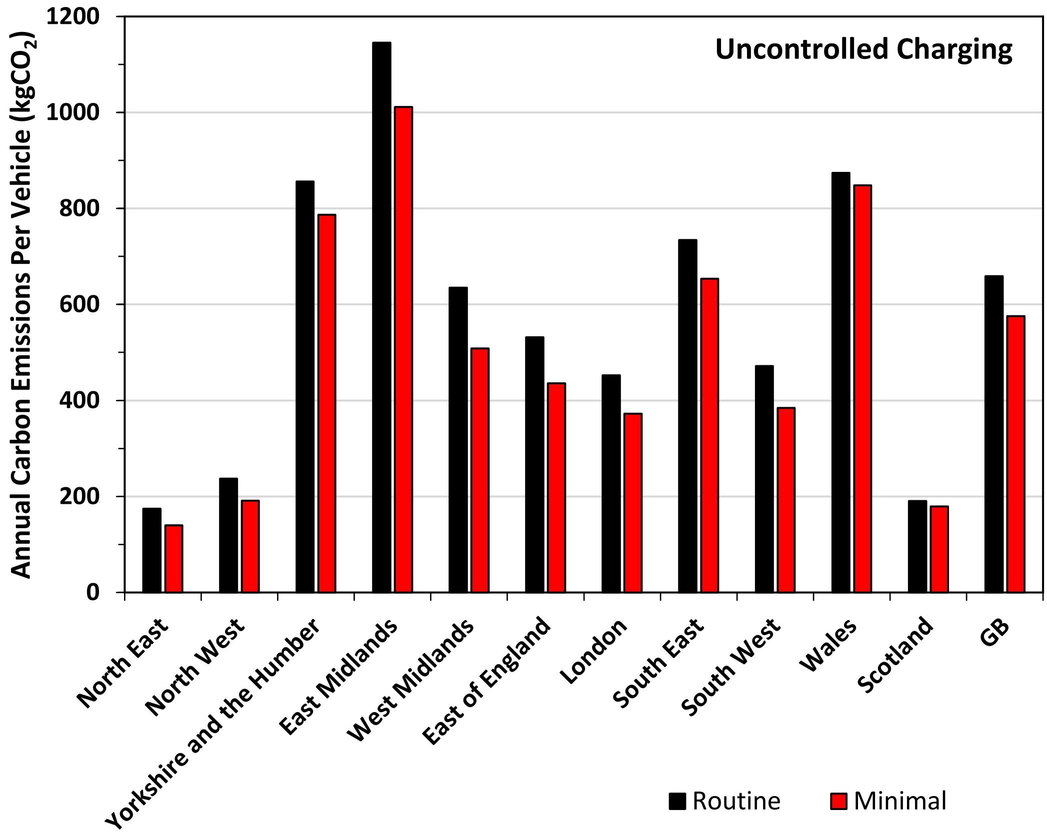

Figure 4.41: Annual carbon emission per vehicle using uncontrolled charging under routine and minimal schedules for each GB region.

Comparing both charging schedules shows that the minimal schedule has lower carbon emissions than the routine case in GB, leading to a yearlong saving of around 84 $kgCO_2$, 12.7% reduction. The percentage of reducing carbon emissions increases in the West Midlands to 19.9% but drops to 3% in Wales. In the routine schedule, the charging events will be relatively short, around 1 to 1.5 hours, since a small amount of energy is needed. Therefore, a routine schedule has higher carbon emissions because when routinely plugging in the vehicle at 6 pm and charging starts immediately, nearly the entire charging event will happen during peak hours of electricity demand, where carbon intensity is usually the highest (Figure 3.10 and Figure 3.11). For the minimal schedule, while the first part of the charging event will occur during peak hours, the charging will continue beyond the period of high electricity grid carbon intensity, as a typical EV takes around 7 hours to charge the battery from 15% to 90% SOC using a 7kW charger.

Delayed smart charging

Figure 4.42 shows the annual carbon emissions when using delayed smart charging, shifting the start of charging events from 6 pm to 10 pm for routine and minimal schedules, based on the new government regulations for smart charging. Delaying the charging from 6 pm to 10 pm will reduce annual carbon emission for both charging schedules, as charging events are shifted away from peak hours with high carbon intensity. Switching from uncontrolled charging to delayed smart charging reduces carbon emissions on a national level by around 21% and 12% for routine and minimal charging schedules, respectively. Regions that benefit the least from delayed smart charging, such as Wales, have relatively flat electricity grid carbon intensity compared to the other regions. East Midlands, with the highest annual carbon emissions, can save 229 kCO_2 by switching from an uncontrolled routine schedule to a delayed charging or 110 $kgCO_2$ for the minimal case. The gap in carbon emissions reduction between the two schedules in some regions, especially London, is due to the larger drop in carbon intensity during off-peak hours, partly covered by the minimal schedule, thus leading to a higher reduction for the routine schedule when charging is delayed to start at 10 pm. Regions with low annual carbon emissions will still benefit from the delayed charging, as the North East region reaches around 32% for both charging schedules.

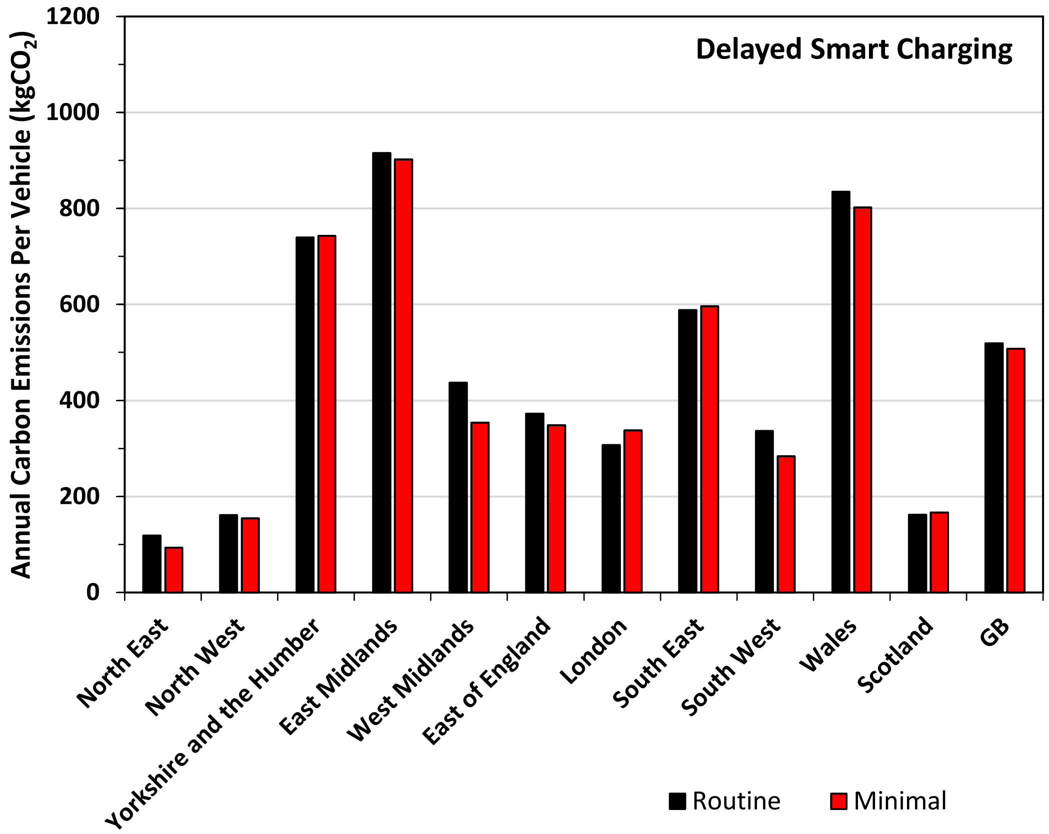

Figure 4.42: Annual carbon emission per vehicle using delayed charging in routine and minimal charging schedules for each GB region.

Optimised smart charging

Figure 4.43 shows the impact of optimised smart charging to minimise carbon emissions for each region under routine and minimal schedules. Opposite to uncontrolled charging (Figure 4.41), using optimised smart charging when plugging in an EV every day has lower carbon emissions than charging once the SOC drop to a minimum value in all regions. When switching from uncontrolled charging to an optimised smart charging that minimises carbon emissions for each region, the maximum reduction of 54% occurs in the North East region, followed by West Midlands with 53%. While the North East already has a small annual carbon emission, switching from uncontrolled to optimised can save 95 $kgCO_2$ for routine schedule. West Midlands will significantly benefit from optimised smart charging for a routine schedule, with 334 $kgCO_2$ saved. In GB, optimised charging reduces carbon emissions by 25% in routine schedule and 12% for minimal schedule.

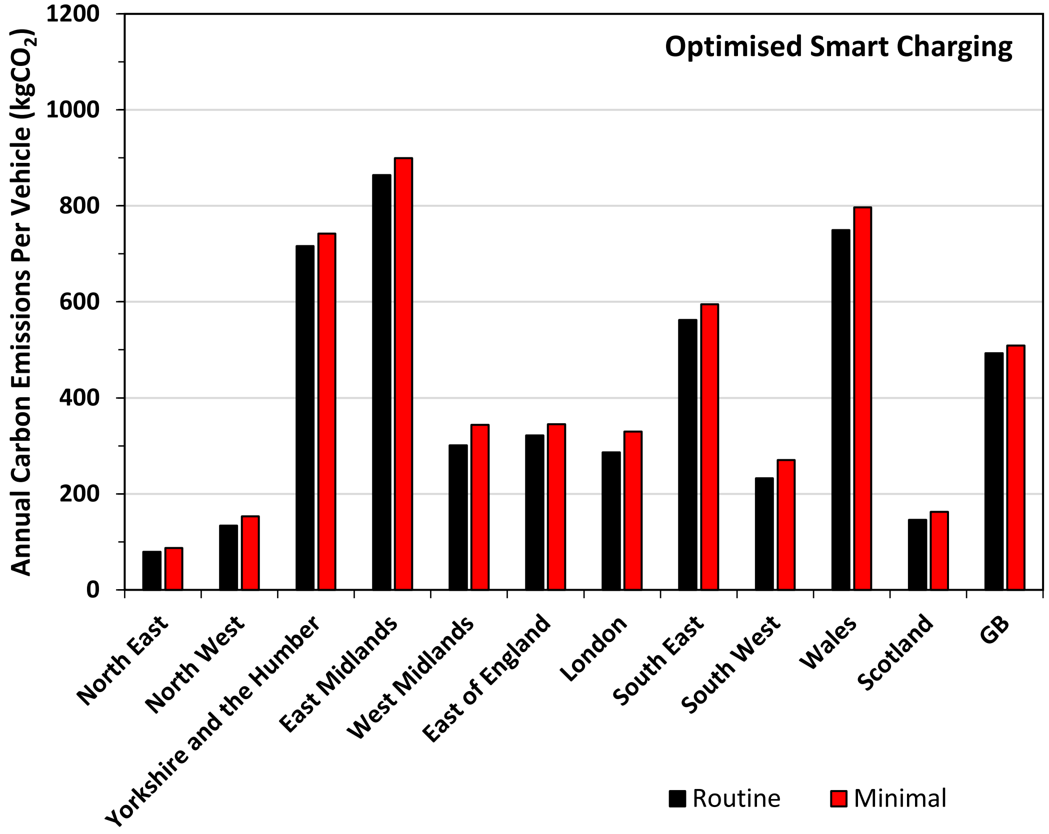

Figure 4.43: Annual carbon emission per vehicle using optimised charging in routine and minimal charging schedules for each GB region.

4.4.4 EV Carbon Emissions per Travel Distance

The carbon emissions per km when charging an EV using uncontrolled, delayed or optimised charging under routine or minimal schedules are summarised for each region in Figure 4.44. The results show the variations in carbon emissions per km impacted by where, when, and how an EV is charged as a direct result of the differences in electricity grid carbon intensity. For example, in East Midlands, the average monthly electricity grid carbon intensity has the lowest value of 309 gCO_2/kWh in August, rising by 57% in January to 489 gCO_2/kWh. In the North East, the average electricity grid carbon intensity ranges from 26 gCO_2/kWh in August to 70 gCO_2/kWh in November. In addition, the higher energy consumption in winter due to lower ambient temperature leads to an additional impact on increasing the carbon emissions of an EV.

Carbon emissions reduction varies between regions when switching from uncontrolled to smart charging. For example, delayed charging reduces carbon emissions by 4% to 33%, while optimised charging cuts carbon emissions between 6% and 55%. When comparing the regions, the carbon emissions per km trend follows a similar pattern to the overall carbon emissions, except for London. While the overall carbon emissions for London are lower compared to East of England, the carbon emissions per km for London are between 43 gCO_2/km to 39 gCO_2/km compared to East of England, 36 gCO_2/km to 22 gCO_2/km. Therefore, if the distance travelled per year was the same for both regions, charging an EV in London would lead to 23% to 18% higher carbon emissions than in East of England.

In the minimal schedule, optimised charging has little benefit in reducing carbon emissions for most regions compared to delayed charging. This behaviour is due to the less flexibility in moving the charging events in the minimal schedules as a result of the longer charging time compared to the routine schedule, which has a short charging window, making it more flexible to move. Also, delaying the charging to 10 pm already shifts the charging from the period of high carbon intensity, thus there is less opportunity to reduce carbon emissions further. In routine schedules for some regions, the benefits of optimised charging are far higher than delayed charging in reducing carbon emissions, such as West Midlands, South West and Wales. The variation in smart charging benefits under different charging scenarios in each region suggests that to maximise the opportunity for EVs to further reduce transport sector carbon emissions, charging strategies for EVs should be planned based on regional basis.

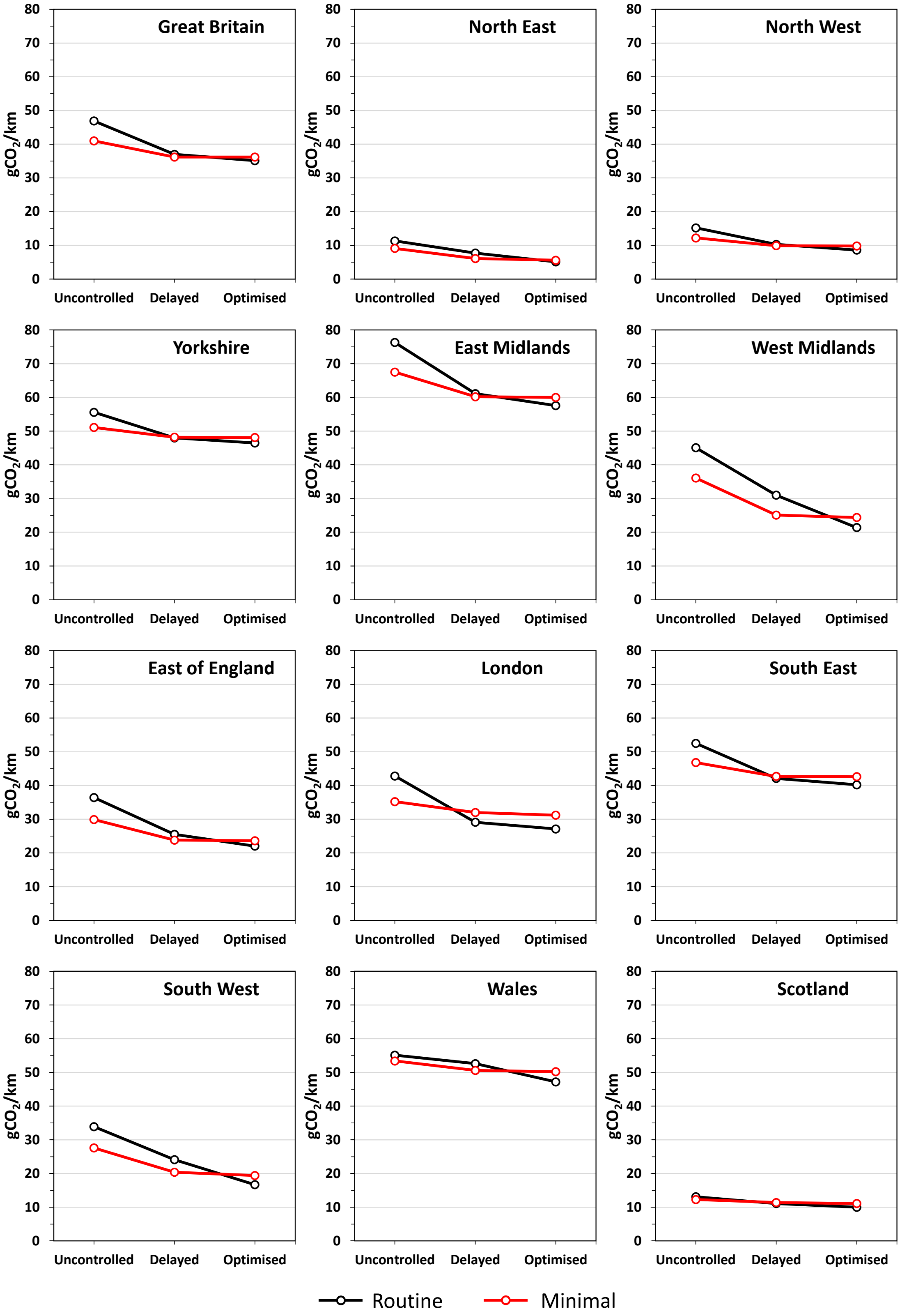

Figure 4.44: Carbon emissions per km under different charging scenarios for each GB region.

4.5 Chapter Summary

4.5.1 Electric Vehicle Energy Consumption

The energy consumption of an EV was evaluated using real-world driving data collected in Birmingham, the second largest UK city by population. The trips were selected according to fully compliance with the RDC test in the individual operation modes based on vehicle speed – urban, rural and motorway – and those with shorter distances than the specifications. The driving behaviour was classified as aggressive, moderate and passive, according to dynamic operation limits, and the parameters representing the traffic conditions were stop time percentage and average vehicle speed in urban driving. From the results obtained in this investigation and the performed evaluation, the following conclusions can be drawn:

- Ambient temperature is the parameter that can exert the highest influence on the specific energy consumption of an EV, with larger variability during cold conditions, nearly doubling SEC from operation at moderate temperatures around 19°C to operation at temperatures as low as 0°C in short trips.

- Changes in auxiliary energy consumption with ambient temperature are largely related to the use of HVAC system, as there is no evidence the other auxiliaries have a significant impact. Short-distance trips combined with high stop time percentage and low ambient temperatures produce the most favourable condition to increase SEC, as the HVAC system is more required.

- Aggressive driving increases SEC by up to 16% in comparison with passive driving and up to 7.1% compared with moderate driving, with more prominent effects in trips shorter than 16 km, highlighting the important role of driving behaviour on the efficiency of energy utilisation by an EV.

- Short distance trips produce large scattering of energy consumption and, in average, 9.7% higher SEC than RDC compliant trips over 16 km; this increase can reach up to 29% for trip distances lower than 4 km in motorway operation.

- Traffic conditions also shows its importance to energy consumption, showing a consistent rise of SEC with increased stop time percentage and decreased average speed in urban operation, reaching up to 19% higher energy demand at the most unfavourable condition.
- Ascending the road grade of 3% increased the SEC by 50%, while descending road grade of -3% decreased SEC by 80%, in comparison with flat roads.
- Urban and rural driving complying with the RDC procedure produce near SEC results in both cold and moderate temperature ranges, with motorway operation always producing higher SEC. Urban driving requires more energy to the auxiliary system, but also regenerates larger amounts of energy than rural and motorway driving.
- The vehicle range calculated from the RDC is about 30% lower than the value declared by the manufacturer from laboratory tests following the NEDC standard. Urban EV driving at cold conditions has a range 28% lower than operation under moderate temperatures.
- The EV energy consumption is minimum at the average speed of 55 km/h under cold conditions from 0°C to 15°C, and, for moderate temperatures from 15°C to 25°C, the lowest SEC value is obtained at 45 km/h.

4.5.2 Carbon Emissions Projection

This portion of the thesis has presented an investigation of carbon emissions projections of passenger vehicles in Great Britain considering the expected large EV market penetration between now and 2050. In addition, the impact of changes in travel demand on carbon emissions based on vehicle ownership and usage scenarios has been evaluated. From the results of this work, the following conclusions can be drawn.

- The decline in carbon emissions will continue until 2050, reaching a 97.5% and 98.1% decrease from 2020 and 2019 levels, respectively. Efficient BEVs and a cleaner electricity grid mix are the reasons for the reduction. Emissions from fuel production are relatively higher than expected and will remain above electricity production emissions until 2040.

- Petrol and diesel vehicles will contribute to 69.1% of total cumulative carbon emissions in 2050, even with the current government target to end the sale of these vehicles. At the same time, electricity production accounts for less than 5.3%.

- If the government fails to increase the appeal of public transport and move commuters to active transport modes, there will be an increase in vehicle number by 29.5% and usage by 17% in 2050. BEVs cumulative carbon emission will increase by 28.3%. A future with increased ride hailing services could result in lower cumulative carbon emissions even with higher vehicle usage only if the overall vehicle ownership is reduced and BEVs cover most of the driving. A scenario of low vehicle number and usage by 23% and 17%, respectively, could see reduction in BEVs cumulative carbon emissions by 22.1% and electrical energy demand by 36% in 2050.

- Changes in travel demand will have a larger impact on road traffic than cumulative carbon emissions during the use phase. The road traffic in the best-case scenario is 58% lower than road traffic in the worst case of high vehicle ownership with high usage in 2050. The difference between the best and worst cases in terms of cumulative carbon emissions is only 11% reduction, resulting from a cleaner electricity grid and highly efficient vehicles,

- The amount of 52 $MtCO_2$ can be reduced from cumulative carbon emission if clean air zones can reduce the usage of ICE vehicles by 17% in 2040. A further improvement to the electricity grid through added renewable energy sources will lead to an additional reduction of 36.8 $MtCO_2$ in electricity production cumulative carbon emissions.

4.5.3 Regional Comparison

A model was created to investigate the regional differences in energy consumption from driving an EV in each region and the associated EV carbon emissions while charging.

The developed model considers the difference in road class, mileage, ambient temperature and electricity grid profile in each region. The impact of two charging schedules – routine and minimal – on carbon emissions was evaluated for each region using uncontrolled and smart charging. The impact of delayed charging on carbon emissions based on the new government regulation was investigated. A charging optimisation model was created to minimise carbon emissions when charging an EV in each region. From this investigation, the following conclusions can be drawn.

- Charging an EV daily at peak hours regardless of the battery SOC under uncontrolled charging results in 15% higher carbon emissions than charging the vehicle once the battery drops to a specific SOC.

- A variation in reducing carbon emissions between the regions was observed using smart charging. Delayed charging reduces carbon emissions by 4% to 33%, while optimised charging to minimise carbon emissions led to a reduction between 6% and 55%, depending on the region.

- Delaying the charging reduces carbon emissions for routine and minimal schedules by 21% and 12%, respectively, as charging events are shifted away from peak hours of high electricity carbon intensity.

- Optimised charging reduces carbon emissions by 25% in routine schedule and 12% for minimal schedule compared to uncontrolled charging. However, optimised charging has little benefit in reducing carbon emissions compared to delayed charging, as delaying the charging to 10 pm already shifts charging events away from the period of high carbon intensity.

Chapter 5

Conclusion and Recommendations

5.1 Thesis Conclusion

The thesis aimed to investigate EV energy consumption under real-world driving and the associated carbon emissions during charging in the UK. First, EV energy consumption was evaluated following a standard real driving cycle (RDC) schedule based on the European RDE test procedure. The projected carbon emissions from passenger vehicles were determined considering the latest UK policies under different vehicle ownership and usage scenarios. Finally, the impact of different charging scenarios on reducing carbon emissions was investigated on a sub-national scale.

From the parameters investigated, ambient temperature and stop time percentage highly influence EV specific energy consumption. These parameters caused the largest variation of SEC in the range of trip conditions investigated. The effect of short trips on EV energy consumption is assessed under RDC for the first time. Short trips below 16 km, which are very common, exhibit high SEC during cold temperatures due to the heating system operating at high power for that short period, thus, repeated short distance trips will report lower driving range and increased energy consumption by an average of 10% compared to trips over 16 km.

While the existing regulations focusing on tailpipe emissions will reduce road transport carbon emissions, other actions can also lead to further reduction. Current policies and the suggested mandate do not differentiate between EV models. If implemented, the mandate should not only focus on vehicle numbers but be extended to consider the efficiency of EVs under real driving, which will ensure more efficient future vehicles operating on the road that further reduce carbon emissions.

The future cumulative carbon emissions from vehicles can be lowered by as much as 70 $MtCO_2$ from reducing their usage by switching to active travel. Extending clean air zones is another policy to consider lowering ICE vehicles usage, thus reducing their emissions further without introducing expensive and energy-intense alternative fuels. Additionally, to enhance the effectiveness of EVs in decarbonising transport, charging strategies should be planned based on regional basis.

The RDC/RDE test procedure here employed can be replicated to different EV models and locations in future studies. The current RDC/RDE standard has some limitations as it dismisses certain driving situations, including trips shorter than 16 km in a driving mode. It is expected that the results here produced can contribute to further developments of the RDC/RDE methodology in order to achieve a larger representation of real-world scenarios, especially short trips, as these are very common in urban driving. Since being incorporated to Euro 6 emissions standard in 2016, the RDC/RDE test procedure went through subsequent enhancements. In March 2020, the European Commission issued a combined evaluation roadmap for the development of Euro 7 emissions standard [257], including the RDC/RDE test procedure.

The results of this study provide useful information for the development of simulation models and prediction methods to estimate energy consumption that will aid car manufacturers with electric powertrain optimisation. They can also help with the development of more accurate tools to assist drivers for better planning of trips and recharging, as automotive manufacturers size the energy storage in EVs based on standardised driving cycles in laboratory tests. These tests lack representation of the real-world, as driving behaviour, traffic, road and temperature conditions are not fully reproducible. Therefore, the provision of actual EV energy consumption under real-world driving enables the correct sizing of EV batteries.

The outcomes of this work add additional evidence to support the government targets for EVs and provide useful information on the impact of current events and short-term strategies on transport decarbonisation, fleet compositions and energy demand. The results can also inform policymakers regarding the feasibility of long-term objectives and options for better planning to reduce road transport carbon emissions by 2050. The expected increase in EVs involves optimising charging infrastructure through the foresee charging demand and requirements. Analysis of EV driving behaviour alongside charging patterns provides valuable information on the development of charging infrastructure. Therefore, the outcomes of this investigation give assistance to local authorities for better infrastructure planning to meet the extra energy demand from the widespread of EVs. While this study focuses on EV market penetration in the UK, the results can guide other countries aiming to follow a similar path in decarbonising the road transport sector.

5.2 Future Work Recommendations

The influence of ambient temperature, traffic and driving conditions on EV energy consumption has been evaluated in this study. However, the role of other factors that may affect SEC, such as battery SOC and degradation, should be covered in future studies. In addition, the energy consumption of other EV models using the RDC test procedure could be investigated in further work at different locations or under extreme climate conditions while considering preconditioning the vehicle cabin for thermal comfort [258] and battery for charging [259]. Some EV models have different regenerative braking settings that the driver can choose from and offer optional advanced driver assistance systems. An interesting further work could evaluate the impact of these features on EV energy consumption tested under different operation modes using the RDC test procedure described in this study. Another aspect to consider for future work is the impact of power consumed by the BTM system under different climate conditions and the effect of battery pre-conditioning during driving on energy consumption.

Light duty vehicles, heavy goods vehicles and buses account for a third of road transport carbon emissions. The UK government has set to end the sales of new heavy goods vehicles with tailpipe emissions by 2040, while vans are included in 2035 targets [260]. The method applied in this study can be used by future research to evaluate light duty and heavy goods vehicles cumulative carbon emissions and the likely regional differences in carbon emissions utilising different charging strategies. Although this thesis has briefly discussed the changes in vehicle and battery production carbon emissions under different vehicle ownership and usage scenarios, the analysis can be extended by considering the complete life cycle analysis while recognising recycling and reusing EV batteries at the end-of-life impact on carbon emissions.

This study has focused on home charging only to evaluate the impact of uncontrolled and smart charging on carbon emissions in each region. However, the new charge points regulations also identify a part of morning hours as peak times. Further work could incorporate smart charging in workplace locations, shifting the charging schedules at mid-day and covering the impact on carbon emissions. The concept of vehicle-to-grid (V2G) technology offered by some EVs in which power could be discharged back to the grid has been covered in the literature focusing on maximising revenue, balancing the grid and impact on battery degradation [261]. The approach used in this study to develop the regional differences model could be adopted in future research covering V2G impact on carbon emissions and the possibility of optimisation for emissions reduction from a regional perspective.

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Appendix

Appendix A. Supporting Information

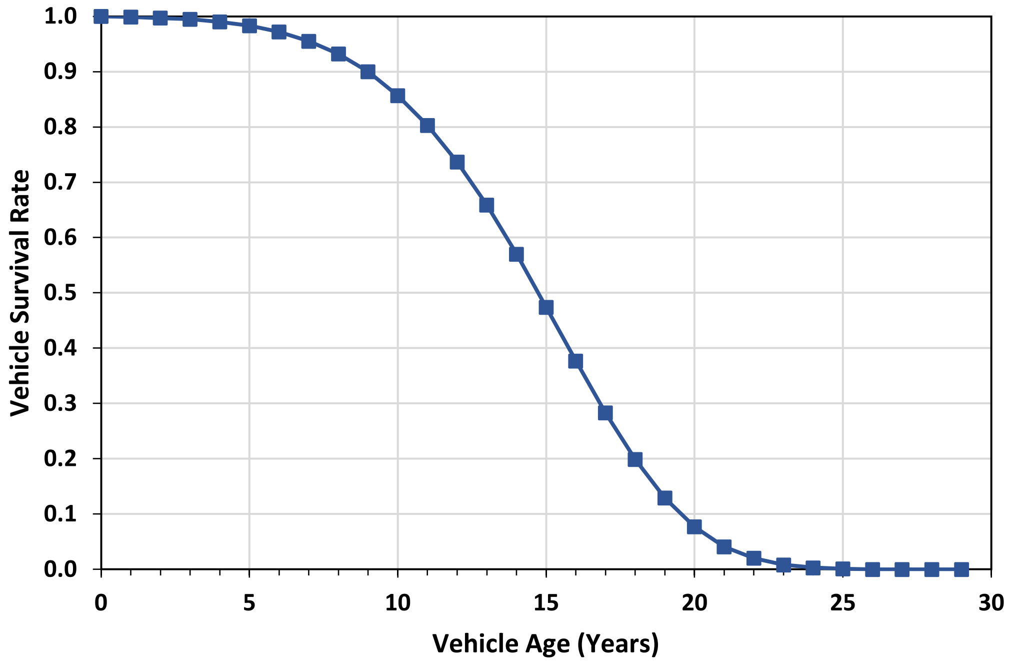

Figure A 1: Survival rate estimate of passenger vehicles with age in Great Britain.

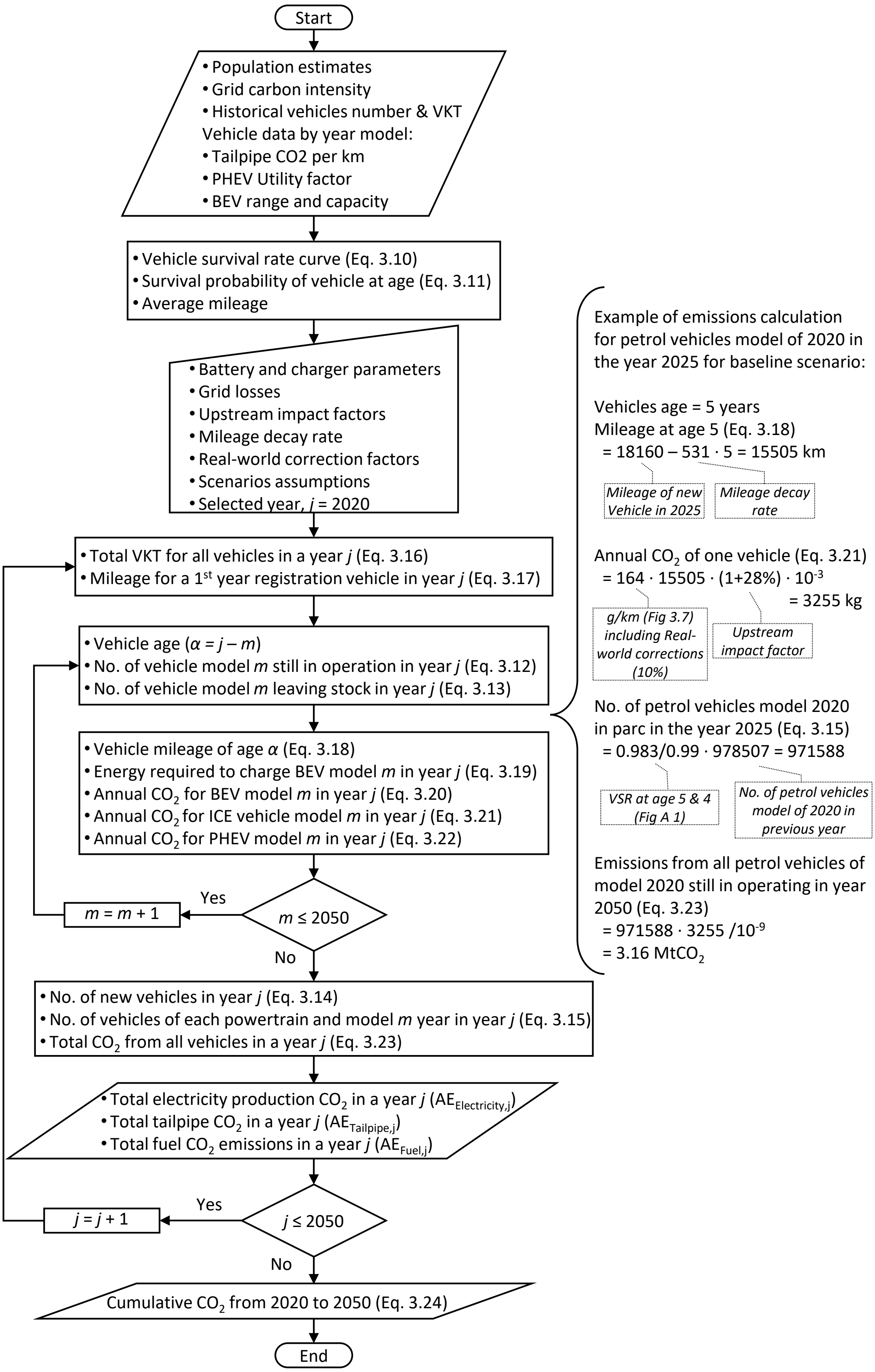

Figure A 2: Carbon emissions projection model flowchart.

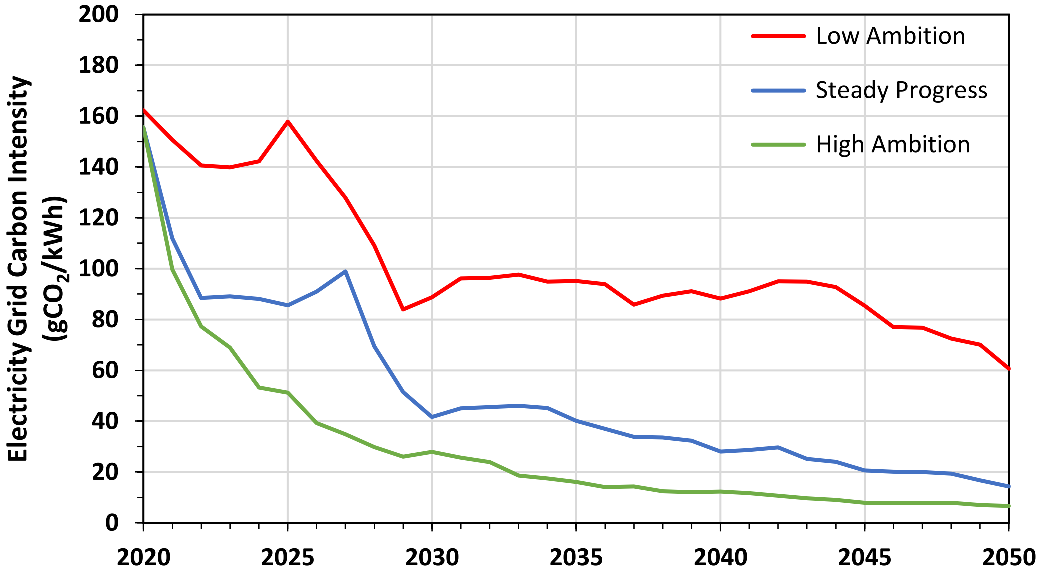

Figure A 3: Electricity grid carbon intensity projections from 2020 to 2050 under different scenarios, adapted from National Grid.

Appendix B. List of Publications

Part of this thesis contributed to the following publications:

Al-Wreikat, Y., Serrano, C., Sodré, J. R., (2021). "Driving behaviour and trip condition effects on the energy consumption of an electric vehicle under real-world driving," *Applied Energy*, vol. 297, pp. 117096. https://doi.org/10.1016/j.apenergy.2021.117096.

Al-Wreikat, Y., Serrano, C., Sodré, J. R., (2022). "Effects of ambient temperature and trip characteristics on the energy consumption of an electric vehicle," *Energy*, vol. 238, pp. 122028. https://doi.org/10.1016/j.energy.2021.122028.

Al-Wreikat, Y., Sodré, J. R., (2022). "Evaluating the energy consumption of an electric vehicle under real-world driving conditions," *SAE Technical Paper*, 2022-01-1127. https://doi.org/10.4271/2022-01-1127

Al-Wreikat, Y., Attfield, E. K., Sodré, J. R., (2022). "Model for Payback Time of Using Retired Electric Vehicle Batteries in Residential Energy Storage Systems," *Energy*, vol. 259, pp. 124975. https://doi.org/10.1016/j.energy.2022.124975.