Modelling Energy Use in Commercial Electric Vehicle Fleets

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Abstract

Emerging electric powertrain technology applied to motor vehicles, together with recent technological advances in battery technology and electric motor design, has significantly decreased vehicle lifetime carbon dioxide emissions. Similarly, an increase in vehicle energy efficiency is also expected as battery technology matures. This process, also known as motor vehicle electrification, is expected to lead to the decarbonisation of the automotive and transportation industry sectors, which will be a key step towards meeting climate accords targets.

Privately-owned passenger electric vehicles (EVs) have been thoroughly studied in recent years by the scientific and industrial communities alike, demonstrating their potential to reduce tailpipe vehicle-produced carbon emissions. However, there appears to be a significant gap in research literature covering the potential carbon reduction emissions in other classes of motor vehicles, such as heavyweight trucks and motorbikes. The operation of these vehicle categories has been shown to produce a significant amount of carbon dioxide and other greenhouse gases [1]. Therefore, a reduction in the emissions generated by these vehicles will prove to be key in the overall decarbonisation of the transport sector.

This thesis presents a novel, state-of-the-art, highly modular vehicle simulation model that can be configured to simulate the energy use of a wide range of electric vehicles, including electric refuse collection vehicles (eRCV), eBuses, eHGVs, as well as electric motorbikes. The simulation model features original, model-based programming techniques that utilise the Matlab/Simulink environment, to achieve minimal error rates in energy usage predictions. The simulation results are expected to provide a better understanding of the energy requirements of vehicle categories that have not yet been thoroughly researched.

Additionally, this thesis also provides example energy usage investigations as model applications that are expected to help towards examining the feasibility of electrified alternatives to conventional vehicles. These investigations rely on simulation-based research for specific types of vehicles, such as heavyweight public service vehicles (PSVs) and electric motorbikes. The simulations upon which the research is built utilise real-life data, recorded as vehicle telemetry, in order to provide the closest possible conditions to normal vehicle operation.

Finally, the thesis presents a potential battery pack concept as a potential solution for battery electric trucks. This is based on large-capacity electrical energy storage systems, packaged as pallet-compatible cargo loads, which can serve as vehicle range extenders. This concept, if implemented correctly, is anticipated to ensure that the range performance of current electric trucks is capable of meeting the demands of the current logistics operations and business models. Furthermore, as most of the electrical infrastructure required for the operation of the proposed concept pre-exists, costs related to system implementation and maintenance are expected to be minimal.

The research featured in this thesis is intended to kickstart further refined investigations towards a better understanding of the energy requirements these transportation modes will attract. Additionally, as the solution, concept and investigations presented in this thesis are presented in a technology-agnostic context, the featured research approach may be successfully extended to other vehicle categories and technologies not explored here. These include passenger EVs, but also vehicles powered by other green alternative energy sources (i.e. hydrogen fuel-cell, hydrogen ICE). Finally, the results and methods presented aim to fill in the identified research gap represented by energy prediction solutions and understanding electric energy requirements of EVs, especially focused on heavyweight public service vehicles (PSVs) and electric motorbikes. The research carried out, will also serve as a cornerstone for future technical evaluations.

Declaration

I, the author, confirm that the Thesis is my own work. I am aware of the University's Guidance on the Use of Unfair Means. This work has not been previously presented for an award at this, or any other, University.

Tudor Stincescu

30/03/2023

Acknowledgements

Well, it’s definitely been an interesting ride. It still feels a bit surreal having such a complex product of my work for the last three and a half years. There is a big list of people that have aided me throughout the research side of academia, which I will be always grateful to. However, I do have to admit Mr. Google, Google Academic can work wonders whenever you’re stuck on one concept that doesn’t seem to have a solution…

I realise now that, back when I have started this journey in 2019, I was little more than a bachelor’s graduate with ideas and a passion for optimising and linking things together. I won’t say that it was always easy – it wasn’t. But the satisfaction that I’ve got whenever my simulations finished without any errors or the acceptance letters I’ve got whenever I was rooting to have a research piece published will be something that will stay with me forever and always cherish. The most important progress that I’ve seen in myself, however, is in my ability to understand and interpret real life, which I feel enables me to conceptualise things to a whole new level. Some would call it…” growing up” I guess?..

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“What a long, strange trip it’s been” – although I couldn’t be happier about it.

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Publication List

Journal Articles

- **T. Stincescu**, R. Zhao, E. E. F. Ballantyne, D. A. Stone, "Optimising Number of Refuse Collection Stops per Street for Maximising Energy Efficiency of an Electric Refuse Collection Vehicle", *Journal of Transport Geography*, Place-based Decarbonisation special issue (under review)
- R. Zhao, **T. Stincescu**, E. E. F. Ballantyne, D. A. Stone, (2020) "Sustainable City: Energy Usage Prediction Method for Electrified Refuse Collection Vehicles.", *Smart Cities*, 3, 1100-1116. Available: https://doi.org/10.3390/smartcities3030054

Conference Proceedings

- **T. Stincescu,** E. E. F. Ballantyne, D. A. Stone, R. Zhao, M. P. Foster, (2023) "Predicting Energy Use of An Electric Vehicle using Vehicle Dashcam Telemetry Data.", World Conference on Transport Research (WCTR), Montreal, Canada, 17-21 July 2023
- M. N. Munoz, E. E. F. Ballantyne, D. A. Stone, **T. Stincescu**, (2023) "Using Locally Generated Renewable Energy to Charge Depot-based Electric Freight Fleets", World Conference on Transport Research (WCTR), Montreal, Canada, 17-21 July 2023
- **T. Stincescu**, R. Zhao, E. E. F. Ballantyne, D. A. Stone, M. P. Foster, (2021) "Matlab-based, High-performance Electric Motorbike Energy Model, Utilising Video Data.", 2021 Sixteenth International Conference on Ecological Vehicles and Renewable Energies (EVER), Monaco, 5-7 May 2021, pp. 1-5. Available: https://doi.org/10.1109/EVER52347.2021.9456609
- R. Zhao, **T. Stincescu**, E. E. F. Ballantyne, D. A. Stone, M. P. Foster, (2021) "Dashcam Vide-Driven, Route Distinctive Energy Consumption Pre-Evaluation for Electrifying Public Services Fleets.", 2021 Sixteenth International Conference on Ecological Vehicles and Renewable Energies (EVER), Monaco, 5-7 May 2021, pp. 1-5. Available: https://doi.org/10.1109/EVER52347.2021.9456625

Conference Presentations

- E. E. F. Ballantyne, D. A. Stone, **T. Stincescu**, (2023) "The feasibility of replacing conventional urban motorbikes with electric alternatives", Production and Operations Management Society (POMS) Conference, Rennes School of Business, Paris, France, 18-20 July 2023
- **T. Stincescu**, E. E. F. Ballantyne, D. A. Stone, "Pallet-sized, Hot-swappable Battery Packs for Electric HGV Range Extension.", Logistics Research Network (LRN) Conference, Aston University, UK, 7-9 September 2022
- **T. Stincescu**, E. E. F. Ballantyne, D. A. Stone, (2022) "Assessing Energy Usage of Public Service Vehicles in Urban Areas", EURO2022 Conference, Aalto University, Finland, 3-6 July 2022
- **T. Stincescu**, R. Zhao, E. E. F. Ballantyne, D. A. Stone, (2021) "Understanding Fleet Energy Use of Electric Refuse Collection Vehicles in Urban Environments.", Logistics Research Network (LRN) Conference, University of Cardiff (Cardiff Business School), UK, 8-10 September 2021
- R. Zhao, **T. Stincescu**, E. E. F. Ballantyne, D. A. Stone, (2021) "Energy Usage & Sustainability Prediction for Electrified Public Service Vehicles (PSVs) – A City Distinctive Pre-Deployment Solution.", Logistics Research Network (LRN) Conference, University of Cardiff (Cardiff Business School), UK, 8-10 September 2021
- **T. Stincescu**, R. Zhao, E. E. F. Ballantyne, D. A. Stone, (2020) "Modelling Energy Use in an Electric Refuse Collection Vehicle using a Novel Interval Method.", Logistics Research Network (LRN) Conference, University of Cardiff (Cardiff Business School), UK, 9-11 September 2020

Abbreviations List

AC – Alternative Current
AI – Artificial Intelligence
BESS – Battery Energy Storage System
BEV – Battery Electric Vehicle
DC – Direct Current
EV – Electric Vehicle
FCHEV – Fuel Cell Hybrid Electric Vehicle
GAMS – General Algebraic Modelling System
GDP – Gross Domestic Product
GHG – Greenhouse Gas
GIS – Geographic Information System
GPS – Global Positioning System
GUI – Graphical User Interface
HEV – Hybrid Electric Vehicle
HGV – Heavy Goods Vehicle
ICE – Internal Combustion Engine
ICEV – Internal Combustion Engine Vehicle
IM – Induction Machines
LEAP – Long Range Alternative Planning
LGV – Large Goods Vehicle
MILP – Mixed Linear Integer Programming
ML – Machine Learning
NLP – Non-Linear Programming
NN – Neural Network
OCR – Optical Character Recognition
OEM – Original Equipment Manufacturers
OS – Operating System
PID – Proportional-Integral-Derivative
PMSM – Permanent Magnet Synchronous Machines
PSO – Particle Swarm Optimisation
R&D – Research and Development
RAM – Random Access Memory
RCV – Refuse Collection Vehicle
RPM – Revolutions Per Minute
SoC – State of Charge
SoH – State of Health
SRM – Switched Reluctance Machines
SUMO – Simulation of Urban MObility
T2W – Tank to Wheel
TDS – Tree-based Deterministic Sampling
TSP – Traveling Salesman Problem
UI – User Interface
V2G – Vehicle to Grid
ZEV – Zero Emission Vehicle

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1. Chapter 1 – Introduction

The last decade has seen an important increase in the adoption of lightweight motor vehicles utilising the Electric Vehicle (EV) powertrain technology. These and other vehicles, now constitute a significant proportion of total vehicle Carbon dioxide emissions [2] and according to current predictions given by mathematical models, they may represent a bigger proportion in total emissions in the years to follow, as seen in figure 1.1 [3][4].

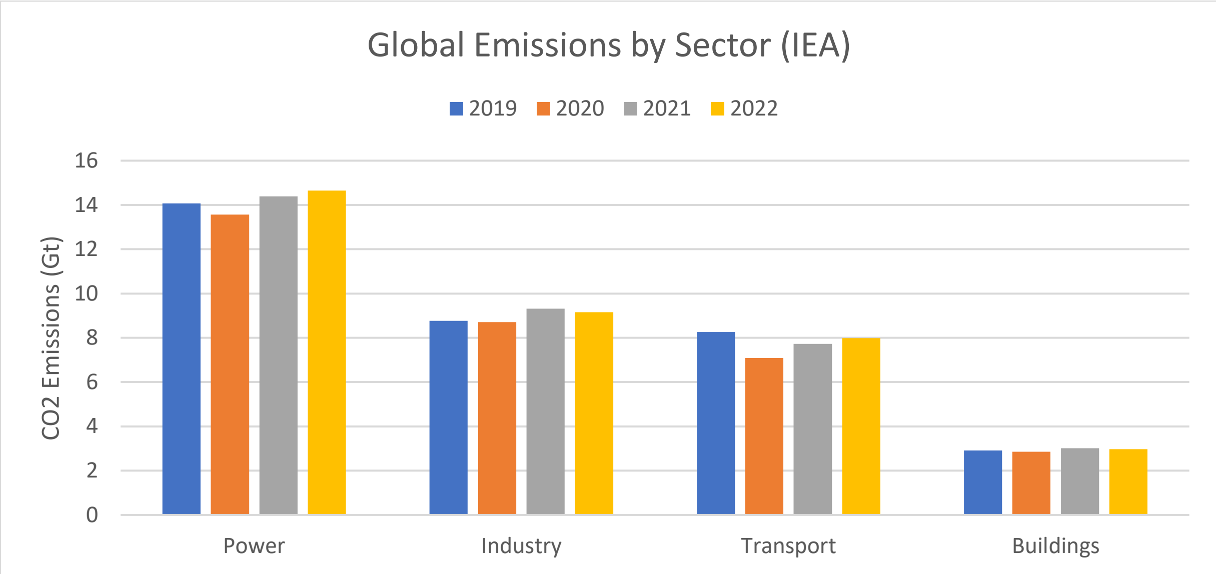


Figure 1.1 - Global Emissions by Sector

Whilst there is a significant amount of literature focusing on the energy consumption of popular, lightweight passenger EVs, there appears little understood regarding the energy usage of other types of electric vehicles. Therefore, applying EV technology to various drivetrains, together with other novel software-related technologies that benefit from the growth in computing power, may prove a research field with maximum impact towards overall tailpipe CO_2 reduction and the sustainability of the transportation sector.

1.1. Context & Justification

In recent decades, a significant increase in average global temperature has been highlighted by many studies in the field of climatology [5]. This process, known as climate change, has been ongoing at an increasingly alarming rate since the Industrial Revolution, as observed in figure 1.1 [6]. The outcomes of this process are primarily climatological, with recent observations indicating significant alterations in precipitation and oceanic current patterns. This has the effect of changing weather-specific phenomena in relatively short amounts of time, usually insufficient for populations in a given area to adapt to these. Consequentially, the meteorological phenomena associated with climate change have led to significant human, as well as financial losses.

The main catalyst contributing to the increasingly negative effects of climate change has been identified as being the increased atmospheric emissions of carbon dioxide and other gases. It has been demonstrated that when these substances are emitted into the atmosphere their molecules act as heat deflectors, effectively creating a greenhouse-like phenomenon. This has the effect of trapping atmospheric heat behind the ozone layer, which leads to an increase in global average temperatures

[7]. Although CO_2 molecules do not exhibit the biggest potential in heat blocking, the substance is usually cited as the most influential factor leading to increased atmospheric temperatures due to the total emitted amount [8]. To that end, increased carbon dioxide emissions have been strongly correlated with an increase in global temperature averages, as presented by the data [9] displayed in figure 1.2.

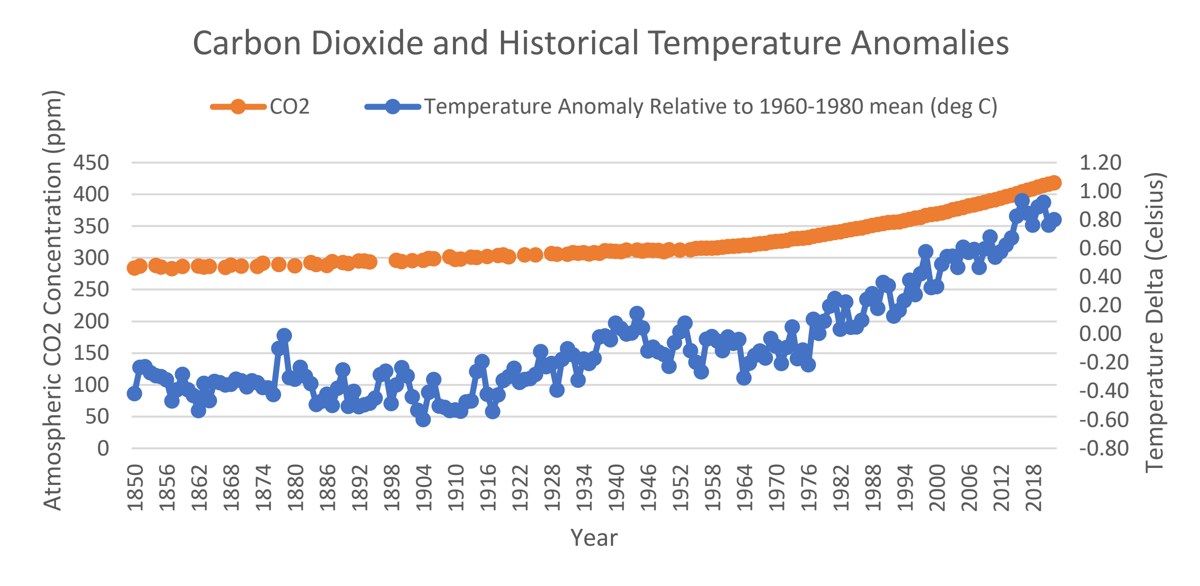


Figure 1.2 - Atmospheric carbon dioxide levels and increase in global temperatures [9]

Although initially questionable, a link between man-made emissions and the general increase in atmospheric CO_2 is increasingly established. This hypothesis is strongly supported by the rate at which carbon dioxide emissions have increased since the industrial revolution [10]. Therefore, in order to minimise the impact of man-made emissions, there has been a global push towards significant CO_2 and other greenhouse gas reduction. Carbon dioxide emissions have been experiencing significant growth since records began in the 1800s [9], and despite the multinational emissions reduction agreements that were signed to date, decreasing this trend is of primary importance [11]. This reduction is important as it is expected to prevent further temperature increases.

The automotive and transportation sectors have been identified as being significant CO_2 polluters [12]. One of the main polluting components in these industries is road transport, represented by the motor vehicle, which has traditionally been powered by internal combustion engines. Freight and public transport have been recently estimated to comprise more than 30% of the emissions produced by the transportation sector in the UK [13]. These achieve traction by employing various types of fossil fuels, which generate energy through combustion or compression, emitting carbon dioxide and other greenhouse gases as a by-product [14]. Consequentially, the rise of adoption in private-owned vehicles has brought a significant rise in CO_2 footprint attributed to these industry sectors.

Due to the increase in the usage of motor vehicles, motor vehicle-specific applications that target emissions reduction are expected to have a significant impact towards CO_2 minimisation and will likely have a beneficial impact towards minimising climate change effects. To that end, several low and zero-carbon alternatives to the traditional internal combustion engine (ICE) have been developed. One of the most popular solutions is represented by the electric motor. This enables vehicles to run on electrical energy, which can be provided by various energy generation sources, including renewables. Moreover, research extensively shows that electric vehicles have the potential to ultimately enable the transport and automotive industry become zero-carbon emission sectors, if applied correctly [15]. Additionally, as electrical energy can be produced through various means, it provides additional benefits of energy security, strengthening logistics and supply chain operations in the process. This has led to a significant increase in the use of electric vehicles in recent years [16][17].

Additionally, the use of heavy commercial vehicles such as RCV's and buses may lead to an advantage if converted to electric propulsion. Typically, commercial public service vehicles have fixed operating schedules, leaving and arriving at the depot at pre-determined hours of the day. If such vehicle fleets are then grid connected for charging, the use of proposed vehicle to grid (V2G) technology could make a large number of vehicle batteries available for grid support during the early afternoon, and especially during the evening peak periods for utility supply support. In addition, if an accurate estimate of the remaining battery capacity in the fleet of vehicles was available at the end of the day's collections, extra income may be generated by the local authority by providing grid support services during the peak period before the fleet was fully recharged overnight with lower cost electricity ready for the next day's operation. However, in order to facilitate research towards these applications, the energy requirements of such fleets must be better understood.

Similarly, electric alternatives to lightweight vehicles, such as motorbikes and scooters, are yet to be thoroughly researched. According to the DfT, these vehicles comprise a significant part of the motor vehicles (up to 1.1 million in the UK at the end of 2016 [13]) on the road in several parts of the world, and are increasingly used as means of transportation for food and package deliveries, due to the increasing popularity of gig-based economy. However, the full extent of the energy requirements produced by such vehicle fleets remain to be fully understood, although the decarbonisation of this vehicle category is expected to produce significant reductions in CO_2 footprints. This is especially true for the developing world regions, where these vehicles are extensively used.

Finally, due to the ever-increasing capabilities of computation power in recent computer systems [18], application of complex software algorithms to analogue, continuous-time mathematical systems is no longer a theory, but a strong possibility [19]. Continuous-time mathematical equations can accurately describe many systems, and the automotive industry makes no exception. Recently, complex software packages have been employed in this industry to simulate various engineering system designs, and to estimate and predict their behaviour in a virtual environment, as opposed to the traditional project lifecycle approach that consists of stages implying exhaustive validation and testing on prototype custom-spec hardware.

1.2. Research Aims & Objectives

This thesis proposes a model-based software design involving a Matlab/Simulink-based approach. This software solution is targeted towards simulating an electric vehicle, modelled using a set of technical specifications in order to understand its energy requirements. The proposed software simulation solution is capable of simulating a wide range of electric powertrains, including eRCVs, eBuses and eBikes. The developed solution presented consists of model-based programming that employs state-of-the-art software subsystems (toolboxes). This is a novel solution to simulating this type of drivetrain that aims to attenuate the errors many traditional approaches based on speed profiling prediction. The benefits of model-based programming are concerned with the model's overall versatility and minimal training required to operate such solutions. The proposed solution serves as a tool to aid the investigation concerning the energy requirements of the abovementioned electric vehicle alternatives, as well as a facilitating the move towards powertrain electrification.

Additionally, the thesis will also feature investigations focused towards understanding the energy consumption of electric motor vehicle alternatives beyond passenger lightweight EV cars as a further primary focus. This includes a range of various vehicle types, including eRCV, eBuses, as well as eMotorbikes/eBikes. The research will take advantage of the developed software solution in order to provide sensible energy usage estimations. This is done through analysing real-life telemetry data and understanding key driving aspects, such as road characteristics and driver behaviour. The results will provide insight towards the energy requirements related to the abovementioned vehicle types, as well as proving the usability and flexibility of the proposed software model. Moreover, it will be demonstrated how the estimations produced by the solution can be further employed in order to determine or justify other ways to supply energy to EVs, including swappable batteries, which have the ability to be replaced quickly to maximise productivity.

In order to achieve the proposed objectives and due to the multidisciplinary scope of the thesis, the thesis has been split into several chapters, each fulfilling one of the abovementioned targets, in order to ensure a clear outline of the achieved outcomes. Broadly, the research aims and objectives of the thesis are:

1) **Research Aim 1** – To understand the scientific context and current status of recent developments and identify current research gaps in the fields of automotive electrified transportation, as well as simulation-based experimentation and estimation. This aim is fulfilled within chapter 2.
    a) **Objective 1a** – To conduct a literature review on transportation and automotive-focused subtopics, including economic output of the automotive sector in transportation industry, main technological drivers of powertrain electrification and psychological factors controlling the public perceptions of the EV technology.
    b) **Objective 1b** – To conduct a literature review on recent developments in software modelling, simulation-based experimentation, as well as novel modelling techniques, including model-based programming.

2) **Research Aim 2 –** To examine the electric energy consumption of EV alternatives to various types of vehicles, including eRCVs, eBuses, and eBikes/eMotorbikes.
    a) **Objective 2a –** To develop a software model based on state-of-the-art simulation modelling techniques that is capable of estimating energy usage of such vehicles in given contexts, using speed-time value pair datasets and a technical vehicle specification. The development of this model is described in chapters 3 and 4.
    b) **Objective 2b –** To validate and test the model appropriately, using realistic telemetry data and compare the output energy usage with real-life recorded values. The results of these are presented in chapters 3 and 4.

3) **Research Aim 3 –** To employ the developed model as a tool for more refined investigations focused on energy consumption.
    a) **Objective 3a** – To estimate fleet-level energy usage of various public service vehicles (PSV) through simulation-based experimentation using the proposed software solution, and provide recommendations concerning scheduling, driving and vehicle specification. This is further detailed in chapter 5.

b) **Objective 3b** – To assess the feasibility of using ePSV fleets as grid support during peak hours by investigating energy usage throughout the day. The analysis is presented in chapter 5.
c) **Objective 3c** – To understand the impact on energy refuelling costs and carbon footprint reduction caused by implementing electric fleets. The findings are outlined in chapter 5.
d) **Objective 3d** – To assess the limitations of the developed simulation solution through stress-testing simulations of high performance, motorsport-spec electric motorbikes. The investigation is detailed in chapter 6.
e) **Objective 3e** – To estimate eBike/eMotorbike energy usage and determine the difference between these and their ICE counterparts when considering CO_2 emissions and costs. This is further elaborated in chapter 6.

4) **Research Aim 4 –** To prove how energy usage investigations in electric vehicles can be further employed as a basis towards building and implementing concepts with higher complexity, including systems that act as range extenders for electric motor vehicles. This is proven in detail in chapter 7.
   a) **Objective 4a –** To produce an ferasbility analysis for eHGVs focused on energy consumption and introduce an eHGV battery swap concept, indicating how these may be adapted to exhibit similar performance to conventional Diesel HGVs.

The findings of the proposed research can be easily identified as key characteristics towards a much more efficient process. Software simulation has been proven to significantly reduce cost and time spent during R&D stages of any given project because of its high degree of flexibility and scalability compared to a traditional approach. Additionally, the results produced as part of the presented energy usage investigation will aid in filling in the research gap concerning the electric energy consumption of various, specialist vehicle categories, including eRCVs, eBuses and eMotorbikes. The findings are expected to be of interest since the technical specifications used in energy prediction simulations have been compiled using real-life data.

Similarly, when considering the potential of the proposed solution, the results will serve as a cornerstone and may provide the first steps, together with existing research, towards a more complex solution that is also able to include traffic management systems. These include transportation-focused applications, such as AI-enhanced fleet-level operation, with the final aim of simulating all aspects of motor vehicle energy consumption and optimise these at a city or country-level. Accurate predictions of these characteristics will offer companies and local authorities a much more comprehensive view towards energy production and consumption that can positively reflect in finding an optimum in future business and economic strategies, while also keeping environmental disruption at a minimum.

1.3. Overview of thesis chapters

In order to better understand the objectives and findings of the thesis, as well as where can they be found, a short overview of the following chapters is provided.

In chapter 2 of this thesis, a literature review of the main findings and the current state of the art concerning the relevant research will be presented. This has been carried out in order to fulfil the objective of understanding the current developments in the automotive and transportation industries. It is performed by investigating similar, topic-focused literature describing recent progress in the topics of interest. The literature review enables better understanding of the context of the research presented in this thesis, as well as indicating specific research gaps and where exactly the findings presented in this thesis integrated in the grander research picture. The topics of interest that have been investigated include economic output of the automotive field, the recent advances in powertrain electrification, alternatives to the EV technology, as well as current progress in the field of software-based simulation methodologies.

Chapters 3 and 4 of the thesis will present the development and capabilities of a novel eRCV vehicle model. The developed model is able to deliver accurate predictions on energy consumption and electrical/mechanical system losses alongside vehicle behaviour and other important parameters at a subsystem-level. Additionally, a software-based solution generating mathematically modelled routes that can be integrated with the vehicle model will also be presented. This will enable predictions on estimating how much energy remains at the end of a given route and provide further scenario-based energy predictions. These two components have been developed as a software simulation solution towards providing energy usage estimates for various electric powertrain specifications, including eRCV, eBus and eMotorbikes/eBikes.

Chapters 5 and 6 include applications concerning the novel developed model. The applications include investigating the energy consumption for a wide range of various powertrain categories. These are then utilised in order to provide estimates concerning the potential carbon reduction and cost implications. This has been done through use of real and simulated driving telemetry, in order to reflect a wide range of driving scenarios. The results presented in these chapters constitute a significant step forward in understanding the energy requirements of heavyweight electric vehicles, as well as two-wheel, two-axle lightweight vehicles such as electric motorbikes. Furthermore, the presented research demonstrates the flexibility of the proposed solution, through its suitability for simulating vehicles with significantly different characteristics, with minimal setup changes.

Chapter 7 presents an investigation that demonstrates how the software-based energy estimations can be further used towards understanding the feasibility of applying novel concepts to the EV technology.

Finally, chapter 8 includes considerations towards the research limitations and suggestions concerning future research avenues as well as what further improvements may be brought to the current novel solutions and findings will be outlined. These include potential improvements that may be brought to the proposed software simulation solution, as well as suggestions focused on future work targeted on refining and improving the research.

Having discussed the introductory aspects of this thesis and briefly explaining the justification behind the work included in this thesis, a literature review indicating the current state and recent evolutions of relevant topics will be presented in the next chapter.

2. Chapter 2 – Literature Review

As outlined in the introductory chapter of this thesis, the process of motor vehicle electrification is expected to bring significant cuts to carbon dioxide emissions across all vehicle categories. However, whilst the energy consumption of lightweight powertrain electric cars is well documented and understood, some inconsistencies exist regarding the energy requirements of other EV categories. The investigations presented in this thesis aim to provide a better understanding of the status of these other vehicle categories and fill in the research gap related to their energy consumption performance in various environments.

Additionally, due to recent advances in computation capabilities, the implementation of model-based solutions for providing simulation-driven energy usage estimations may prove feasible. The fast-paced development of simulation-purposed software tools has enabled users to create accurate models mimicking complex real-life systems, including powertrains and vehicles. Therefore, it is expected that recent simulation techniques, such as model-based programming, will provide a approach to generate data where real-life experimentation is difficult.

In this chapter, an overview of the current performance metrics of the automotive industry will be presented, along with statistics concerning the carbon footprint emissions of related industries, such as transportation. Moreover, a summary regarding the current technologies, challenges, limitations, and a future outlook on transportation will be provided. Secondly, current state of the art in simulation technologies, their applications and most recent progress milestones will be outlined. Finally, a short summary of telemetry work will be presented.

A system diagram-like map detailing the logic flow of the literature review carried out can be found in figure 2.1, below.

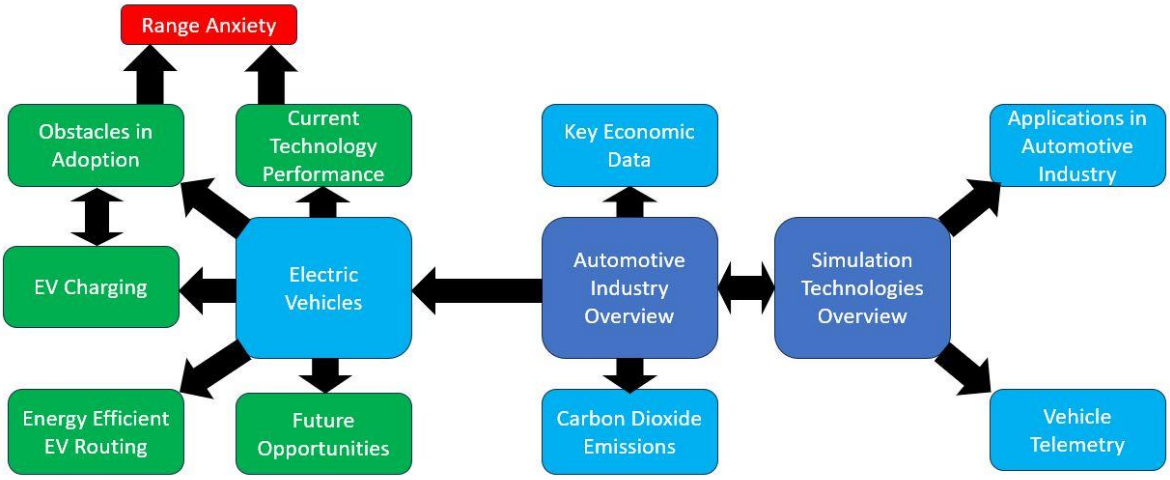


Figure 2.1 - Literature Review Map

2.1. Automotive Industry – Key Facts, Economy, and Manufacturing Output

Automotive ventures comprise one of the most valuable and widespread industries worldwide and the supply chain consists of companies and other organisations connected with the design, development, manufacturing, marketing, and selling of motor vehicles. It also has been historically one of the largest industries by revenue [20], with contributions of up 2.86 trillion USD in 2022, which comprises approximately 3% of world's economic GDP (gross domestic product) [21].

Similarly, it is also one of the highest spending industry concerning R&D (research & development) operations [22].

Since its emergence in the 1860s, with the invention of horseless carriages [23], the adoption of the motor vehicle has progressively increased, especially in recent years [24], as indicated by vehicle production statistics in figure 2.2. This has been further accelerated by historic technological innovations, country-specific policies, as well as global growth in economic output. Consequentially, motor vehicles have become the primary mode of transportation in many developed countries due to their convenience and accessibility. Furthermore, the recent drop in production due to COVID-19 is beginning to recover and total production output is anticipated to resume and increase as the supply chain issues caused by the COVID-19 pandemic are addressed.

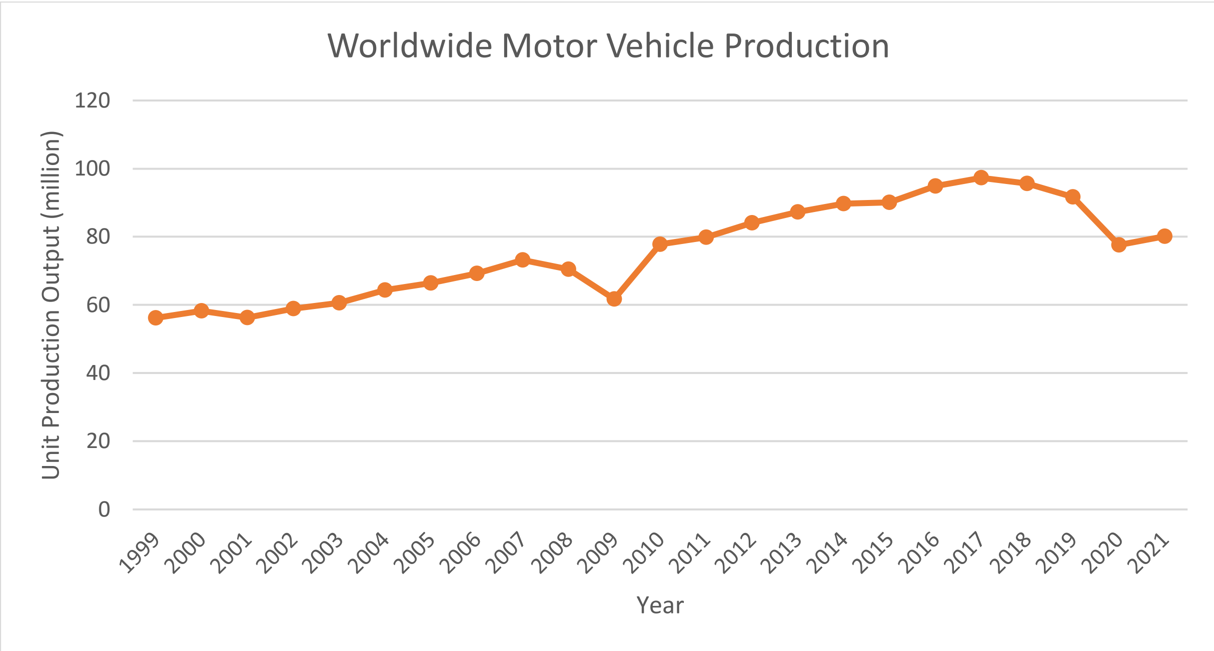


Figure 2.2 - Vehicle production, historical values [24]

Throughout most of the automotive industry's history, the United States of America (USA) has been at the forefront of many automotive endeavours [24]. However, in recent decades many of the manufacturing operations have been assigned to other countries due to lower labour and production costs. This has been particularly aided by the globalisation process of the supply chain and improvements in logistic operations. Figure 2.3 shows the 2021 statistics on unit production output by country [24].

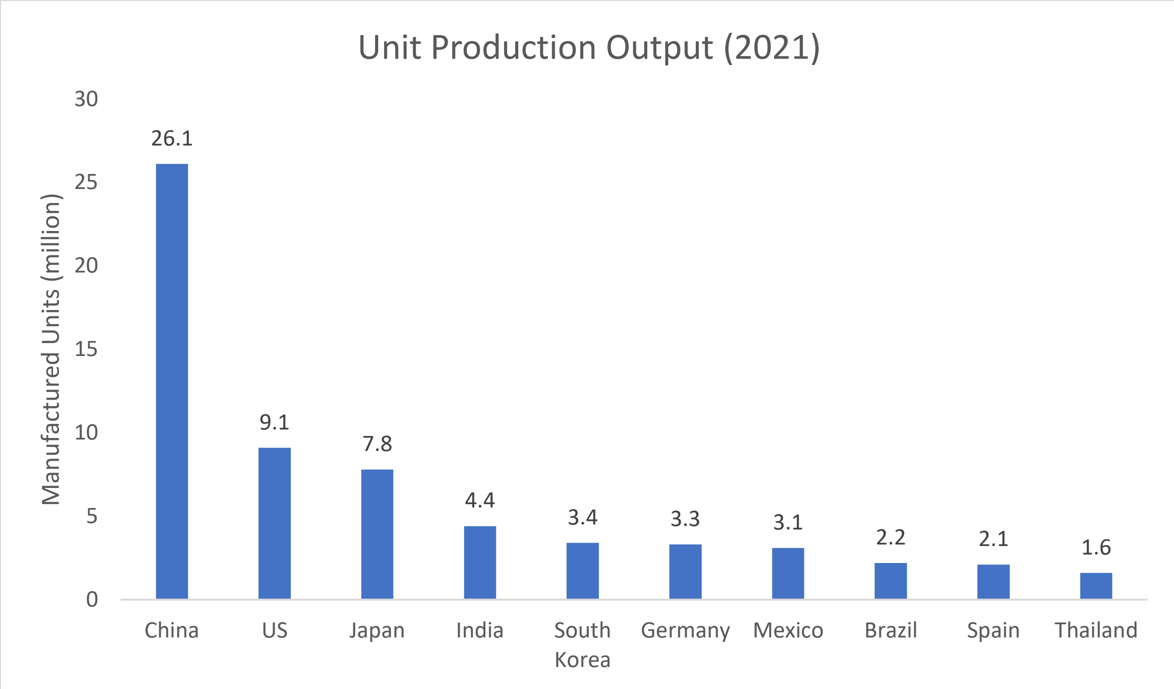


Figure 2.3 - Vehicle production by country [24]

Similar trends to country-specific output may be observed in unit import-export mechanics. Data presented in figure 2.4 [25] underlines the significant influence posed by the automotive industry in global trade.

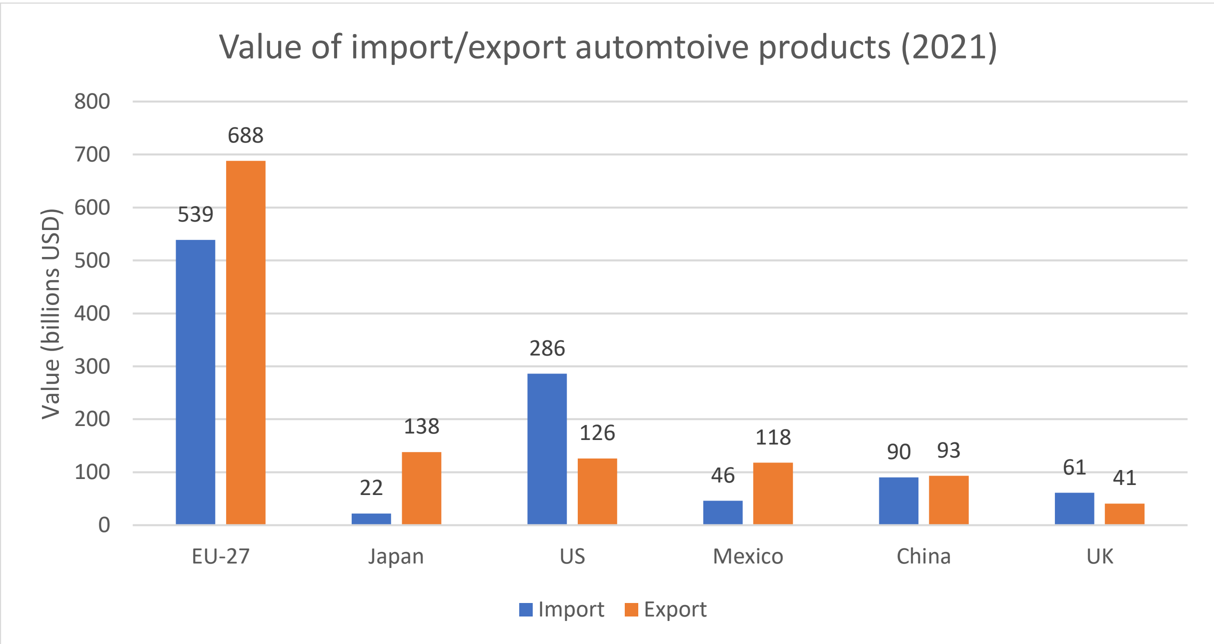


Figure 2.4 - Valuation of automotive trade by country [25]

The data presented throughout this subsection demonstrates the economic importance of the automotive sector and its applications in the transport industry in the wider context of the global economy. This industry is also considered a key factor in the sustainability of economic output and productivity worldwide, as it enables the possibility of all global logistics operations [25].

2.1.1. Transportation Sector Produced Emissions

As suggested by the ever-increasing manufacturing output of the automotive industry, historic data concerning emissions and other pollutants related to the transportation sector also suggest an increased trend. Whilst several worrying greenhouse gases (GHG) are produced including methane (CH_4), nitrous oxides (N_2O) and fluorinated gases (halocarbons), this review will mainly focus on understanding the origin of carbon dioxide (CO_2) footprint, as this substance is the main GHG by-product of the transportation industry [8]. Moreover, the transportation sector has overtaken the energy grid generation sources as the largest emitted of GHGs in 2019 in the UK, comprising 27% of the national industry emissions [26], with similar trends in growth observed in other countries [27].

Sources of carbon footprint production of the automotive industry are mostly correlated with the product lifecycle of a motor vehicle. Broadly, this may be split into 3 major phases: manufacturing, usage and end-of-life/recycling [28][1]. However, the exact share of emissions produced throughout these stages varies largely depending on the fuel type employed by the vehicle as well as its weight category.

Recent reports put the annual average carbon footprint of a US passenger vehicle at 4.6 metric tonnes [29]. Comparatively, the annual average emissions of a typical US commercial truck are set at around 223 metric tonnes [29]. Whilst the difference in emissions is significant, the difference in the number of on-the-road lightweight vehicles is significantly higher than the heavy-duty ones, which leads to the emissions of these two vehicle categories being within the same order of magnitude. [30]. Regardless, recent estimates show that lightweight passenger and heavy-duty-purposed vehicles emit over 80% of the total emissions caused by the transportation sector worldwide [31]. This demonstrates the significant influence posed by road transport over the larger industry.

Broadly, current statistics indicate that transportation emissions represent approximately 27% of total GHG emissions worldwide [31]. Similarly, the carbon footprint of this sector has risen consistently as global emissions have increased, as highlighted by the data [32][33] in figure 2.5. This also underlines the importance of decarbonising the transport sector as part of a general effort to reduce global GHG emissions in order to match climate accords' targets, such as the Paris Agreement's goal to limit global warming to below 2 degrees Celsius [11].

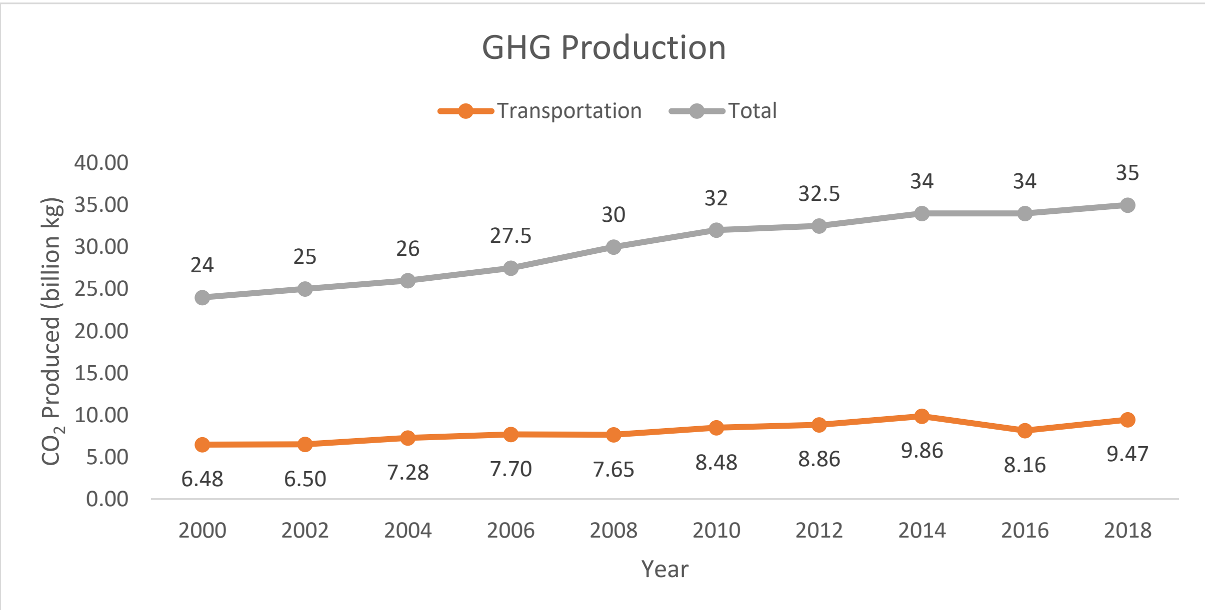


Figure 2.5 - Historical yearly GHG production [32][12]

2.1.2. Powertrain Electrification

One of the most popular mechanisms through which the decarbonisation of the transport sector is being undertaken is through the electrification of motor vehicle powertrains. This is the replacement of the conventional internal combustion engine (ICE) and its energy source with the use of an electric propulsion mechanism with an electrical energy storage system. Historically, early designs for electric vehicles date back to 1828, with Anyos Jedik's electric motor design, that includes a stator, rotor, and commutator. Designs have progressively evolved and by the early 1900s the first mass-produced vehicle has appeared, made by the Studebacker Automotive Company [34].

Whilst electrified powertrains have been present in the engineering field for many years, its popularity as a concept has not been significant, due to design complexity and lack of general electric infrastructure support. However, since the 1990s, this concept has gained interest thanks to its ability to minimise or eliminate vehicle tailpipe emissions. This is supported by several recent studies [35][36][37], that investigate the lifetime emission reduction potential of all categories of electric vehicles compared to their conventional, Internal Combustion Engine (ICE)-powered counterparts. Statistics presented in figure 2.6 as a scatter plot indicates the potential reduction of CO_2 emissions in the transport sector for Germany [38]. Similar trends can be observed in other countries [39].

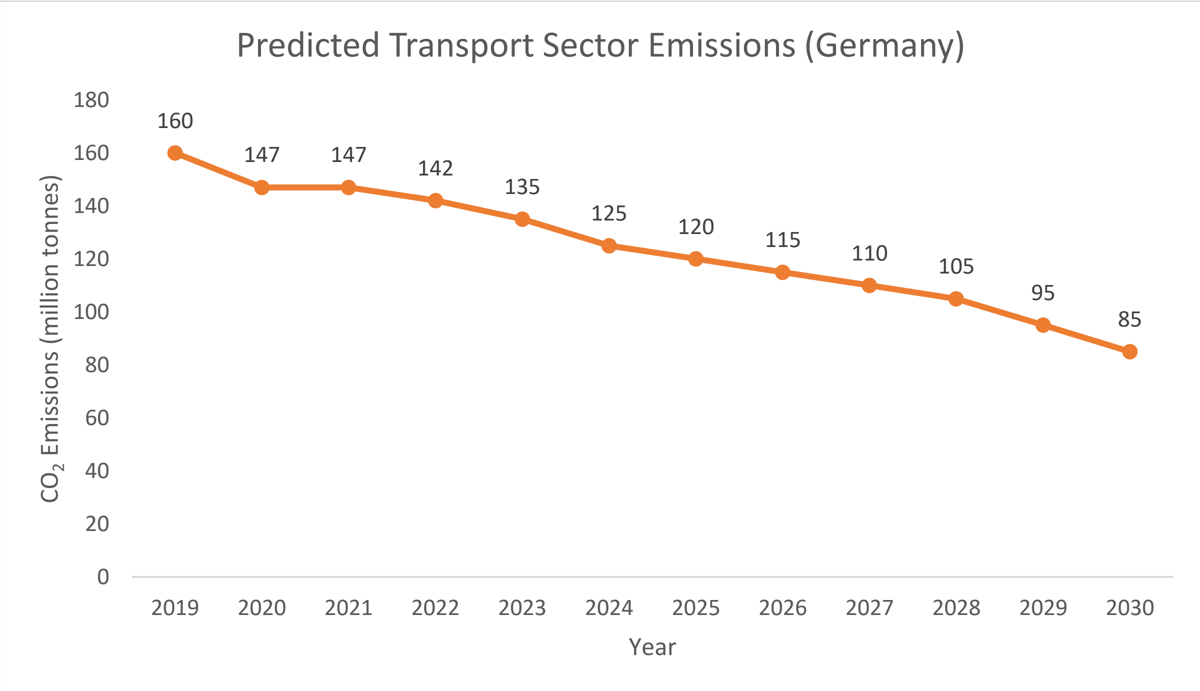


Figure 2.6 - Prediction in carbon dioxide emissions from the transport sector [38]

Electric powertrain technology is expected to have a significant impact on the carbon footprint reduction. However, the potential for emission reduction through the implementation of electric powertrain technology is variable, depending on usage, manufacturing, and recycling processes.

Whilst electric vehicles do not emit carbon dioxide directly during their use, studies [40][41] show that the carbon footprint during the manufacturing process of an EV can be significantly higher than the one generated during an ICE vehicle production. Similarly, end-of-life material processing and recycling for electric vehicles appear to be higher than conventional powertrain solutions, as indicated by recent research [42]. However, it is expected that as technology evolves [43] and EV uptake increases, the difference in generated CO_2 footprint and other pollutants will significantly decrease, perhaps even becoming a zero-carbon emission process [44]. Additionally, as demanded by market mechanics and customers, a number of electric-powered vehicle designs have been created, with various contributions from the electrical side to the vehicle capability [45]. These are expected to ensure a smooth transition towards a zero-carbon lifecycle by enabling some degree of progressive emission reduction [46].

The potential in CO_2 reduction of electric powertrains has been extensively discussed in various contexts. One study [47] presents a mathematical model that aims to assess the impact on energy usage and CO_2 emissions of electrified powertrains, reduction in vehicle size and substitution of conventional automotive building materials with lighter ones for the Japanese market. As part of the scope of this paper, a scenario-based comparison between the adoption of four types of powertrains have been considered: BEV (Battery Electric Vehicle), HEV (Hybrid Electric Vehicle), ICEV (Internal Combustion Engine Vehicle) and FCHEV (Fuel-Cell Hybrid Electric Vehicle). The presented model uses a dynamic bottom-up accounting energy-economic model developed in LEAP (Long-range Alternatives Planning System)[48].

The results of the study [47] have been categorised in several areas of interest: CO_2 reduction, cost implications and impact on the overall electricity consumption. When benchmarked against the proposed 2050 CO_2 70% reduction target imposed by the Japanese regulators [49], a scenario in which the current trends will carry on will not generate enough reduction to meet the criteria, only being able to reduce CO_2 tank-to-wheel emissions by 51.9%. The 2050 target is only achievable by the BEV and FCHEV scenarios. Moreover, the medium-term target (25% CO_2 reduction by 2020 compared to 1990 level) is not achievable by any scenario. The BEV mass-adoption scenario provides the best figures in terms of energy consumption and CO_2 emissions reduction, with up to 61.5% energy reduction and 91.1% CO_2 emission attenuation. Moreover, these figures are improved when mini lightweight BEVs are adopted, reaching up to 70.6% energy reduction and a decrease of 92.2% in CO_2 emissions. [47] Whilst all of these figures are mostly focused on vehicles sold on the Japanese market, the figures outline the potential CO_2 reduction capability of the EV technology.

The same study [47] also noted that employing lightweight materials in the build of the car reduces the net cash flow, due to the reduction in vehicle class which in turn affects the energy cost. Finally, by 2050 electricity consumption in Japan is predicted to increase by up to 240 PJ/year in the BEV scenarios, while hydrogen demand can increase up to 356 PJ/year in the FCHEV scenarios. These numbers can be further reduced by usage of lightweight materials and a higher proportion of the small class vehicles, down to 176 PJ/year for a light mini-BEV scenario and 226 PJ/year for a light mini FCHEV scenario.

Additionally, the previously presented research [47] has also been extended to understanding the impact of deploying electrified powertrains for heavier vehicles, through modelling a 5-scenario approach [50]. Results of this model [50] suggest that by 2050 the tank-to-wheel CO_2 emissions are reduced by 51.9%, which is insufficient towards meeting the proposed carbon dioxide reduction targets. Moreover, despite the aggressive powertrain electrification deployment trends, it is predicted that gasoline and diesel will still account for at least 52% of all energy demand regardless of the scenario employed by 2050. Finally, tank-to-wheel CO_2 emissions can be reduced up to 55.8% in both scenarios regarding BEV and FCEV adoption, while well-to-wheel CO_2 emissions see a reduction of 43.9 and 27.6% in this context. A scenario that employs a combined BEV/FCEV approach can reduce the well-to-wheel emissions down to 29.5% compared to the baseline scenario. [50]

Similar studies looking into simulating the economic competitiveness of EVs exist. Currently, data-based investigations show that initial upfront costs of an electric vehicle are higher than ICE-based market competitors, up to price differences of 70% for similar vehicle specs [51]. This has been proven to be because of the high costs in battery manufacturing [52]. However, during its lifetime, total EV ownership costs throughout the vehicle's lifecycle are likely to be equal or lower due to the lower costs of electrical energy compared to petrol or diesel. Data gathered in 2018, presented in figure 2.7, suggests that this trend is consistent among all vehicle categories, ranging from small vehicles (5-passenger, private cars) to large powertrains, such as electric buses and trucks [53]. Furthermore, the data suggests that electric vehicles are cheaper overall in the long if the vehicle is used intensively. This is mainly attributed to lower costs related to energy refuelling.

Additionally, the higher upfront costs of electric vehicles (including heavyweight ones) are partly alleviated due to government incentives, such as the UK's Department for Transport electric car grant scheme [54]. Moreover, as new battery designs appear and battery recycling technology evolves, battery manufacturing is expected to become significantly cheaper [44], therefore driving down total cost of ownership.

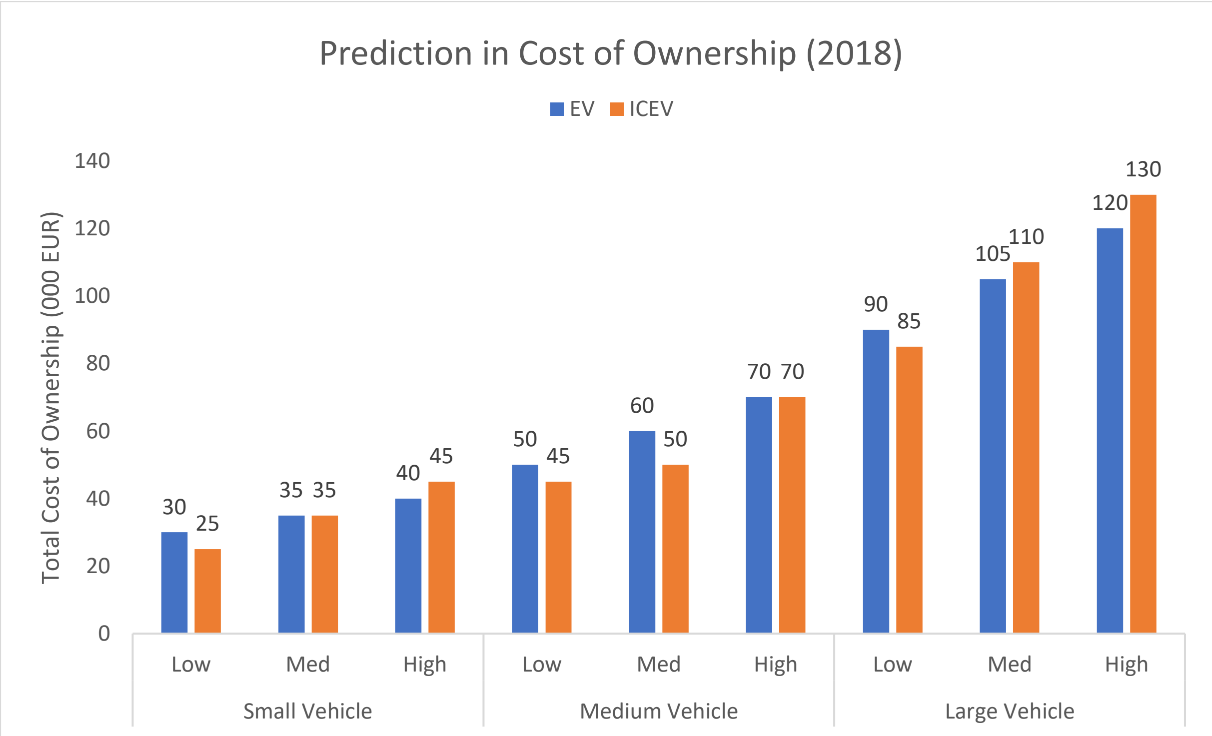


Figure 2.7 - EV cost of ownership prediction [53]. Small/Medium/Large indicates vehicle size and Low/Med/High relates to vehicle use. Total cost of ownership includes energy refuelling, maintenance and taxes.

Consequentially, EV technology in motor vehicles has recently seen wide adoption across several transport subsectors including passenger vehicles and public transportation. This has been particularly facilitated by a large number of automotive original equipment manufacturers (OEMs) increasing their EV manufacturing output. This can be demonstrated by the current amount of stock motor vehicles that include some degree of powertrain electrification, including BEV, HEV and PHEV, which has recently exceeded 2 million worldwide [55]. Additionally, the automotive market has seen significant EV sales, recorded at 750 thousand worldwide in 2016. This represents a year-on-year increase of more than 30%, underlining the significant interest in this technology [56]. Furthermore, future trends are expected to experience an acceleration in electric vehicle adoption, as presented by the stock data in figure 2.8 [55].

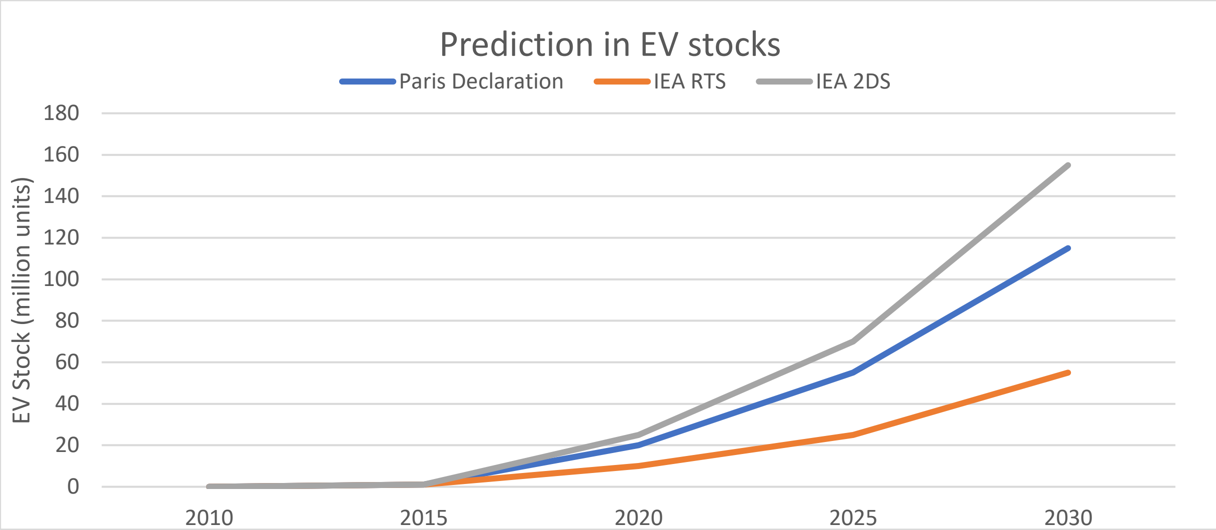


Figure 2.8 - EV stock prediction according to various economic models [55]

Finally, another benefit of this technology is its ability to contribute to energy security [57]. As opposed to their conventional, ICE-powered counterparts, which are confined to one energy source (i.e., petrol or diesel), vehicles based on electric powertrains have the ability to acquire their energy from various energy sources, such as renewables or nuclear. Currently, there are several methods to generate electricity in large quantities, ranging from burning various fuels to the use of renewable sources, such as photovoltaic generation through solar panels and harnessing wind energy through turbines. Having vehicles with the ability to use energy that can be produced through multiple processes is expected to strengthen the transportation energy supply chain resilience in the long term. This is achieved through two aspects: independence from petrol market mechanics and the ability to function purely on energy sources that work independently relative to the petrol market. The benefits related to energy security of electric motor vehicles have become increasingly relevant due to current geopolitical conflicts [58] and the ongoing energy crisis [59].

2.1.2.1. EV Technology – Overview on Current Improvements & Challenges

Due to the high demand, financial incentives, and intense market competition in the field, EV technology has seen significant improvements in efficiency and accessibility, as well energy refill capability. These improvements have resulted in some of the inconveniencies related to electric motor vehicles becoming significantly minimised.

One of the leading reasons for decreased EV charging times is the significant improvements [60][61] to the materials employed for building the battery cells. Many of the existing technologies have been significantly improved in terms of energy density, with recent battery designs featuring increased kWh/m^3 and kWh/kg performance metrics. This allows for a higher electrical energy storage capacity, which in turn has a positive effect on vehicle range. Moreover, battery cell interfacing has been thoroughly researched and implemented, with new designs featuring tab-less cell interfacing becoming more prevalent in the electric automotive industry. Through eliminating the need for battery cells to contain a tab, more space is freed for electrical storage, increasing the battery's energy capacity. [62].

Similarly, recent research also indicates that there are several emerging materials that have been considered strong candidates for replacing the current dominant battery manufacturing technologies. Li-Polymer and Li-Air have been hypothesized and prototyped, indicating that battery cells manufactured with these element combinations are capable of holding significantly higher charge at similar cell weights and volumes when compared to their conventional Li-Ion counterparts [63]. However, some safety concerns have been raised with the use of these materials at large-scale, as some studies [64] suggest they may be more potent safety hazards than current technologies. Similarly, the electrical storage capabilities of these materials are yet to be fully realised and implemented in a consumer-ready device.

Another aspect that has led to higher capacity batteries and consequentially better EV range is the use of novel materials such as gallium and silicon-based alloys, together with improved power conversion strategies in manufacturing power electronics. In the context of the electric drivetrain, these are responsible for managing the power and torque potential of the motor-battery system, as well as other auxiliary power consumers. Firstly, power electronic devices featuring conventional materials have been improved in terms of power conversion efficiency [65], as well as displacement and weight by employing novel power management strategies, such as resonant switching [66]. This allows the power switching performed within the devices to occur with no power losses, by taking advantage of the parasitic capacitance and inductance of the electric components. Similarly, components manufacturing using novel material alloys, such as Gallium-Nitride (GaN), have gained interest due to their ability to operate at significantly higher frequencies, allowing for better power conversion efficiency and enabling the electric filtering components to be much smaller relative to traditional silicon and silicon-carbide alternatives [67][68].

Charging has also improved with the use of concept technologies that have been successfully trialled in smaller consumer electronics, such as mobile phones. The idea of "fast-charging" has been intensively investigated and applied to electric vehicles, resulting in significantly decreased electric vehicle charging times [69]. Besides injecting a constant amount of high power in the battery, one of the highly used methods to achieve this employs high power electronics that are able to manage a specific power cycle [70]. The charging interface injects a high amount of electrical power over a relatively short amount of time followed by a cool-down period, which is controlled through thermal management. The reduced time spent for energy refill has shown to increase productivity [71]. However, if used incorrectly, fast charging has been shown to negatively affect battery health over time [72]. One study [73] shows that Li-Ion battery cells that have been recharged using excessive fast charging have aged much quicker than units that have been charged at lower power ratings. The reason behind this may lie in the material's lack of capability to preserve its electrical storage properties at high temperature, which is caused by the effect of depolarisation. Therefore, fast-charging capabilities should be used carefully in order to minimise battery health loss over time, for example limiting the fast-charging periods depending on battery temperature and state of charge (SoC).

Additionally, the charge/discharge battery cycles have also proven to have a negative effect on battery health over time, when performed at a suboptimal level [74]. Studies indicate that deep charging (i.e. charging that refills the battery from 90+ beyond) and deep discharging (battery discharge below 10%) should be generally avoided [75]. In order to prevent these phenomena, battery and EV manufacturers employ the use of smart battery management systems (BMS) that impose software limited conditions on the battery's SoC management [76][77]. The limitations prevent battery exhaustion by limiting vehicle performance and/or stopping vehicle operation in the case of severe discharge. Similarly, deep charging should generally be avoided, with little to no exceptions in order to further discourage deep battery cycling. However, this does lead to a situation where the effective operation battery capacity is significantly lower than the realisable capacity at manufacture.

On a more general business level, studies have also looked at how electric plug-in vehicles can be integrated in with the fleets of public authorities in various countries. Studies [78] have been looking at the impact of the pro-EV policy entrepreneur's actions in integrating this technology in local communities by analysing how they have been introduced in communities in Sweden. It concludes that, when raising the implementation of electrified vehicles in the local politics agenda, if sufficient material and information is offered and an expert role is assumed by the entrepreneur, this will increase knowledge and awareness in the decision-making process. User feedback also plays a role in this process. However, the change momentum is highly dependent on the person/entity that introduces the community to the EV technology and a situation which implies a loss in the role of the entrepreneur will negatively affect the end result. [78]

The results previously mentioned can be consistently correlated with a different study [79] that suggests what benefits could be adopted by local and national regulators, as well as showcase technical solutions that seek to hasten the adoption of electrified powertrains. Modern composite materials are suggested as a solution to make the vehicles lighter, that in turn brings other energy-saving benefits, such as decreased rolling resistance and required braking power. In fact, modular designs for heavyweight powertrain vehicles for goods delivery already exist, with the potential to reduce production costs and make the EV technology more attractive to corporations. Other technical elements to improve EV attractiveness include the implementation of super and ultra-capacitor networks in the vehicle battery system to support energy delivery when high bursts are required. Standardisation of charging interfaces is also proposed as a cost-saving measure. Approaches regarding novel policies are also treated as a means to achieve mass EV deployment in Europe. Based on other case studies, the paper [79] points out the importance of applying certain measures, such as providing financial incentives and imposing restrictive rules on combustion engine-powered vehicles. Battery leasing is also proposed as a way to reduce the EV initial cost and ensure an efficient battery resource lifecycle.

Propulsion systems in electric motor vehicles have also seen significant improvements recently. Whilst the most established electric motor technologies are based on Permanent Magnet Synchronous Machines (PMSM) and Induction Machines (IM) [80], novel technologies that do not require the use of rare earth elements have gained popularity. This is primarily due to the scarcity of these materials as well as their upfront high costs. A particular design that has seen a significant increase in usage in consumer ready EVs is represented by the mature squirrel cage IM [81]. Furthermore, novel designs based on reluctance machines, such as Permanent Magnet Assisted Synchronous Reluctance Machines (PM-assisted SynRM) and Switched Reluctance Machines (SRM) are gaining popularity in the scientific community [82][83]. This is due to their ability to exhibit similar system efficiency figures at significantly lower manufacturing costs, as presented in figure 2.9. Finally, data presented [56] under table 2.1 indicates the key differences between these types of these electric motors.

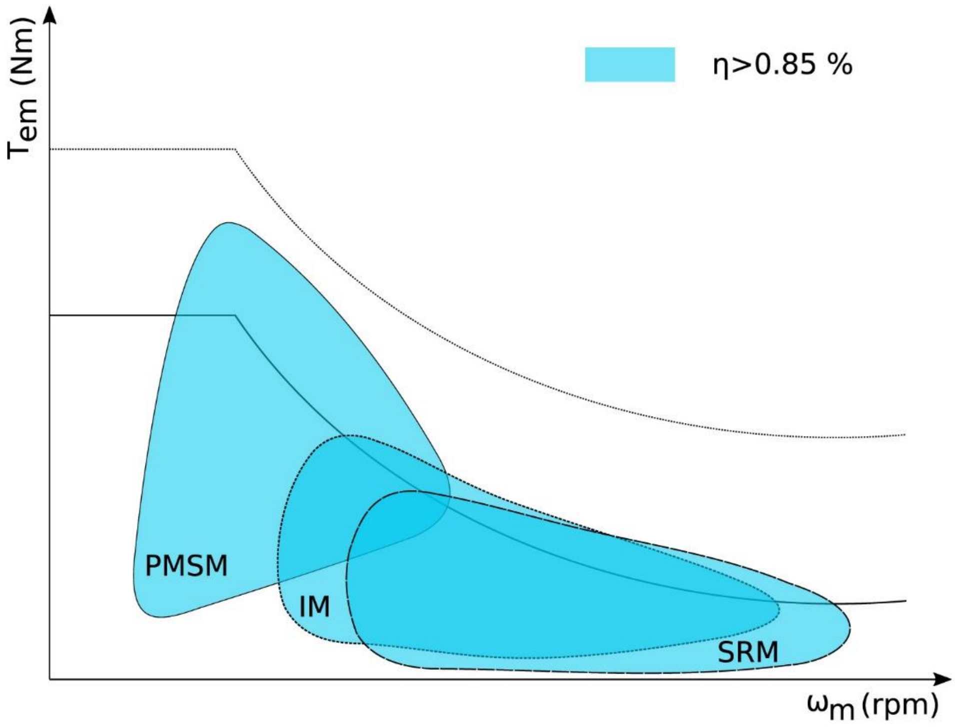


Figure 2.9 - Performance range and efficiency of various electric motor types [84]

Features	Motor Type			
	PMSM	PM-assisted SynRM	IM	SRM
Fault Tolerance	Yes	Yes	No	No
Robustness	No	No	Yes	Yes
Reliability	Medium	Medium	High	Medium
Average Efficiency @ Constant Torque (%)	93.6	90	82.5	87
Typical Average Power Density (kW/l)	6.8	6.8	2.5	3.6
Overall Technology Costs	High	Medium	Medium	Low

Table 2.1 - Comparison between popular electric motor types [56]

The mass adoption of the electric powertrain has been predicted to have a significant impact on the energy grid, as all of these vehicles will require relatively high-power access to it. Studies estimate that increases ranging from 6% to 10% in overall electric grid power demand are likely to occur [85]. However, whilst the overall increase is modest, the magnitude of energy demand during peak times is expected to be significantly higher [86]. Depending on the future market penetration of electric vehicles and how swift the transition to complete or near-complete electrification will occur, strategies concerning green electric energy production may have to be changed. Investigations aimed towards understanding how the renewable energy production varies depending on weather conditions and time of year should be carefully considered. Many countries and governmental institutions have plans in place for these, for example the UK's intention to build small-scale nuclear fission reactors and increase offshore windfarm energy generation [87].

Moreover, energy production is not the only part that is prone to significant strain as EV technology becomes more prevalent. The electric energy transport infrastructure will likely need to be revamped, starting from small scale residential power interfacing, as more EV users indicate their intention to buy home chargers [88]. The residential energy grid infrastructure upgrade is even more important in the case of rural environments, where power lines are unlikely to be capable of withstanding several high-power connections for EV charging [89]. In urban environments, unconventional power generation, such as small-scale, localised solar panels, should be considered in order to fulfil the increased power demand. Integrating these as an off-grid system, separate from the main energy grid, could prove especially beneficial to electrified public service vehicle fleets, such as refuse collection trucks and public transit vehicles such as buses. Work investigating these has been carried out in previous research, looking into how a biomass incinerator could provide electrical power to an electric heavyweight vehicle fleet [90]. Additionally, if these energy production systems are producing an energy surplus, the leftover energy could be fed into the energy grid or be extended to privately-owned electric vehicles.

However, the energy grid infrastructure will likely require upgrading that goes beyond just investigating rising energy demand based on population density [91]. Whilst battery technology is likely to have significant leaps in storage performance, therefore increasing vehicle range, the current situation indicates that EV technology has introduced a new paradigm in human mobility, consisting of long layovers or stops mid-journey for battery charging [92]. Therefore, as the number of EVs on the road will increase, energy infrastructure will have to be upgraded even in very low-density population areas, such as at motorway junctions, petrol stations and other areas with dense traffic where EV charging facilities could be placed.

As power demand will increase and the energy grid will be upgraded to be able to transport more energy throughout regions, power flow management systems will likely require rework. Higher power ratings in the energy infrastructure are likely to attract more potent implications if the balance in the network is not correctly managed. Moreover, auxiliary power generation plants that are able to be switched on and off with relative ease, depending on short-term grid requirements should be considered [93]. The ability to fulfil a temporarily increased power demand is especially important in world regions which are considered net energy importers. An alternative to the auxiliary power plant option may be represented by the ability of residential owners and other privately-owned entities to have power generation installations fitted within their buildings. These systems could be then used to satisfy the building's energy demand temporarily or permanently or have some of their energy production fed back into the main energy grid, through a financial incentive scheme. Such localised, small-scale energy production systems are already widely available and are likely to become more affordable as the supply-demand market mechanics will adapt to this. Moreover, many governments and organisations already offer financial incentives for the installation and energy production of such renewable power generation devices [87].

2.1.2.2. Energy-Efficient EV Routing

Another important factor in the adoption of electric powertrain technology in transportation is represented by the ability to provide energy efficient routing tailored specifically for this propulsion method. GPS-based routing through tailored devices and popular software systems, such as Google Maps, have seen a significant uptake along with the rise in popularity of high-speed mobile internet access. Therefore, in order to ensure the same level of accessibility and efficiency, understanding EV-based vehicle routing is important. However, additional constraints need to be considered due to the differences in the energy requirements of electric vehicles compared to their ICE-powered counterparts. New custom routing algorithms have been developed both in the industrial sector, as well as the scientific community. These have been proven to be capable of creating routes that take into account EV-specific constraints, such as long stops for vehicle charging and ensuring prolonged running at optimum energy efficiency speeds [94].

Whilst most frequently routing algorithms based on Tree-based Deterministic Sampling (TDS), A* or Dijkstra-derived methods usually perform consistently, predominantly generating optimal solutions, these can be further improved for EV-specific route planning. One aspect that has been considered is represented by the optimal “speed zone” at which electric vehicles should be driven. This has been shown to be different compared to traditional ICE vehicles, primarily due to differences in mechanical design and capabilities, such as instant torque-to-wheel delivery and limited vehicle range performance which is affected by road characteristics and outside weather conditions. [95]

Existing research on this topic indicates the development of new methods in energy-efficient routing tailored for EV cars based on location data points. These range from simple heuristic algorithms to meta-heuristic techniques. Several applied mathematical methods have been applied to an EV car context, with varying degrees of success depending on the degree of algorithm flexibility and complexity. Applied to a 1st order vehicle model, methods such as particle swarm optimisation (PSO), has been found to decrease energy usage by 9.2% relative to a conventional vehicle routing algorithm. These findings may potentially be able to open up new research strategies in the field. Some potential directions include improving the PSO algorithm to introducing and applying new algorithms to the presented problem [96]. Similarly, other optimisation approaches like the ant colony algorithm exhibit abilities to optimise solutions to the problem given enough calculation factors [97]. A Tabu Search-based solution has also been considered and due to its flexibility in problem solving it has been found to be a robust solution for solving similar routing problems [98].

Additionally, Bellman-Ford algorithm approaches have been attempted and while the method works well with small-scale datasets, problem solving targeted towards finding the optimum problem solution utilising large datasets is not consistent. A potential solution may lie with data pre-conditioning, consisting of map pre-processing, although it may be impractical depending on the size of the geographical data. Finally, further alterations of the metaheuristic techniques described in other papers written by the same authors produce better accuracy results than the original implementations, although they are slower in processing small datasets. [99]

Applications recently developed by the scientific community have also been further refined in order to be integrated with popular routing software. These new features ensure minimal energy consumption and duration optimised for traveling using an electric vehicle [100]. Moreover, improvements have been developed on top of existing EV routing frameworks that have been shown to reduce energy consumption further, by up to 11% [101].

It must be noted that regardless of the chosen algorithm, a significant factor in the overall accuracy of the solution consists of the input data. As raw data geographical maps cannot be properly processed by these algorithms, instead these are converted to mathematical graphs, where intersections are represented by vertices and roads by graph edges. The conversion can be performed using traditional methods, but integrating other machine learning (ML)-related techniques, such as applied computer vision and 2D image processing algorithms is worth considering giving that application of such methods are still considered novel. [102]

Additionally, studies have also examined energy efficient EV routing for heavyweight vehicles. One study [103] analysed novel applications of mixed integer linear programming (MILP) models coded in general algebraic modelling system (GAMS) software applied to electrified refuse collection vehicles shows that integrating this optimisation method into a refuse collection truck fleet in the context of a large city (Istanbul region, Turkey) can positively impact energy consumption, and estimates a 31.77% reduction in overall vehicle energy consumption.

Similarly, the previous study correlates well with findings stated in a preceding one [104]. This study is focused on investigating refuse truck scheduling in the city of Chicago, USA and presents the application of a decision model based on the Markov chain stochastic model that aims to optimise collection at city ward-level. This model maintains the same basic workday and work rules as the traditional routing approaches used then and combines route types so that some refuse collection points can be visited multiple times, while maintaining snake-like routes as well as monitoring vehicle weight as a function depending on route parameters. When applied to a test dataset describing 5 wards, the model is able to significantly optimise the procedure as well as the resources employed. An up to 16% reduction in the number of routes required to pick up all the refuse, together with cost savings of approximately 13% compared to current maintenance and running costs have been observed, projecting financial savings of up to $9 million, effectively validating flexible stochastic models as an application for this field. [104]

Finally, EV-specific routing algorithms may also be interfaced with adjacent, unconventional energy generation or energy storage systems, modelling a vehicle-to-grid (V2G) vehicle charging paradigm. The possibility of employing such systems in routing and charge scheduling has been thoroughly researched and findings suggest that such integrations can be highly beneficial from a cost perspective [105]. Similarly, integrating power generation elements closer to the vehicle charging points indicate benefits regarding overall efficiency [106]. However, such systems may also be disruptive to the overall energy grid and EV charging if inadequate energy management scheduling is applied.

2.1.2.3. Range Anxiety

One of the major hurdles opposing adoption of electric powertrain technology from a consumer's perspective is highlighted by the "range anxiety" concept. This idea has been formulated as being a psychological anxiety experienced by the consumer related to vehicle range [107]. Whilst initially, this has been thought as having a technical nature, due to the low range capability of early EV designs, it is increasingly thought of as a psychological barrier [108]. This is further highlighted by data [109] based on interviews organised in EU's Nordic countries questioning stated reasons for EV disinterest, as presented in figure 2.10.

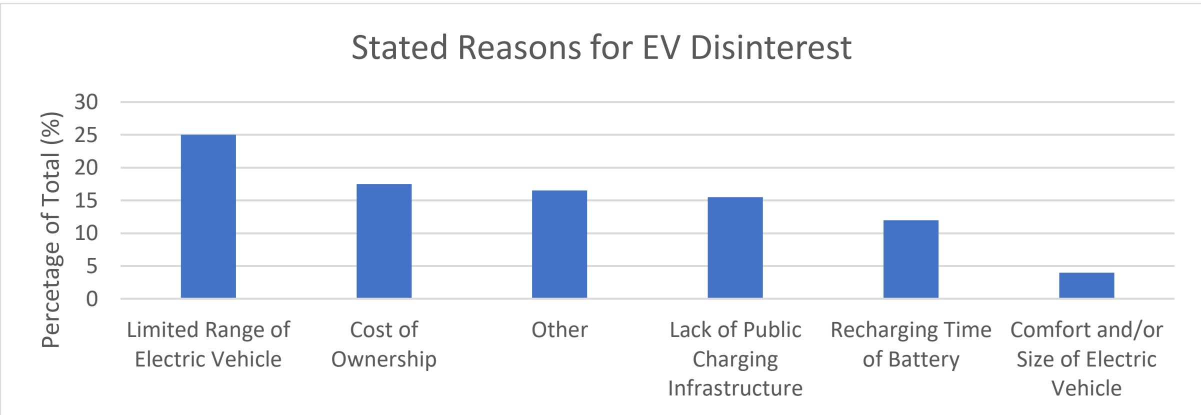


Figure 2.10 - Consumer reasons behind lack of interest for EV technology [109]

However, recent studies based on interview and case study data suggest that both the technical and psychological arguments towards range anxiety are incomplete. The psychological barrier attributed to the fear of not having the EV meet the consumer's requirements can be addressed by investigating the average consumer daily driving needs. Previous studies indicated that an EV could fulfil up to 95% of these requirements if a change in behaviour lasting for 10 calendar days can be performed yearly [110]. This conclusion has been based upon an outdated assumption that implies an EV has a range of 100 miles per full charge. Furthermore, it has been determined that even after the electric vehicle's battery has been significantly degraded, EVs are still able to meet the daily travel needs of more than 85% of US drivers, averaged at 96 miles [111].

Setting aside vehicle range capabilities, it has been demonstrated that range anxiety becomes even less relevant if vehicle charging infrastructure is widespread in a given area from a psychological standpoint. Previous statistics show that up to 98% of local driving and 88% of long-distance driving may be covered by electric powertrain vehicles with a small number of charging locations [112]. Moreover, the long-distance driving requirements may be further satisfied by employing fast charging technology based on high power applications [113].

Additionally, it has been demonstrated that EV owners are much more comfortable with EV range capabilities compared to the rest of the automotive consumers, suggesting a psychological link which is based on biased interpretations [107]. Previous research also recommends further education on EV capabilities and vehicle charging infrastructure in order to increase uptake in electric-powered motor vehicles [114].

However, studies suggesting the opposite also exist. Case studies based on consumer experience with EV technology over 3 months indicate that vehicle range was mentioned more often as a barrier to EV deployment. Moreover, a change in driving habits has also been observed, as consumers attempted to minimise their daily travel needs [115]. Therefore, the psychological aspect of range anxiety has been deemed unclear or inconsistent in a best-case scenario. Additionally, some papers have argued that the anxiety factor may be rhetorical, as it fits Hirschman's Rhetoric of Reaction theoretical , which explains the reasoning behind reactionary narratives towards EV [109].

Similarly, the range anxiety rhetoric has also been associated with other ICE vehicle alternatives, particularly with alternative fuelled vehicles such as cleaner energy fuelled vehicles [116] [117]. These types of powertrains, which rely on alternative fuels as the energy source, such as ethanol, methanol or liquified petrol gas (LPG), have been considered a viable alternative propulsion technology to conventional ICE vehicles for some time now [118]. This is mainly due to their ability to use the same engine type as petrol and Diesel cars, with minimal modifications and additional costs [118]. Additionally, the fuels used by these types of vehicles has recently started to be manufactured using methods which are significantly more sustainable than sourcing conventional fuels [117]. However, the vehicle range of alternately fuelled vehicles has been shown to be smaller than their ICE counterparts, while the refuelling infrastructure for alternative fuels remains undeveloped, effectively creating a range anxiety-based obstacle. These issues have been observed as being consistent throughout vehicle categories, ranging from private passenger to freight heavy vehicles [119]. Additionally, other technology-related problems have been raised, such as safety concerns related to storing alternative fuels, such as LPG or ethanol, due to their dangerous chemical characteristics [120]. Moreover, whilst cleaner energy fuelled vehicles have been proven to emit less carbon dioxide emissions over long distances relative to conventional ICE-based powertrains, they cannot be considered a long-term solution if the target is zero emissions, since a CO_2 footprint is still produced [116].

Comparatively, from a technological standpoint, electric motor vehicle range performance has seen a sustained increase in recent times due to advances in battery technology, packaging and lighter materials [94]. As recent as 2021, the US average range figure of an EV was set as 349 km per charge [121]. This represents an increase of 44% relative to 2017 and a 152% increase when compared to figures featured in 2011. Similarly, the maximum range-per-charge offered by the models available for purchase on the EV market has steadily increased, up to 837km in 2021 [121], as outlined in figure 2.11.

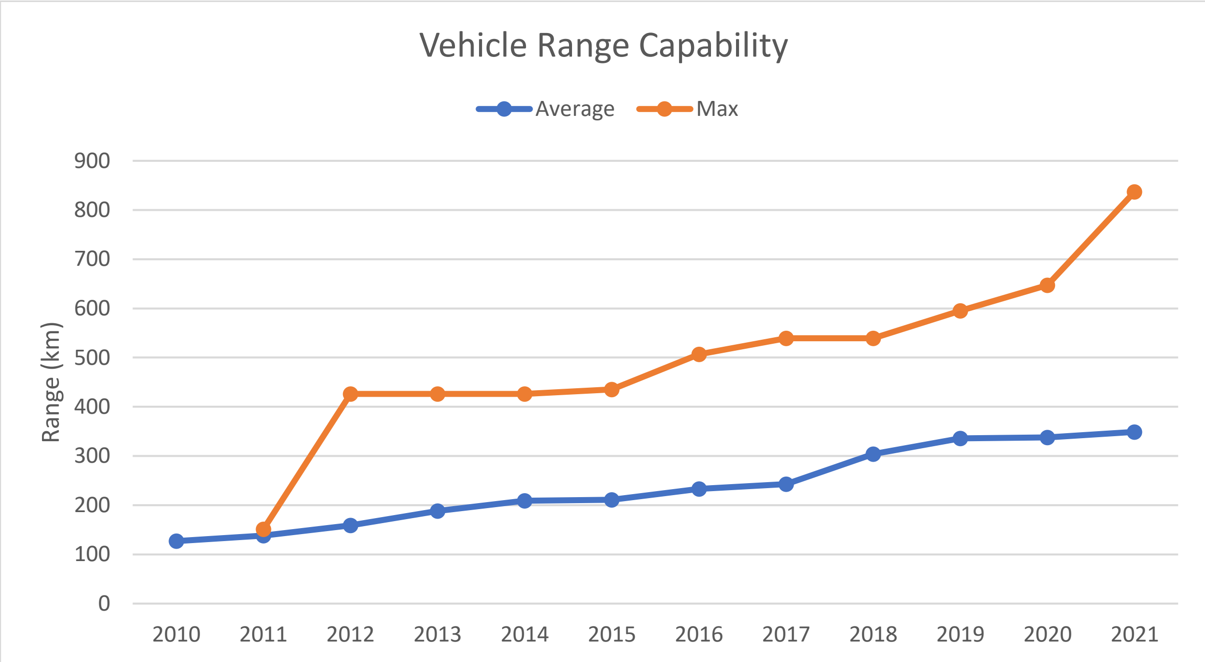


Figure 2.11 - Evolution of EV range capability [121]

When considering the adoption of EVs in other, large-scale applications, such as company logistics, it appears that the companies tend to generally echo the decisions made by private, consumer-oriented passenger vehicle owners [122]. Whilst the literature looking into the reasons behind company disinterest in EV adoption is far less detailed, recent investigations indicate that the general scepticism towards adopting freight application focused EVs can be broken down into two categories [123].

Firstly, companies mention cost-related issues, such as the higher pricing of electric heavyweight powertrains relative to their ICE counterparts [123], as a primary source of concern. The upfront price gap between these technologies can be explained by the relative novelty of electric powertrains. Although the technology has been present on the passenger vehicle market for several years now, heavyweight electric powertrains are still considered as being in their “early days” [124]. This has a negative effect on manufacturing costs, as fabricating these requires use of a different production process, which is costly to implement. However, recent studies [123] indicate that, if reasonable government financial incentives are offered, companies would be significantly more open towards adopting and integrating electric heavyweight powertrains within their logistic operations. Moreover, as battery technology evolves and electrical energy storage designs are further optimised, it is expected that the upfront purchase costs of electric heavyweight vehicles will ultimately converge with the pricing seen with their ICE conventional alternatives [125]. This is likely to result in a higher degree of attractiveness of heavyweight electric vehicles.

Additionally, operational-focused problems, are also mentioned among the main reasons behind the limited adoption of EV technology in company logistics. There are represented by vehicle range performance and lack of appropriate charging infrastructure [123], effectively creating a similar range anxiety phenomenon, similar to the one experienced by private passenger EV car drivers . However, both issues are expected to be addressed as technology evolves. Range performance will likely increase as battery technology evolves [126], whilst charging infrastructure for all electric vehicles is consistently upgraded and extended throughout the world due to government programmes, such as the UK's Road-to-Zero [127] and the EU's Green New Deal [2]. Moreover, it is expected that electric truck drivers will be able to learn a more economic driving style which will have a beneficial effect on range performance, similar to what has been observed with private passenger EV drivers.

As previously presented, the literature findings and current performance of EV technology suggests that concerns due to vehicle range are increasingly purely psychological. Most often, it appears that the reasons behind inconsistent EV adoption are based on ill misconceptions about travel demands, driving habits, and the electric powertrain technology.

2.1.2.4. Research Gap

Whilst the focus of analysing the benefits, challenges and opportunities of electric motor vehicles have been centred around lightweight powertrain, private passenger cars, little research examining other vehicle categories exists. Whilst literature on other types of vehicles employing electric powertrain exists, the scientific community appears to be in the "early days" of understanding the implications and advantages of employing EV technology in other automotive categories. Although some research looking into the energy requirements of heavyweight powertrains has been undertaken [128][129], the findings are insufficient to reach a unanimously valid consensus. This has been mainly attributed to the differences in logistics worldwide, as well as the driving characteristics of these vehicles[130][131].

Moreover, whilst the methodology of literature-featured investigations is reasonably explained, the findings appear inconsistent depending on various factors influencing the usability of electric vehicles. Additionally, as previously stated, heavyweight powertrains and other vehicles comprise a significant part of carbon emissions produced by the transport sector [132].

The findings presented in this thesis aim to help towards understanding energy usage, carbon footprint reduction and consequentially energy requirements of deploying other types of less common EVs, such as electric RCVs, buses and motorbikes. Having the ability to grasp the impact from an energy demand standpoint will serve as a cornerstone for more refined analyses on long-term feasibility. This will help in further understanding current literature results [133] of what a fully decarbonised transport sector should look like.

2.1.2.5. Future Trends of EV Technology

As the adoption of electric powertrains in the transportation sector increases, studies predict that a decrease in produced CO_2 emissions is imminent [134]. This will be aided significantly by ensuring increased green energy production through various means, such as wind, solar and nuclear. Additionally, from a technological perspective, electric powertrain designs are expected to feature increased system efficiency, through optimised electric motor designs and use of novel battery materials that exhibit increased energy density [126]. Further efficiency improvements may also be brought by usage of lighter materials in chassis builds, resulting in vehicles having increased range and performance[135]. Moreover, as electric powered vehicles will become widely adopted, psychological concerns related to their capabilities are likely to be significantly attenuated [136]. Finally, whilst not limited to EV technology alone, Internet-of-Things capability (IoT) of vehicles are likely to be further expanded and integrated into automotive systems. This is likely to result in increased accessibility, optimisation of driving behaviour, as well as safer traffic [137].

However, some research indicates that the decarbonisation of transportation may be a more prolonged process than expected and may be aided by alternative technologies [138]. Therefore, understanding the capabilities of EV alternatives is important.

2.1.3. Alternative Technologies

The alternative technologies to the adoption of EVs can be broadly classified based on their feasibility timescale. Short-term alternatives, such as hybrid and new-generation ICE-powered vehicles are widely available on the market and praised for their range capabilities at a lower cost relative to BEVs.

Hybrid powertrains are based on two propulsion technologies, the conventional internal combustion engine (ICE) and a separate electric motor. They have been a topic of interest due to the higher degree of system autonomy given by the conventional petrol/diesel-based engine [139]. This technology is unable to provide net zero carbon emissions during the usage lifecycle phase; however, the overall footprint can be significantly smaller compared to a conventional ICE-only powertrain. A particular subcategory existing in both the hybrid powertrain and fully-electric powertrain families consists of the plug-in hybrid/full electric powertrains, that are able to increase the flexibility and versatility of the vehicle thanks to the ability to charge the battery used by the electric motor by using a standard-issue power interface that connects to the energy grid or various fast-charge energy interfaces [140] that are able to deliver higher power to the battery, resulting in faster charging times at the expense of some minimal additional battery wear.

Additionally, another important technology that has recently seen massive improvements in efficiency [141] are energy recovery systems, which is relevant to both battery electric vehicles (BEV) and hybrid electric vehicles (HEV). Energy recovery systems enable an electric vehicle to recover some of the wasted energy during its operation and convert that energy into electrical energy to be stored in the battery, resulting in a higher overall energy efficiency. Most efforts in this field have been concentrated into recovering the kinetic energy vehicle braking during friction. This technology has been present for quite some time in other fields, such as motorsport, where its applicability in the automotive field was first significantly investigated during the early 2010s Formula 1 series, with the prevalence of kinetic energy recovery systems (KERS)[142]. Today, most of the available BEV and HEV on the market have powertrain systems that include the ability to harvest braking energy to various degrees of efficiency, but nonetheless positively contributing to the powertrain's efficiency. Similarly, research has also been carried out into the feasibility of harvesting the heat of the exhaust gases [143] and converting it into electrical energy for HEVs, but to date that research is inconclusive and has not been meaningfully applied at scale.

Similarly, new generation of ICE-based powertrains (EURO6/EURO7 certified engines) have been thoroughly researched and provide a strong competitor for the abovementioned propulsion alternatives in the short-term. These 'new generation' engines are highly efficient and provide a smaller carbon footprint when compared to older ICE technologies, usually employing multi-stage turbo systems to increase the base engine efficiency coupled with smaller engines with less cylinders. Further mechanical improvements brought to engines include electronically controlled, improved ignition timing as well as multi-rail fuel injection and engine cylinder deactivation, in an effort to maximise engine efficiency. Some of these engines also employ gas-based fuels with lower carbon emissions per litre, as well as micro-hybrid systems, such as start-stop technologies, that minimise vehicle emissions when idling [144].

However, whilst the carbon dioxide footprint of these engines is significantly smaller than older designs, they do not eliminate carbon dioxide emissions altogether. Therefore, similar to hybrid powertrains, they can only be seen as short-term alternatives since the current worldwide perspective of governments is to eventually discard all ICE-only powertrains from use [145]. Nonetheless, both technologies can still be used as an intermediate step in the progressive process of transport decarbonisation, as presented in figure 2.12.

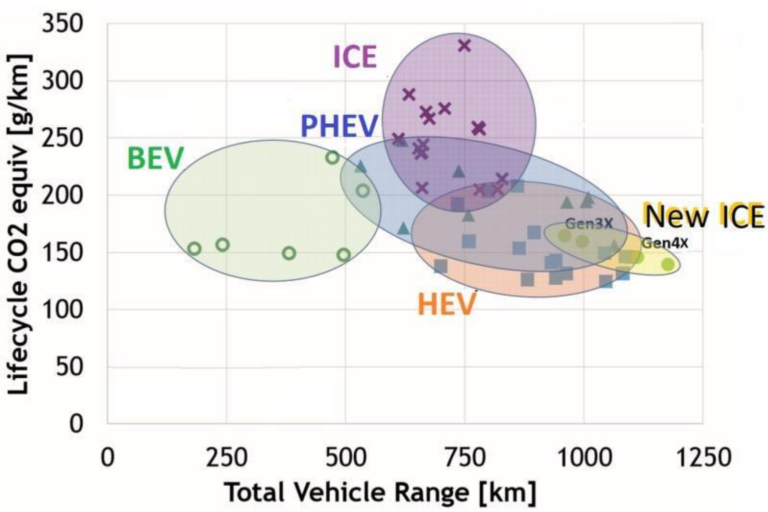


Figure 2.12 - Carbon Dioxide emissions vs vehicle range for different powertrain technologies. (Source: 27th Aachen Colloquium Automobile and Engine Technology, 2018)

An emerging technology that may enable the previously discussed technologies to be considered as long-term alternatives to electric vehicles is the use of methanol as engine fuel [146]. Whilst the chemical composition of methanol still contains carbon that, when burned, binds with atmospheric oxygen creating carbon dioxide, the amount is smaller than what is found in conventional ICE fuels. Furthermore, methanol manufacturing has been proven to have the potential of harvesting CO_2 in the atmosphere as an ingredient for its production, effectively enabling the possibility of a net-zero carbon emission mechanism [147]. There is a significant amount of research [148] looking into the feasibility of employing this substance as an energy source for ICE-based vehicles and several findings suggest that current engine designs may be capable of burning methanol with minimal modifications. Trials focused on using methanol as ICE fuel are already being carried out on heavyweight powertrains in Iceland, with satisfactory progress [149]. Additionally, net-zero carbon methanol manufacturing is expected to be produced on an industrial scale if deemed economically and technically viable in the near future, with experimental production already in place [150].

Conventional long-term alternatives to EV technology are mostly focused on use of hydrogen. One of the most researched hydrogen applications is fuel cell-based vehicles. These employ compressed hydrogen which is stored in a pressurised tank that is then fed into a fuel cell system, together with atmospheric oxygen. These substances are then combined and generate electricity and water (as a by-product) through molecule polarisation. This results in vehicle mobility through electricity with zero carbon emissions [151]. Most of the benefits of fuel-cell electric vehicle (FCEV) over standard EVs are related to accessibility and ease of use. Energy refuelling of hydrogen fuel cell vehicles has been shown to be significantly quicker than current capabilities of EV recharging, with an average hydrogen tank refill lasting 5 minutes [151]. This benefit is consistently being raised by consumers participating in case studies [152]. However, whilst the performance of these vehicles is generally on par or slightly better than their electric counterparts, several concerns with hydrogen alternatives have been repeatedly raised and still exist.

Firstly, the energy efficiency of standard fuel cell-powered vehicles is bound to always be lower than electric vehicles. This is because, unlike EVs, an energy conversion step is performed through polarising hydrogen, which is expected to have losses [153]. The energy loss problem becomes even more significant if the entire fuel supply chain is considered, as indicated in figure 2.12. Furthermore, concerns regarding fuel storage safety have been raised, due to the potential container leaks that may arise and the high flammability of hydrogen as a substance [154]. Finally, costs related to hydrogen manufacture and its transportation are still highly variable due to variability in electrical energy pricing, as evidenced in recent publications [155].

Another hydrogen powered alternative that has recently gained interest is represented by ICE-based systems capable of burning hydrogen. This method has been shown to have the advantage of extracting energy from hydrogen without requiring additional energy conversions. Research indicates that such engines have the potential to have similar performance figures to conventional ICE vehicle with no carbon dioxide emissions [156]. Furthermore, companies have already been commissioned to research the feasibility of hydrogen-powered ICEs [157]. However, the apparent lack of consistent literature on this topic suggests that the technology has not fully matured, and its potential not completely understood.

As demonstrated in this subsection, there are several alternatives to EV technology already on the market or in advanced stages of research, some of them having the upper hand in terms of apparent performance but lack a competitive edge in other areas. Nonetheless, it is expected that EV technology will be the main focus for supporting the decarbonisation of the transportation sector, as evidenced in recent research materials [158].

2.2. Simulation

Having discussed the current status of electrification in the automotive industry and the transportation sector, the second important topic that has been investigated is related to simulation and its current status in the scientific and industrial communities. This has been done in order to better understand the picture of automotive simulation focused on energy usage, the main aim of the research material featured in this thesis.

Simulation is defined as the process of imitating real-life systems and phenomena over time. This process is carried out through the use of models, a representation of the most important characteristics or behaviours of the real-life element to be simulated [159]. The model is usually described with limited detail relative to the real-life element. Albeit simulation has been conventionally performed through real-life, controlled environment experimentation, computers are increasingly being employed in the process of building a model which is then simulated over time. This has been made possible due to recent significant advances in computational power [160].

Currently, simulation is being used in many disciplines and contexts, predominantly for system performance tuning and optimisation, but also stress testing and training. However, as computing capabilities have expanded thanks to increased hardware performance, simulation has been extensively used in scientific modelling of natural and human systems. Depending on the discipline, simulation has traditionally been used in order to determine the behaviour of systems that have a high degree of complexity or cannot be accessible to regular analysis methods [160].

The main challenges related to system simulation are represented by data acquisition (and its validity), the approximations and assumptions taken when building the model, as well as the usability of the simulation results. In order to overcome these obstacles, procedures and protocols concerning model verification and validations are usually defined simultaneously with model development, to avoid result bias. This is currently considered standard practice in many fields, including academic study [160].

Many types of simulation exist, which have generally been developed independently. However, research of systems theory in the 20th century has led to a more systematic perspective over this process [161]. However, the most popular distinguishes between physical and interactive simulations.

- **Physical simulation** constitutes the type of simulations concerned with understanding the behaviour of physical entities. This type of simulation is commonly used in order to minimise costs relative to real-life experimentation. Examples include electronic thermal modelling, electromagnetic simulation, but also model-based system energy usage estimations.
- **Interactive simulations**, also known as human-in-the-loop (HIL) simulations, aim to emulate real life environments for human operators. Examples of these include flight, driving and sailing simulators.

Simulations can also be classified as deterministic or non-deterministic. The former type is widely used for various activities, relying on results computed by deterministic algorithms. Therefore, repeated simulation runs with identical boundary conditions will always compute the same results [161]. However, non-deterministic algorithms have increasingly gained popularity due to the algorithms employed. These have been strongly tied with Artificial Intelligence (AI) technology and are represented by a wide range of procedures [162]. Whilst still considered novel, non-deterministic algorithms have shown capabilities that previously were unattainable through simulation, having the capability to demonstrate chaos-prone systems, such as weather [163]. Similarly, medical applications of novel simulations based on these algorithms focused on cancer screening have been trialled, showing high degrees of accuracy [164].

Finally, another significant novelty in the field of simulation is represented by model-based programming. These rely on models comprised of building blocks that have a given set of properties and constraints, effectively having the capability to emulate any real-life system [165]. The main advantages brought by this type of modelling are represented by its ease of use and accessibility. Due to the existence of predefined blocks with defined properties as well as access to a graphical interface, the development process of these models is swift. Similarly, the required knowledge to run and interpret the results of the simulations is minimal, as understanding the high-level system diagram of the model is the only mandatory element [165]. Additionally, the validation and testing of the simulation is quicker than with a conventional solution, as potential software bugs can be identified and isolated based on the behaviour of each building block in the model. Applications of model-based programming exist in many fields of expertise, ranging from understanding protein behaviour [166] in biology to identifying patterns in trade economy [167].

2.2.1. Modelling & Simulation in Automotive & Transportation Industries

Like other fields of expertise, simulation has been widely used in the automotive industry due to its ability to emulate complex phenomena as well as minimising research & development costs, as suggested by recent literature. Applications have been conventionally focused on investigating physical phenomena happening during vehicle manufacturing, use and recycling. Research focused on numerical analysis, such as computational fluid dynamics (CFD) has been consistently a key area fit for simulation work, albeit considered computationally expensive. This has led to significant advances in understanding automotive aerodynamics, both in road-legal vehicle designs as well as high-performance motorsport applications [168].

There is a significant amount of evidence in literature of work performed towards understanding vehicle dynamics related to suspension and braking, which utilises models and simulation environments. The findings have aided in implementing novel suspension designs that minimise energy consumption and maximise passenger comfort and vehicle handling [169]. Similarly, simulation-based research work focused on optimising power efficiency of ICE-based powertrains has been consistently featured in literature, giving way to innovative concepts such as enhanced cooling for turbocharged engines [170].

The transportation sector has also benefitted from experimentation through the use of simulation. Traffic management has been an increasingly relevant topic for some time now due to increasing numbers of vehicles on the road. However, many active traffic management elements (such as traffic lights) are currently unfit for handling traffic during peak activity hours, especially in urban areas [171]. Moreover, traffic management systems are largely independent and thus not integrated into city-wide traffic systems that are capable of handling traffic based on real time analysis decision-making. Studies employing simulation-based work demonstrate how traffic modelling can successfully emulate real-life conditions and help with optimising traffic management [172]. Furthermore, research employing non-deterministic algorithms that model traffic based on the chaos theory hypothesis have proven that city-wide traffic systems are feasible and can minimise traffic congestion in urban areas [173].

Finally, software modelling and simulation has also been used towards estimating vehicle energy consumption. There is a significant amount of literature investigating individual vehicle energy usage as well as fleet-level utilisation through software applications [174]. Additionally, simulation results can provide a better understanding of incurring costs related to energy refuelling, as well as estimating the carbon footprint at both vehicle and fleet-level. Furthermore, the accuracy of recent models and simulations developed for vehicle energy usage computation have high degrees of accuracy, as evidenced by recent research [175].

2.2.1.1. Research Gap in modelling and simulation

Whilst the use of simulation in estimating energy consumption in vehicle fleets is widely used, literature currently focuses on conventional simulation methods, such as pure mathematical modelling [176]. The results presented in this thesis are computed by a novel modelling and simulation method, formulated using the model-based programming paradigm. A further novelty can be found in the simulation environment in which the modelling is performed. This has been custom tuned to balance error tolerance with execution times in order to maximise the time spent computing meaningful data. The developed solution ensures a high degree of accessibility, due to its system diagram-like structure. Moreover, the block components are highly modular, and can be reused through interfacing with other models, ensuring versatility, as opposed to having fixed-constraint modelling.

Similarly, although some research describing modular models for energy consumption do exist, the simulation solution presented in this thesis aims to offer an alternative and further contribute towards understanding of the energy requirements of EV alternatives [177].

2.2.2. Telemetry

As previously mentioned, one of the main challenges when utilising simulation in order to emulate real-life phenomena is represented by the accuracy and validity of reference data. In the case of time and distance-dependent vehicle energy estimation, input data is generally constituted by speed-time or speed-distance value pairs, also known as telemetry data. In order to better understand the limitations of this concept, the key facts and its evolution must be discussed.

The concept of telemetry is represented by the ability to record and automatically communicate accurate measurements of physical parameters of entities in an in-situ fashion [178]. The first use of telemetry has been recorded in the steam age, represented by James Watt's steam engine (1776) with add-ons employed for monitoring engine parameters [179]. The concept has since been successfully applied to many fields of expertise, ranging from meteorology and medicine to the telecommunication industry, where it gained significant popularity due to its extensive use in space science and military defence [180].

Recently, telemetry systems have seen increases in usability in the automotive and transport sectors, with a range of applications proving their effectiveness. For example, they have been extensively used to better understand potential improvements of logistic fleet usage, such as improved mileage through better vehicle routing and decreased carbon dioxide emissions [181]. Similarly, telemetry data has been proven useful for creating semantic, high-resolution data for maps of urban areas [182]. The accuracy of artificial intelligence (AI) based driving assistants has also been proven to be positively affected by integrating vehicle telemetry in prediction operations, indicated in previous research work [183].

Since the 1980s, the concept has been extensively used in high-performance subsectors of transport, such as motorsport. It has been employed as data-driven feedback for the design of key elements, such as aerodynamics and powertrain sizing [184]. Additionally, telemetry principles have been successfully employed to develop optimised controllers for torque split and velocity scheduling in hybrid vehicles [185]. Evidence represented by improved aerodynamic efficiency as well as increased power-to-weight ratio of motorsport vehicles [178] indicate that telemetry has positively contributed to the vehicle design process, together with other sources of feedback, such as driver comments and computational simulation. This demonstrates that similar ideas have been successfully applied in previous studies, therefore validating the aims of the presented material.

Finally, video acquisition of data using dashboard-mounted video cameras (dashcams) has been widely used and has recently gained popularity in vehicles, especially in PSVs [186]. However, the videos captured from these dashcams are primarily used to provide witness and testimony during traffic violations and accidents [187]. This includes collecting evidentiary journey and real-time vehicle data, such as speed and geographic coordinates, which are overlaid onto the video feed together with a time stamp.

2.2.2.1. Research Gap in telemetry

In order to better understand the purposes of the featured research, traditional telemetry data application limitations must be considered. Conventionally, this data may be extracted for energy usage estimation from driving data obtained from an in-service conventionally fuelled vehicle. Since the electrified vehicles will operate the same routes under the same or similar road restrictions, such as speed limits and time constraints, the on-road EV driving data is the equivalent to that from an available ICE vehicle. Traditionally, this data could be collected by using an on-board GPS logging device installed on the in-service vehicle. However, most logging devices are primarily installed for anti-theft and trip detection purposes hence cannot achieve the essential resolution and logging frequency required to collect data for simulation, such as accurate location, or high resolution logs [188].

The research featured in this thesis includes a section presented in chapter 6 which describes a video format agnostic procedure, able to harvest telemetry data from publicly available vehicle dashcam videos. This is performed by employing image processing techniques on a selection of frame groups extracted from the original video data. Currently, there is no published research describing methods that extract vehicle driving telemetry data from video sources, therefore the presented solution represents a novel application of image processing in the automotive field. It is expected that the solution will provide the scientific community with significant amounts of telemetry data for analysis.

2.3. Chapter 2 Summary

As previously presented, it can be observed that the literature around the EV technology is rich in detail and has analysed many aspects within the technicalities of the electric vehicle, as well as what implications mass electrification could bring. Similarly, concerns regarding EV performance have been discussed. It is generally concluded that the decarbonisation of the transport sector though powertrain electrification can be performed progressively for privately-owned vehicles, although the climate targets imposed concerning carbon footprint reduction means the economic sustainability factor is up for discussion. Moreover, several gaps in understanding the energy requirements of heavyweight electric powertrains remain and will require solutions in order to determine the sustainability of transport decarbonisation. Alternative technologies may also be considered as they have been shown to aid the transition to a zero-emission transportation sector whilst easing the associated costs.

Simulation has also been shown to be consistently used in the automotive field, although many opportunities towards enabling more data to be used remain. Similarly, new software paradigms and non-deterministic simulation algorithms are unexplored. However, novel applications employing these new concepts may prove game-changing in the long term.

Having discussed the background of the research that is presented in this thesis, the next two chapters are concerned with discussing the development of a novel software model that has been employed for estimating energy consumption of various unconventional electric vehicles including eRCVs, eBuses and eBikes.

3. Chapter 3 – EV Model Methodology

3.1. Recent Progress in Automotive Simulation

In the previous chapter the general approach to, and reasoning behind, EV modelling was examined, and relevant literature reviewed. This chapter will expand on this and present the mathematical methods utilised by similar work to achieve robust vehicle simulations.

Firstly, the general, physical and mechanical constraints related to driving have to be considered. Additionally, the vehicles employing an electric powertrain pose several simulation modelling challenges that are unique to this type of technology. Understanding energy-saving mechanisms, such as regenerative braking, is especially important since there is no strict technical specification set to adhere to. This has resulted in various vehicle manufacturers choose to follow different development paths. Similarly, battery modelling is another key element that needs to be understood, both in system-wide possibilities and modelling limitations in order to maximise prediction accuracy and large-scale reliability.

Finally, this chapter also contains the chosen approach employed for developing a two-stage model, together with showcasing all its subsystems and how they interact with each other. Additionally, results concerning the validation and testing stages of the solution are presented, in order to better understand the accuracy and limitations of the model.

3.1.1. Mathematical Approaches

Whilst there is little research regarding the application of EV technology to heavyweight powertrains, many research papers describe models aimed at predicting the behaviour of popular alternative solution powertrains for passenger cars, ranging from full EV/BEV technology to series and/or parallel HEV/PHEV vehicles. Many of the described models ensure a high level of accuracy or simulation of flexibility. Most models [98][96][189] employ a purely mathematical model-based approach, in which only the most important force-based equations around the powertrain system are described, shown in equation 3.1.

$$\begin{cases} F_{tractive} \propto P_{Motor} \\ F_r = F_{rr} + F_\alpha + F_{aero} \\ F_\alpha = mg\sin\alpha \\ F_{aero} = \dfrac{\rho_{air} + A_f + C_d(v - v_w)^2}{2} \end{cases}$$

Equation 3.1 - Basic vehicle modelling equations

where $F_{tractive}$ represents the traction force proportional to the instantaneous power delivered by the electric motor, F_r is the sum of all resistive forces, with F_{rr} representing the resistive force due to tyre rolling resistance, F_α the resistive force resulted from the slope inclination effect and F_{aero} the resistive force resulting from the aerodynamic drag effect. Furthermore, F_α is typically modelled as the classical 1st order Newtonian equation, while F_{aero} is modelled after Betz's Law, with ρ_{air} as air density, A_f as the frontal vehicle area and C_d a linear resistive coefficient related to speed. [190]

The simple equation-based model is the basis of other concepts in this field. It can serve as a "testbench" for implementing a routing algorithm but can also be the basis of a modular subsystem-based vehicle model. However, while this is usually an effective method to save computational resources and make the simulation process faster, it may not always comprehensively analyse the system behaviour. Moreover, while under normal circumstances these simplified mathematical models may output reasonably accurate results for passenger cars, the simulation precision may worsen for different variations of heavyweight powertrains. This is because the equation set presented above does not account for lateral dynamics when steering or driving at high speed.

Many of the models presented in previous research have been implemented in the Matlab/Simulink environment, most likely due to its user-friendly and versatile characteristics. Although some researchers have been using a blend of SysML/Modelica to employ novel simulation methods such as different neural network techniques, results of this latter approach suggest that although the proposed neural network surrogate modelling is not best-suited for control modelling compared to the traditional continuous PID control, the expectations during the concept phase have been met in the implementation and validation phase. [176]

3.1.2. Modelling EV-specific vehicle characteristics

3.1.2.1. Regenerative Braking

An important technical component of most EV systems is represented by the concept of regenerative braking. This allows the use of the vehicles inertia to harvest energy that otherwise would be lost as friction/heat while braking. However, the intensity of this braking is usually controlled by a dynamic factor that changes depending on vehicle and road characteristics, and the charge acceptance of the battery. Normally, under simulation conditions, approximating the dynamic factor to a constant fixed value gives reasonable results, but ongoing research has applied fuzzy logic models to more accurately account for regenerative braking behaviour. One paper [191] states that mean square errors of such an application can be very low. The results suggest that the proposed model can accurately predict energy usage, and can be used for energy management, powertrain design and to simulate fleet-level vehicle systems if the proposed fuzzy logic algorithm is successfully implemented into traffic simulators such as SUMO [192]. Moreover, other papers show significant energy reductions that reflect in increased vehicle range. [191][193]

The impact of the regenerative braking effect in one’s driving style has also been researched under multi-study frameworks. These studies suggest that adaptability to this new driving characteristic is usually quick, in most cases the test subjects being able to adapt to an average intensity regenerative braking effect in less than a day, with trust in the system evolving at similar rates, although some outliers have been found. [194]

3.1.2.2. Software Battery Modelling

Other research forming part of the scope of the literature review in this project includes software battery models. Software battery modelling can vary from simple singular cell, perfect voltage source-internal resistance components, to complex equation system that can also account for charging tolerance and performance with respect to several factors, such as material aging due to continuous battery cycling, temperature, pressure and charge/discharge stress testing. For more complex approaches, usually the model takes advantage of most specifications related to the battery in order to achieve increased accuracy performance. Some papers describe matlab-based multi-cell custom-spec Li-Ion battery models specifically designed for implementation in simulated EV systems, with low-rate error in SoC prediction [195][196]. Similarly, there are several methods for monitoring battery charge and relative percentage SoC, the most widespread one being the coulomb count method [197], also known as current integration, which takes advantage of the time-dependency of charge with respect to current, given by equation 3.2 below.

$$Q = \int I \, dt$$

Equation 3.2 - Electrical charge relationship with current

The main drawback of this method is that due to the continuous nature of the integration operation, which implies that the recorded charge value cannot be reinitialised whilst the simulation is running. Other more complex methods exist, however for the purpose of this simulation project, the coulomb counting method has been deemed sufficient.

Furthermore, some papers have examined the possibility of developing user-friendly interfaces for existing system simulation solutions, to increase end-user productivity. Previous research [189] showcases a GUI developed using Matlab capabilities for a previously developed simple force-based vehicle model. Input data consists of a set of coordinates entered by the user through a PHP page. Google Maps is then employed to compute and load a map with information about the route (presumably XYZ data), which is then exported to a file. Relative slope delta (%) is computed from the altitude (z-data) entries. A driving cycle (speed profile) recorded for the given route is then correlated with the map data and then fed into the algorithm, which models the speed delta as being proportional to the difference between the traction force and resistive force, divided by the product between the mass of the vehicle and a linear loss factor (which models inertia and other rotational mechanics losses), as shown in equation 3.3.

$$v \propto \frac{F_t - F_r}{m * k}$$

Equation 3.3 - Linear force loss factor proportionality

Tractive force, which is effectively the script's output calculation, is then transmitted to the tyre model (ground friction). Although there are no absolute figures in terms of productivity boost, the developed interface is easy to use even for someone with no training in Matlab or knowledge regarding the complex principles of a given EV powertrain. [189]

3.2. Development Process

The proposed vehicle model solution has been developed utilising the MATLAB R2019a release environment, coupled with the related Simulink version. Several model approaches have been considered in order to understand the simulation capabilities of various simulation blocks within Simulink. All of the modelling approaches have then been evaluated and the most promising design in terms of accuracy, versatility and ease of use has been chosen.

Firstly, a purely basic Simulink block approach has been considered. The philosophy behind this consists of a model described by pure mathematical simulation blocks. While this approach ensures a high degree of versatility due to the ability to develop the model equations "from scratch", simulating complex vehicle subsystems in their entirety is almost impossible to achieve in a reasonable period due to the number of mathematical terms and factors, and their intrinsic correlations that need to be taken into account.

Additionally, an approach based on the Matlab motorsport toolbox has been deemed worth investigating. In this scenario, the model has been developed from a base template for a HEV Formula car available in the Simulink example library, as shown in Figure 3.1. The example has then been significantly changed to match the provided eRCV custom specification. However, the template itself has a very complex layout to begin with and understanding the principles behind this approach became too complex. This approach was therefore put on hold whilst alternative methods were investigated.

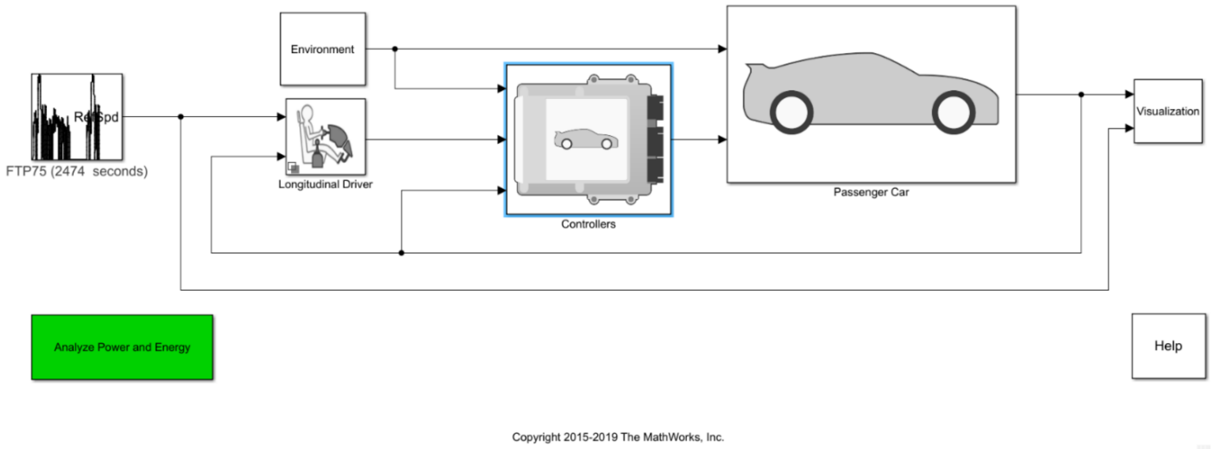


Figure 3.1 - Matlab motorsport toolbox example

Finally, a SimScape-based model has been developed. Two versions of SimScape models have been built, one being based on the MATLAB Formula Student competition courses (v1.x.x), as seen in Figure 3.2, and the other one developed on top of a parallel hybrid vehicle topology example present in the SimScape Driveline Examples library (v2.x.x), present in Figure 3.3. While both approaches present significant advantages compared to the initial models, thanks to SimScape's general flexibility and ability to manipulate multi-domain models in the same simulation, v1.x.x had a higher degree of complexity in terms of the control theory behind the model, therefore it has been dropped.

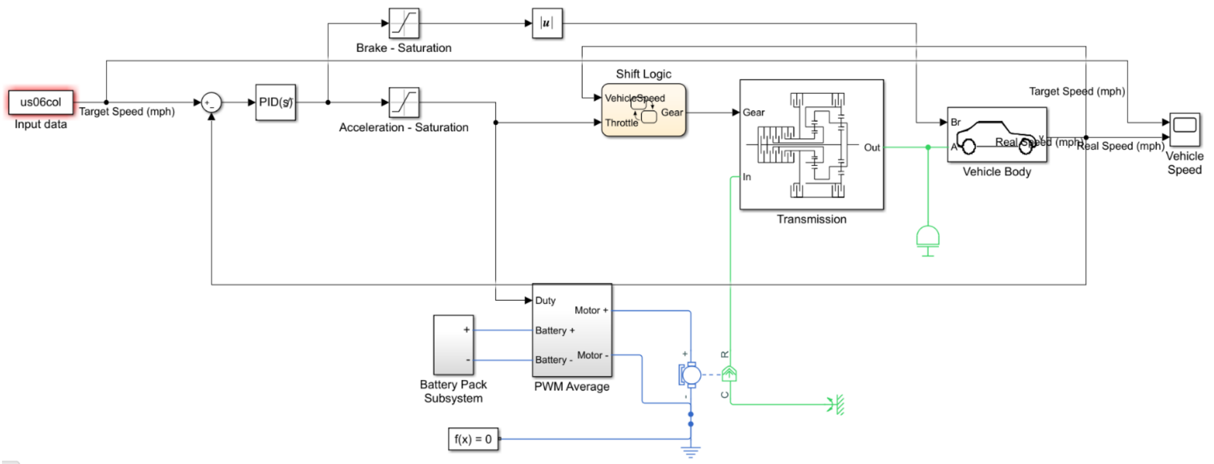


Figure 3.2 - Modelling approach employed by the first vehicle model iteration

Besides bearing significant changes compared to the model of a passenger HEV in order to better reflect an eRCV, v2 (shown in figure 3.3 below) also has a revamped control method, based on an evolution of the control method initially developed for the first simulation version. This "best-of-all-worlds" model that also maintains a high degree of adaptability to accommodate future changes has been selected as the main vehicle model development framework for this project.

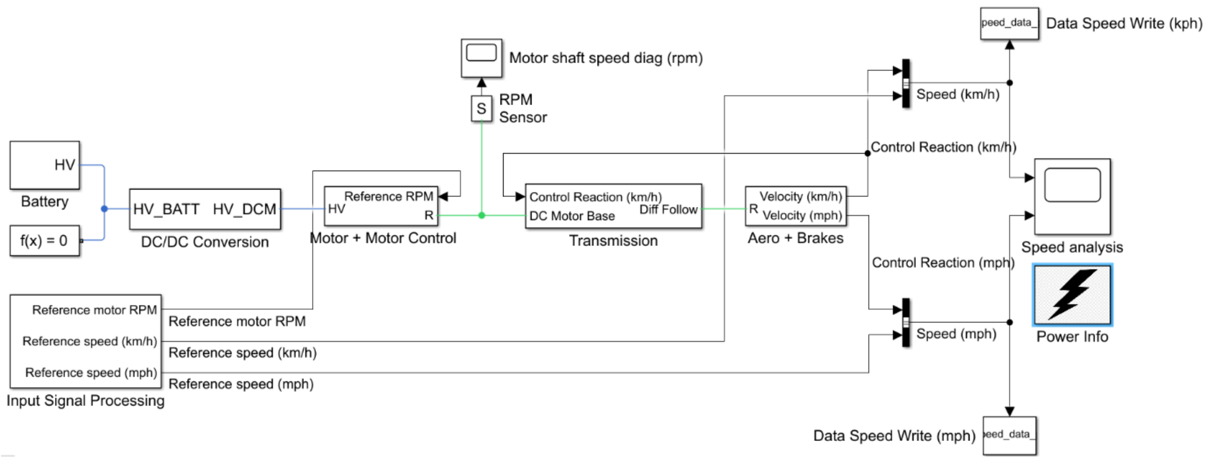


Figure 3.3 - Vehicle model, version 2

As opposed to standard Simulink model blocks, where the output may be observed only if special blocks are attached to the signal line, SimScape-developed blocks are compatible with complete real-time parameter observation through the Solver Explorer application. This allows the user to observe graphs outlining the time-based evolution of all system and subsystem parameters, down to a library-defined block level. This ensures a quick and thorough understanding of the proposed model.

3.3. Subsystem Presentation

The chosen approach consists of a simple unidirectional model that feeds inputs to outputs iteratively, with respect to the time step choice, as indicated in figure 3.4. The input signal conversion block adapts input data which is then fed into the vehicle modelling engine, into the DC motor and transmission blocks as reference speeds for the vehicle motor and ground speed respectively. The DC Motor block uses the reference motor speed in order to compute the required power demand, which is then sent to the battery module through the power conversion module. The power demand is then recorded and monitored in order to generate energy draw. Similarly, the reference ground vehicle speed is used as a benchmark for the speed control capabilities of the engine, together with the vehicle parameter information that is fed into the aerodynamic module. This block contains key parameters for vehicle simulation, such as braking capabilities, tyre modelling, and aerodynamic drag-related mechanics.

Additionally, the vehicle model is also able to display real-time vehicle speed, at a second-by-second resolution. Other recorded parameters of interest include more power-related information, such as instantaneous power, and motor RPM, in order to validate any potential inconsistencies. These are displayed by employing the scope block.

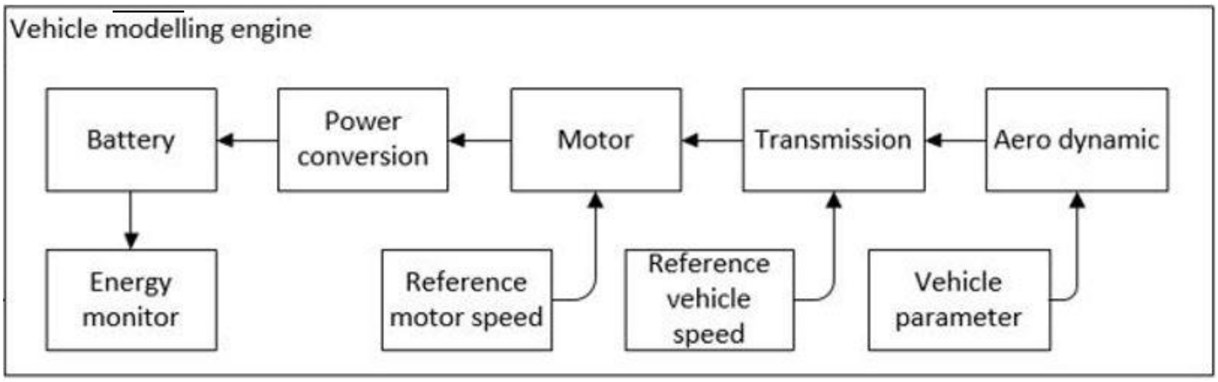


Figure 3.4 - Vehicle model, system block diagram

The battery model shown in figure 3.5 consists of a simple ideal voltage source and a series resistor with its value set according to the target vehicle battery specifications. In parallel to the power source, the main auxiliary energy consumers, for example lights and heating etc., have been defined. Their resistance values are defined in such a way that they reflect the chosen power rating values, effectively acting as current sinks. The compressor power rating has been chosen as an average value over a batch of the input data, while the others have been considered and reasonable approximation figures have been chosen for each.

Charge monitoring is also implemented here using the coulomb counting method. Current demand is integrated to give charge, which is then compared and considered as a fraction of the stated full battery charge to output battery state of charge level (SoC) in a relative percentage figure, as presented in the battery monitoring module, figure 3.6.

A datasheet-based battery model has also been considered; however, this has been dropped due to lack of specification clarity and ability to map characteristics to model specifications. Nonetheless, comparisons between datasheet-based battery models and the simple model approach adopted have been carried out, but no significant advantages in terms of accuracy have been found.

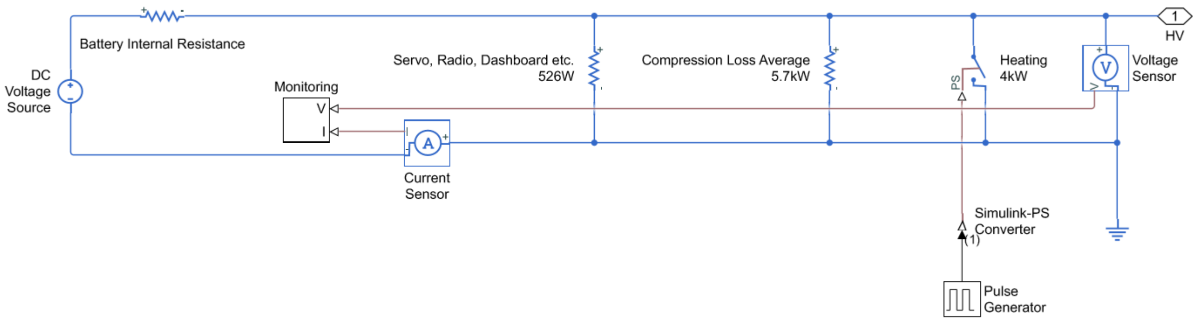


Figure 3.5 - Electrical subsystem model

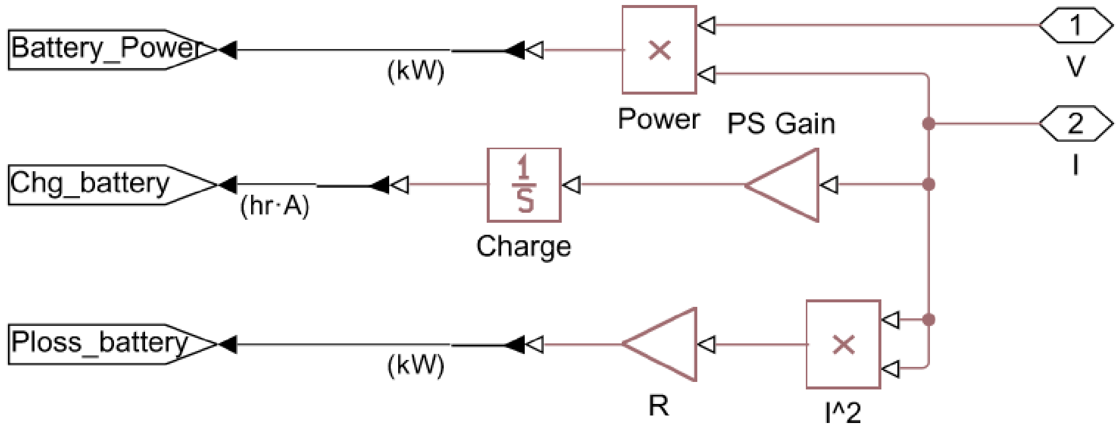


Figure 3.6 - Battery charge monitoring subsystem

The DC motor model is shown under figure 3.7. It consists of two subsystems, the motor control module and the DC motor itself, which consists of a set of equations that also perform logical decisions (regenerating/using energy) depending on the input coming from the control module.

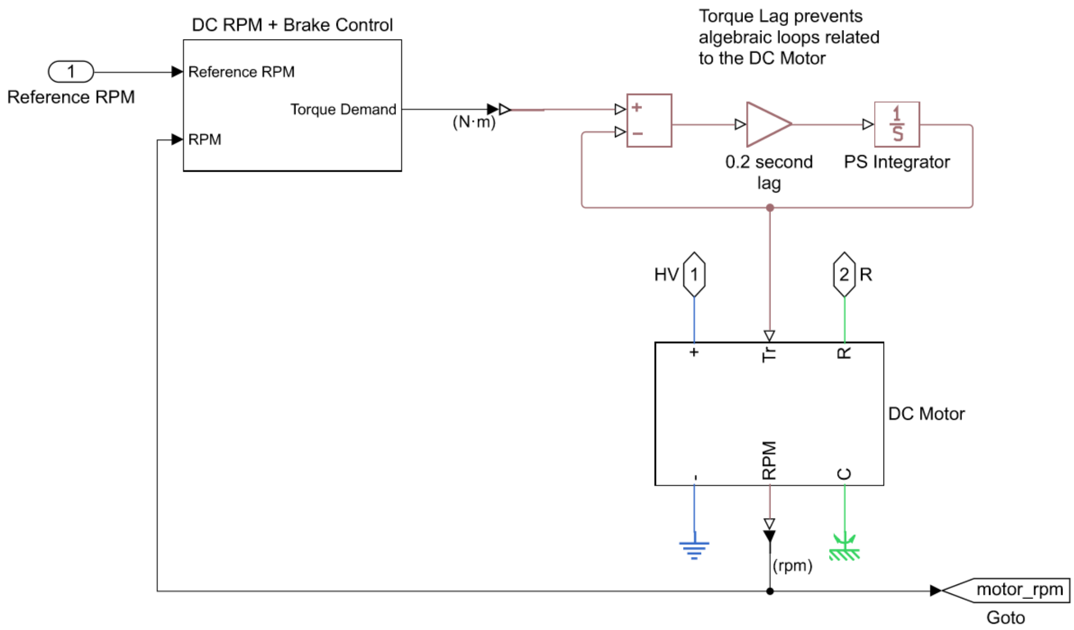


Figure 3.7 - DC motor + motor control subsystems

The control module consists of an ideal PID (proportional, integral, derivative) controller [198] with its output saturated. This takes the input recorded RPM real speed and compares it to the model's current RPM speed. Based on this comparison, it outputs the required torque and conventional braking power in order for the model to reach the set point real speed. The PID output is then further conditioned by saturation blocks to limit the output to real values that reflect the vehicle specifications. Regenerative braking is also accounted for here, as the lower limit of saturation has been set to a negative value. In addition to the saturation process, the braking output also has a linear compensation factor that controls the regenerative braking intensity. Higher values mean less regenerative braking but enables the model to "follow" the real data quicker by not relying on vehicle/motor inertia for braking. The P, I and D values have been initially chosen using the built-in tuner, then adjusted by trial and error in order to ensure reliable vehicle control when matching the input speed set points. The exact control architecture is presented in figure 3.8.

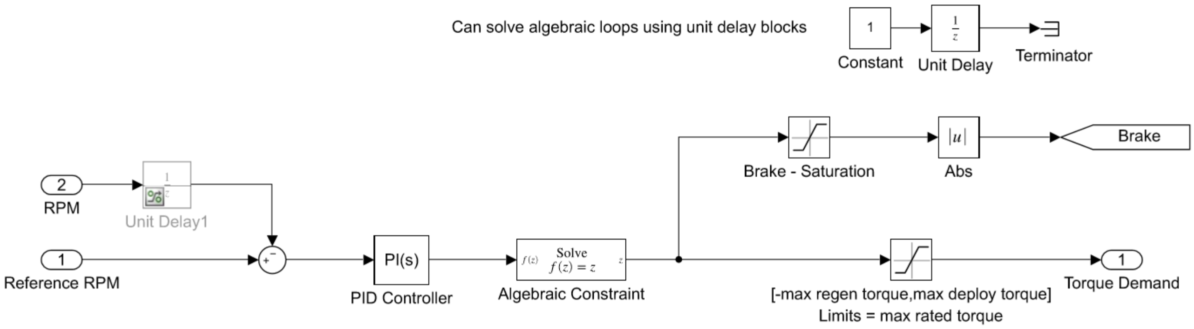


Figure 3.8 - Control module subsystem

Although the control solution for this model is quick and easy to implement and predict its behaviour, there is one main drawback based on the concept of algebraic loops. This mathematical exception occurs when the controller cannot determine causality between its input and output. This can be accounted for implementing a sample hold block at the controller input that will save the system state at input for one simulation time unit. However, this is a naïve and inefficient solution to the given problem, as the simulation speed is effectively bottlenecked by this time constraint, and while this is not a major problem for small data simulations, it can dramatically increase simulation time for big data models. Fortunately, the Simulink solver is able to efficiently solve algebraic loop-related problems by assuming reasonable system-wide parameters at the start of the simulation.

The DC motor subsystem block is presented in figure 3.9. This consists of a set of equations that have as an input, the torque output set by the control module, the vehicle model speed and the battery model voltage, and outputs the required current from the battery. Torque and motor RPM at propulsion level are multiplied to generate power that can vary between specified negative (regenerative braking effect) and positive. The other factor in these equations consists of a torque-dependent linear factor that aims to model inertia and winding losses related to the DC motor. It must be noted that winding losses are ignored for model simplicity. The two factors are added, and their sum is limit-saturated to ensure correlation with the required specification. The saturated power is then divided to the nominal battery voltage to calculate the current drawn from, or pushed into, the battery model. During the first development stages of the base model, the other losses due to the auxiliary electrical systems were modelled here as a fraction of the power output. However, this approach has been deemed unsuitable due to the inconsistency in the ability to control these losses.

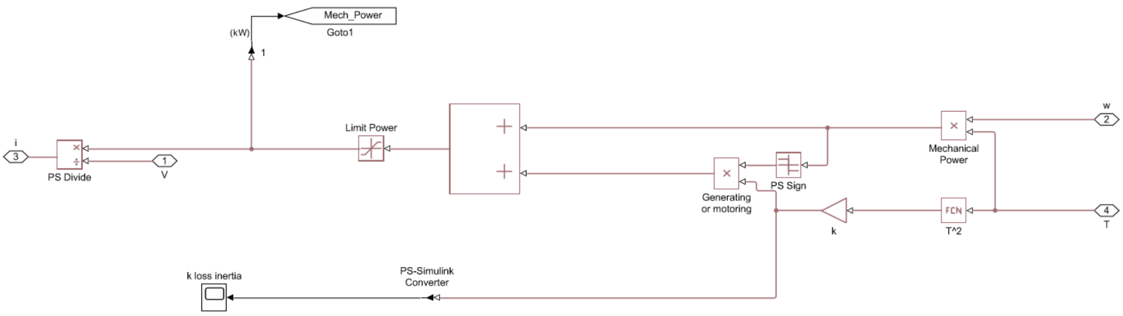


Figure 3.9 - DC motor subsystem

The transmission block shown in figure 3.10 contains the modelling of two subsystems, the gearbox and the differential. Both have been modelled using simple gear ratio models, which transmit speed from their base to the followers proportional to the specified gear ratio, with a similar behaviour for torque. The gearbox consists of a single gear as this is the specified topology.

An improvement in the structure of this modelling block is planned that requires integration of a multi-speed gearbox that is able to react efficiently to speed and mechanical load changes in the simulation. This can be achieved with various approaches. Firstly, multiple SimScape variable gear ratio blocks can be used. Alternatively, a barebones approach can also be employed. Finally, SimScape contains a gearbox library with different gearbox topologies. However, these cannot be changed to suit different vehicle styles. All approaches were under consideration, currently the variable gear ratio block approach has the upper hand in the current model thanks to the environment flexibility.

Figure 3.10 - Gearbox & differential models. Input - RPM/torque @ motor shaft, output - RPM/torque @ vehicle wheels

The aerodynamic model block consists of two subsystems. The brakes are modelled here as double-shoed brakes with their braking force applied directly to both front and rear axles. The double-shoed brake model has been chosen because of its ease to integrate within the model and simplicity in applying the PID control signal at its input. This may be changed if required to better reflect a conventional multi brake-type system.

The vehicle tyres are also modelled here using the magic formula coefficient approach. This ensures consistent grip and vehicle traction behaviour regardless of the instantaneous slope value. Coefficients for dry tarmac have been chosen.[199]

Finally, the aerodynamics of the vehicle body have been integrated into the model. This consists of a base library block that had its intrinsic attributes modified to reflect the aerodynamics of an eRCV. This model building block is highly versatile being able to account for different mechanical dynamics at a vehicle axle-level, while also having the ability to specify physical constraints that are directly linked to the tractive and aerodynamic properties of the modelled vehicle, such as external defined mass or angle of inclination (slope). The vehicle model speed is also extracted here and converted into kph and mph measurements for user-end data visualisation.

The full aero model employed can be observed in figure 3.11 below.

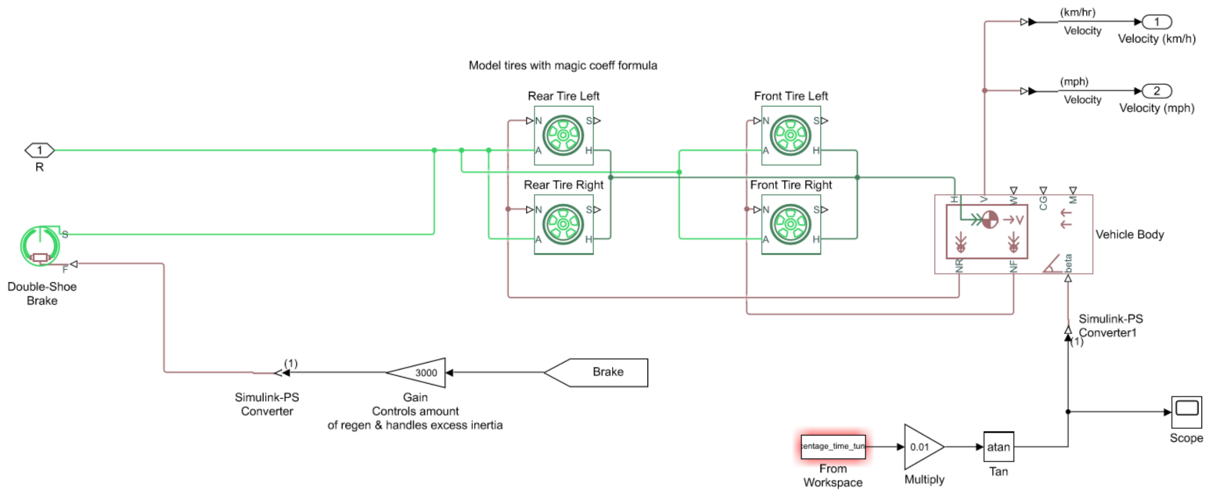


Figure 3.11 - Aerodynamic & brake subsystem models

All information regarding mechanical and electrical power of the vehicle is extracted in a separate monitoring block using goto/from stateful control flow blocks shown in figure 3.11. Although not the most efficient approach in terms of code execution, the routing itself only needs to be carried out once at the start of the simulation. The final stages of SoC monitoring are also performed here.

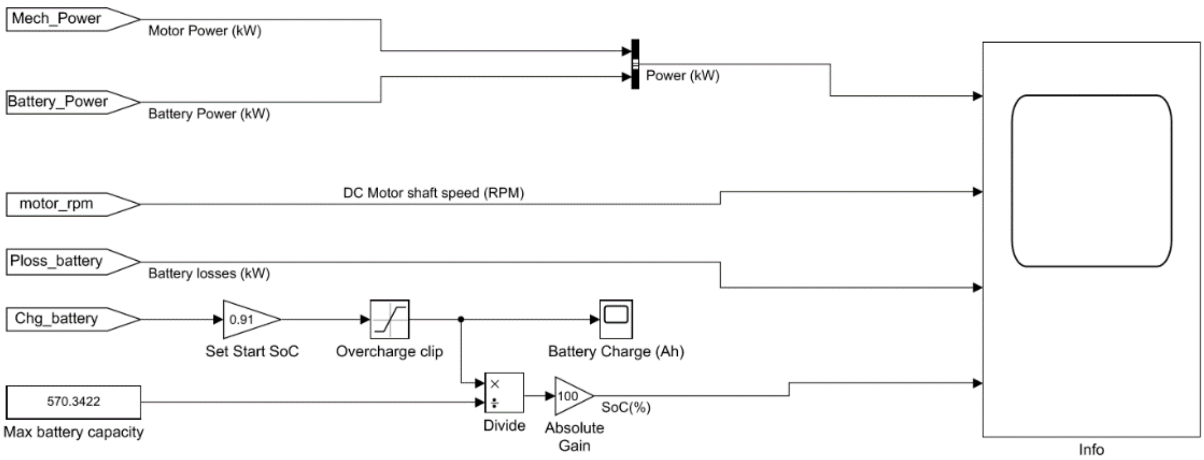


Figure 3.12 - Power information processing subsystem

A separate GUI model block has also been implemented in order to actively monitor the parameters the eRCV user would have access to, in the form of a rudimentary automotive dashboard. Battery level, speed and motor RPM signals are routed to this block. Additionally, this block also contains a Simulink Real-Time Synchronisation block that is able to map simulation times to real-time seconds in order to simulate real-life system behaviour. This is achieved using a special MATLAB C++ based kernel module that is able to keep track of the mapping using the machine's local time.

Output data is processed and saved using scope blocks and classified as either speed monitoring or power related data. An example of the output for one simulated cycle can be seen in the appendix 1.

3.4. Vehicle Model Limitations

In order to ensure the vehicle model has a high degree of functionality, some general assumptions around the physical constraints and the real-life input data had to be taken.

Firstly, a lack of resolution in different monitored variables has been observed in the data provided. While battery level monitoring exists, the related values are only recorded as integers, without any decimal places. From a statistical point of view, it can be derived that the recorded real data may have an error in a worst-case scenario of +/- 1% compared to the actual real data. This has a snowball effect on the accuracy of the data generated by the presented vehicle model and its results have to be adjusted to account for this lack of resolution in input data.

Similarly, the provided specifications point out that the vehicle mass can vary between the base vehicle weight and the maximum rated weight, depending on the amount of refuse collected per driving cycle. For ease of understanding the results, all runs have been simulated with a vehicle weight set as the midpoint of the weight boundaries. While this approach may exhibit large variations in results over small datasets, the provided data creates a big simulation dataset which significantly attenuates any potential data outliers. The aerodynamic subsystem part of the model allows for externally defined mass in various ways, including as step and ramp functions. If deemed necessary, variable vehicle weight may be implemented using this feature.

Finally, vehicle subsystems for which any form of efficiency factor was not specified were assumed to be 100% efficient. This will definitely have an impact on the model prediction accuracy and upon conclusion of testing will be averaged as a linear loss factor that will approximate system losses.

3.5. Choice of Simulation Values

The presented vehicle simulation solution consists of model-based programming that encompasses a blend of basic Simulink and complex SimScape model blocks. Since the SimScape environment is effectively a separate entity that only communicates with Simulink using defined information pipelines, a custom-spec equation solver is necessary. Furthermore, SimScape is able to simulate various physical media, ranging from thermal to mechanical and electrical. Each of these need to have their own solver attached unless specific cross-environment blocks are employed for interfacing, as they are considered different software environments.

Considering the abovementioned, the proposed solution requires two solvers, the predefined default basic Simulink solver and a special SimScape solver. These two communicate with each other using the submask Matlab environment. While setting the SimScape solver is a straightforward process as it only controls the physical model constraints and its related tolerances, tailoring the Simulink model to the SimScape one is more complicated, as this is the main element in solving the modelled mathematical equation system. Fortunately, the Simulink equation solver can be set from an extensive mathematical solver library.

The starting point in choosing and setting the right solver has been the default suggested method for SimScape variable step models and was defined with the commonly used ode23t. This solver is based on the trapezoidal rule and uses a free interpolant that handles solutions with no numerical damping. It is specified for solving moderately stiff mathematical problems that consist of ordinary differential or differential algebraic equations. [200] While this solver showed promising results in the initial stages of model implementation, showing robustness and little to no variance in results over repeated tests on the same input dataset, it started to struggle with large dataset simulation handling once more complexity was added to the model.

The solver was therefore changed to the ode15s method. This is based on the numerical differentiation formula set [201], a more efficient variation of the backward differentiation formulae [200]. This method is recommended for mathematical problems with a higher degree of stiffness.

While the same degree of accuracy is not inherently guaranteed with this solver, comparison tests were carried out, and result accuracy has not been affected.

Finally, in some particularly large datasets describing lengthy driving cycles with lots of variation in operational characteristics, the ode15s solver was not capable of maintaining robustness, crashing in most test iterations of the given dataset. For those models, the daessc method was employed. This solver is an evolution of the baseline differential algebraic solver tailored for SimScape applications. The devised methodology for new datasets consists of an initial solving attempt with the ode15s that, if failed, will be changed to the daessc method.

Finally, after extensive solver fine-tuning, major solution convergence errors were not detected under a level of 10e-5 in relative and absolute tolerances.

3.6. Data Manipulation & Pipelines

In order to make the provided data compatible with the input format required by the vehicle model, a multi-step data conditioning process was undertaken. The first two stages have been entirely performed using Microsoft Excel capabilities and are predominantly concerned with data clean-up procedures, such as column and row restructuring, while the last step is performed by a custom-spec code script developed in Matlab. The script ensures correct input data load into the Matlab environment and clean data organisation employing environment variables. These steps are important because they have streamlined the validation and testing processes for this vehicle model version.

The raw provided data contains several columns of information not directly relevant to the simulation process, therefore they were dropped. Additionally, column re-ordering has been necessary, as well as populating a new column with incremented integers. This will help with offering an iterative measurement during simulation, so that the simulation solvers can “keep track”.

3.7. Model Validation & Testing Performance

3.7.1. Methodology outline and other considerations

In order to effectively validate and test the model, a methodology has been defined as a multi-step process with increasing complexity. Initially, basic model functionality has been assessed. This phase was achieved through the actual validation of the model against a real-life dataset gathered from an eRCV operating under nominal real-life conditions. The simulation results based on the real-life dataset are complemented by results that employ industry-standard emission testing driving cycles. The second part of the testing process consisted of comparing different route setups so that secondary factors that influence energy usage can be determined.

Due to a lack of detailed data regarding the technical specifications of the actual eRCV used in the validation tests, some approximations and assumptions have been taken. In addition to some approximations regarding the power demand generated by the auxiliary systems, some design decisions were taken in the system operation.

Although vehicle mass has been specified in the form of a min-max payload, simulations have been carried out with a vehicle weight set as the midpoint in the specified range as the way in which the vehicle mass changed throughout a refuse collection run will change for each individual run. Similarly, the vehicle tyre parameters have been approximated using the magic formula coefficients [199] and tuned for dry asphalt conditions. The drag coefficient has also been approximated to reflect a general heavyweight vehicle, modelled based on Betz’s Law. These will not necessarily reflect real-life conditions on a 1:1 basis, but it will ensure consistency with reasonable constraints, which is important for a rigid mathematical system. Additionally, given the need to model a fleet of vehicles for the research objectives, the vehicles within the fleet are likely to have differing tyre parameters across the fleet due to varied wear patterns and replacement tyres at various points in the fleet operation.

Similarly, another important factor in simulating this type of powertrain is consisted by the emulation of regenerative braking, a key element that feeds positive battery values back into the battery module. The intensity of the braking must be carefully chosen, as inadequate values may result in highly inaccurate simulations, especially for predictions based on bigger input datasets.

In the presented model, the regenerative braking process is modelled as a constant that is associated with the electric motor inertia and the slope recorded in the dataset. The constant has been chosen by performing a parameter sweep analysis on several development datasets and observing what values would match the logged energy consumption at the end.

3.7.2. Basic Model Functionality

This initial project phase aimed to test and understand the model's limitations and the solver capability to find consistent instantaneous solutions to the system for the duration of the simulation. In order to do this the model has been assessed on publicly available data, used by environmental agencies worldwide for emissions regulations and standards adherence. While the model does not currently support any functionality regarding emissions measurement, these datasets have a high resolution and describe several different driving styles, environments with various simulation lengths. The model has been tested on several of the greenhouse gases emission testing cycles in the EPA library, focusing on the ones that describe highway driving as well as those containing large parameter variations, for example stop-and-go cycles, such as the NYCC, HWFET and HDUDDS cycles, as described in Figures 3.13, 3.14 and 3.15 using speed(mph)-time(s) graphs. Throughout testing the basic functionality of the model, stable response with minimal output speed disturbances has been observed. Similarly, SoC decrease has been consistent, indicating a well-balanced system response.

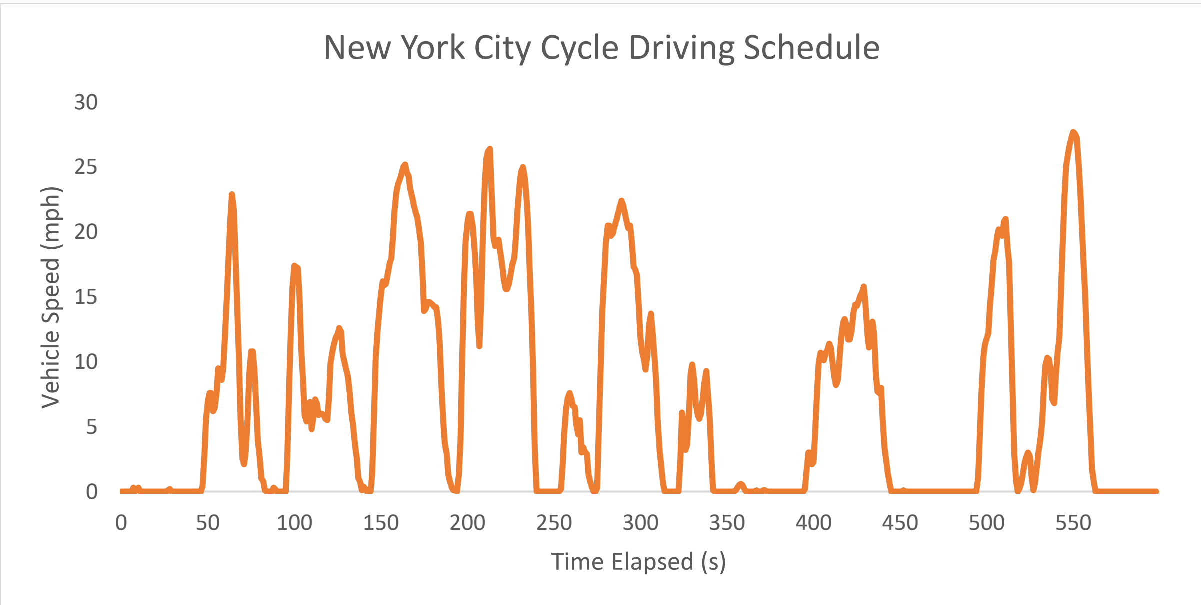


Figure 3.13 - NYCC driving cycle

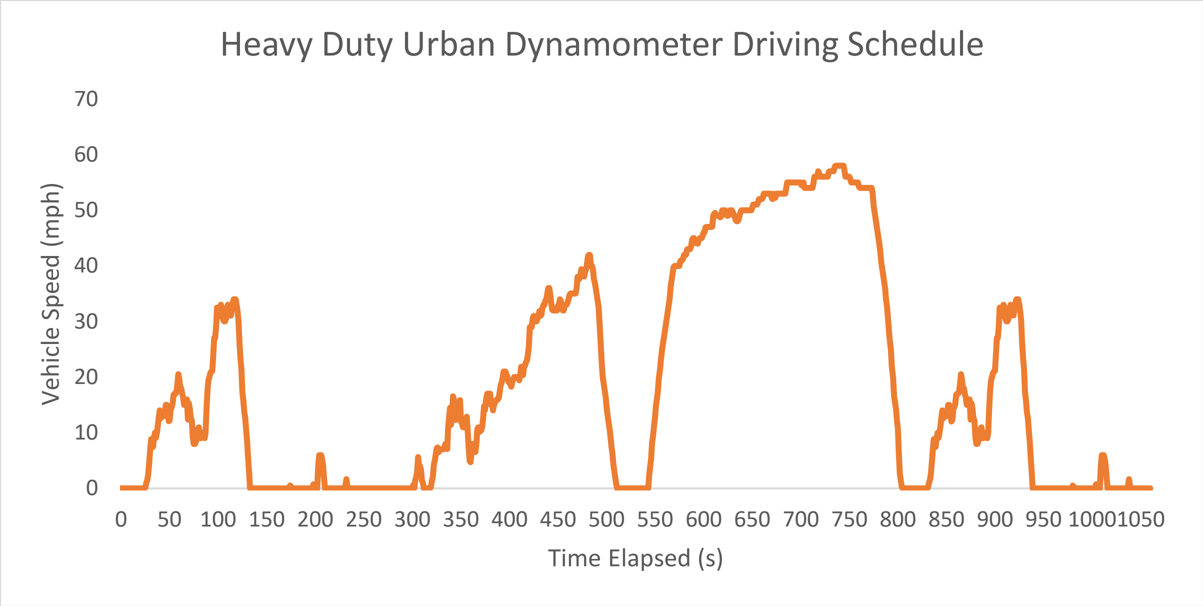


Figure 3.14 - HDUDDS driving cycle

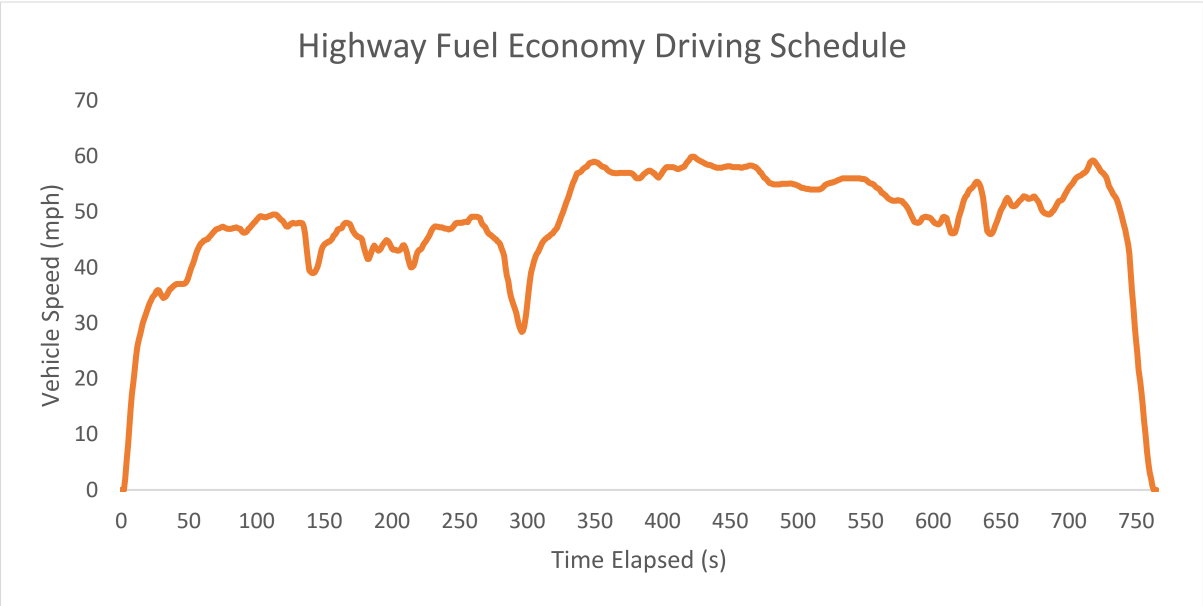


Figure 3.15 - HWFET driving cycle

3.7.3. Model Validation

Validation of the EV matlab model has been carried out by selecting a driving schedule at random from the provided datasets available to the project. Some fine-tuning of the overall relative simulation tolerance was required in order to avoid simulation crashes due to solution convergence errors. The chosen driving cycle has a mix of stop-and-go driving, as well as cruising segments, making a good test benchmark for model functionality and consistency in behaviour, together with parameter prediction over longer simulation periods. Figure 3.16 shows the input data as well as the model's controlled reaction to the input via the control module. Data is shown as a speed-time graph, with speed as kph.

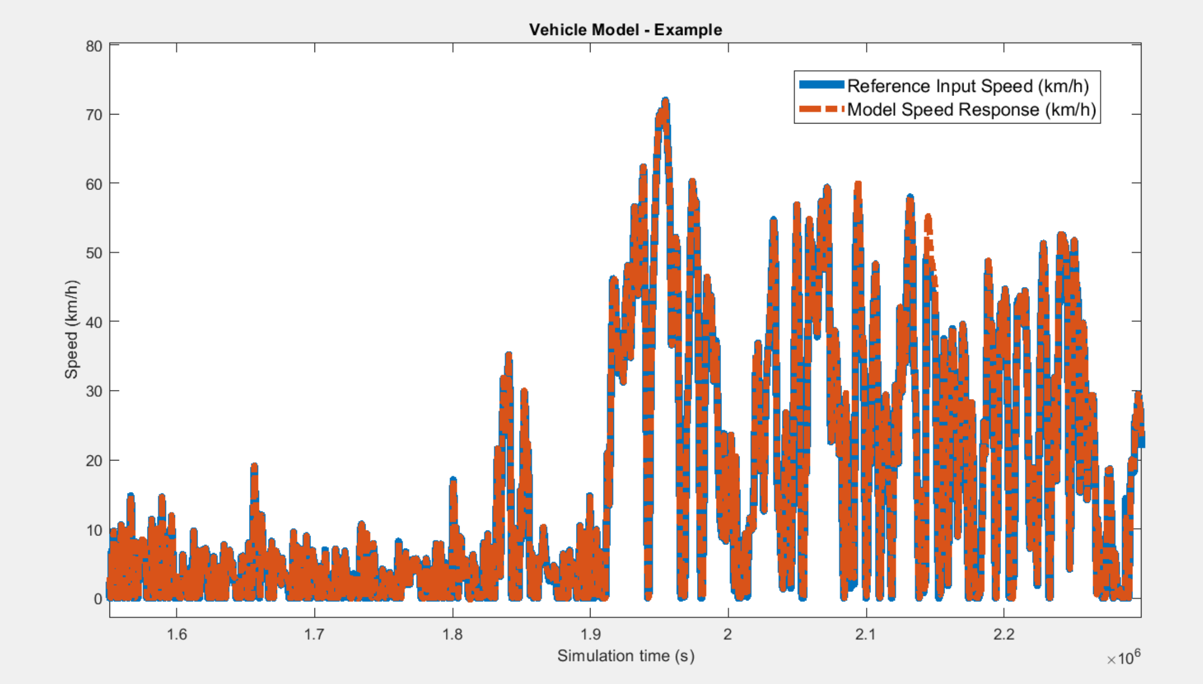


Figure 3.16 - Speed analysis plot example

During this simulation, some problems regarding the controlled system response (as seen in Figure 3.17) have been identified. It has been observed that at the end of sustained periods of acceleration, the control reaction sometimes temporarily appears to lose track of the input data, and therefore the system response drops control reactivity and becomes unstable. However, this is quickly corrected, and the reaction goes back to normal and the overall SoC estimation does not seem to be significantly affected, based on the duration of this behaviour and the energy demand change.

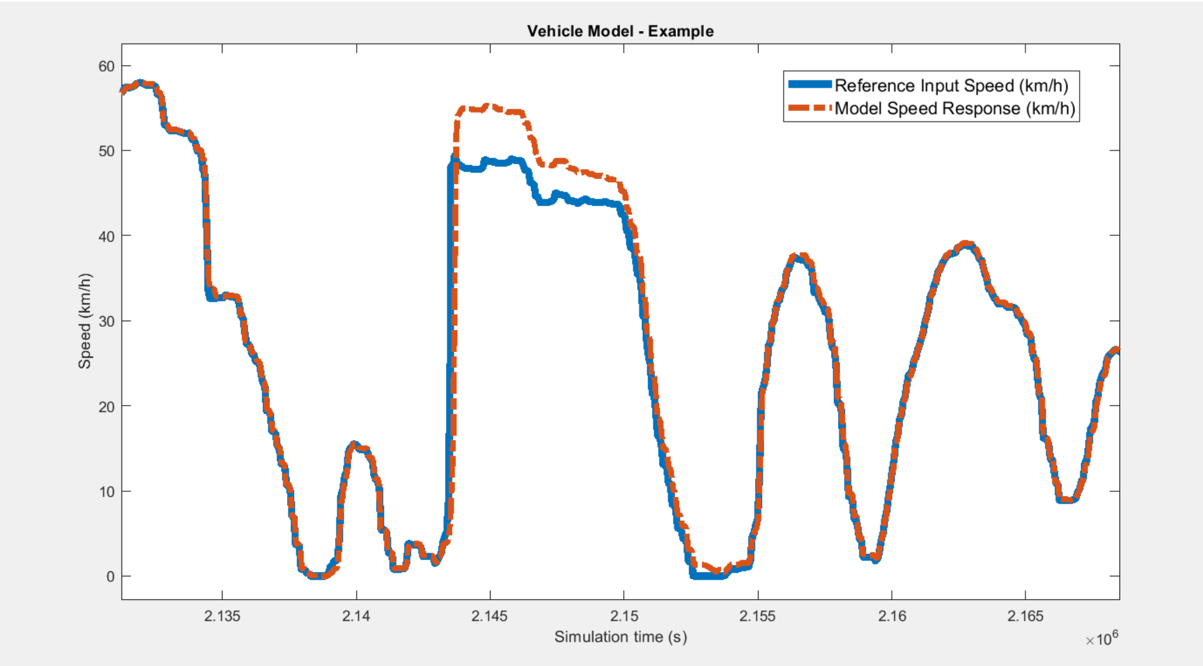


Figure 3.17 - Control module fail (control response overshoot)

This behaviour could be attributed to one or several factors. One of the suspected causes of this is a lack of proper fine-tuning of the integral component in the PID module that controls the reactivity of the response to the input data. Another potential cause could be the solver employed in the simulation that may temporarily run out of cache memory, hence dropping all the variables until more memory is cleared for the simulation thread in the OS.

Besides the minor temporary control loss, no other problems have been identified in prediction or system behaviour. The average relative error rate in SoC estimation compared to real-life data has been observed to be around 7-8%.

3.7.4. Real-Life Dataset Testing

Following the EV model validation, the testing procedure has been initiated. This entailed running all the cycles in the provided dataset and compare the absolute error rate with the recorded ones at the end of the simulation.

Temporary control losses similar to the one identified during the validation phase have been observed, but none seemed to majorly affect the simulation end result. Some minor adjustments regarding simulation solution tolerances were carried out on a case-by-case basis to avoid crashes due to convergence.

The average absolute error rate in battery charge prediction is 6.08%, with some outliers in data that can be explained by looking at the characteristics of their related datasets. Adjusted for outlier marker attenuation this drops to 5.8%, as observed under figure 3.18.

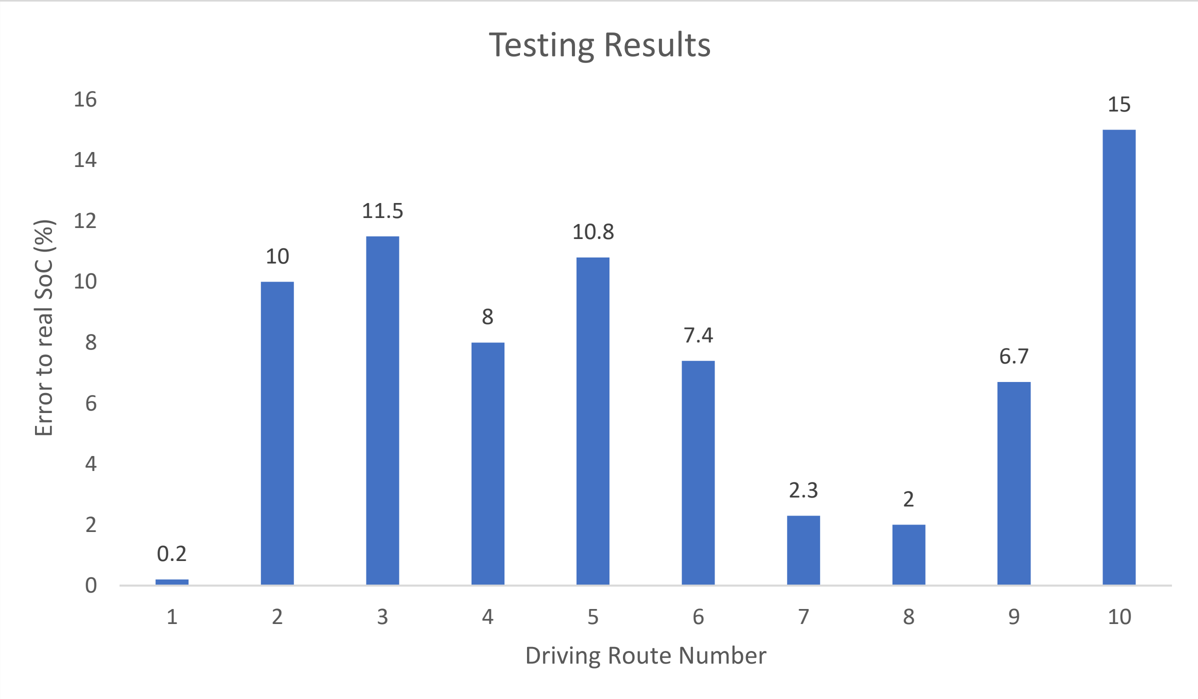


Figure 3.18 - Validation results for proposed vehicle model

3.8. Chapter 3 Summary

As observed, the presented model takes into consideration many factors from both the physical emulation side and the mathematical calculation. Whilst several aspects could definitely be improved, the model is highly modular, offering a high degree of versatility. The subsystems are not interdependent and may be configured as standalone simulations with minimal changes to the original concept.

Furthermore, the model has exhibited strong control dependencies, ensuring reliable and stable simulations. This is also shown by its relatively small degree of error, as well as the minimal changes in it, observed over a high number of testing datasets.

Having considered the heavyweight electric vehicle software model in this chapter, validating the models as appropriate, the next chapter is concerned with the development of a novel data processing script that aims to prepare raw GPS values as input data for the presented software.

4. Chapter 4 – Route Generation Method

4.1. Overview & Development

This thesis chapter outlines the development and methodology of a software script that aids in preparing raw geographical data into model-ready usable telemetry values.

A further aim of this research consists of implementing several functionalities in the information pipeline that will allow the system to process and predict energy behaviour without the need for real-life recorded datasets. Once achieved, this will set the basis for complete automated functionality, including continuous data processing and input data streaming. However, the approach employed by the EV model in processing data has some limitations in this regard. The presented solution has been created as a two-stage data processing system that will always require an input, an instantaneous speed value associated with a progressive incrementing measurement that allows the system to keep track of the elapsed time and previous states.

The Route Builder emulation system therefore consists of a set of Python-coded programs developed to generate input data that is usable by the EV model. By collecting map-based distance and slope data organised in a set structure, as can be seen in Table 4.1, and apply a mathematical approximation to this, the scripts are able to generate speed-time or speed-distance data. For coding this software system Python and some of the common scientific computing libraries, namely matplotlib, tkinter, num.py and pandas have been used.

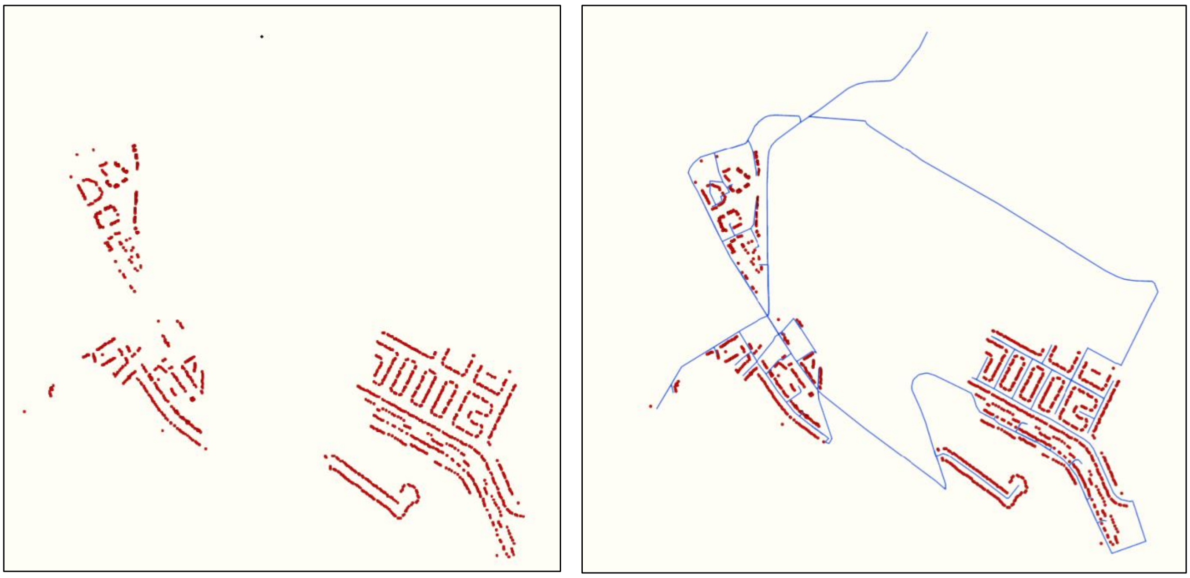
Item	Format	
Round	Integer	A number used to mark each collection runs, i.e. 00000001
Address	String	Address in natural language, i.e. Number 10, ABC Road, London
Postcode	String	Exact postcode of the address showing above, i.e. AB1 2CD
Roundgroup	String	Indication which day of the week this round will operate, unused
Latitude	Float	Latitude of the address
Longitude	Float	Longitude of the address

Table 4.1 - Input data structure

The emulation system consists of a dual-stage information pipeline organised into several code files. The first stage harvests Google Maps Places API data regarding geographical properties (such as distance and slope) between a specified set of map address points using Natural Language Processing (NLP) technology. While processing each address, key indications such as house number and street of are captured by the software and processed in an alphabetical order, to ensure all of the collection points are grouped by their respective street location. This data is then processed and written in a loosely structured pattern. Some novelty in the data processing approach exists in the way the data is being processed and handled, which is different from a conventional genetic 6-step NLP engine. One should note that only the content determination, text structuring and referring expression generation are being processed, whilst a conventional approach would also consider the sentence aggregation, lexicalisation and linguistic realisation[202].

During this process, a limited number of addresses will be spread out due to difficulties in finding its house number and/or street name, due to ambiguity in address description. In order to minimise the ambiguity in the route description generated by these addresses, a geo-location decoder is implemented to further extract information. By querying the addresses' latitude and longitude data from a Geographic Information System (GIS) information provider, such as Google Maps GPS data, these uncertain addresses can be located and integrated with the rest of the route points using GPS coordinates. Although a query may sometimes only return its nearby house number, the effect over the accuracy of the route description is minimal, since an RCV will stop for a cluster of refuse bins, instead of at each bin location. Finally, the processed data is then written in a table as a set of speed-time value pairs in a way that is usable by the next stage in the pipeline.

An example of script-generated routing is presented under figure 4.1.



Sample Dataset

Script-Generated Refuse Collection Route

Figure 4.1 - Example of script-generated refuse collection route

The second stage of the system consists of the actual processing that results in the emulated speed-time or speed-distance data that is usable by the EV Matlab model. The emulation is based on the trapezoidal approximation method, by approximating acceleration slopes based on a set target speed. The trapezoidal rule is a well-known method in numerical analysis that derives from Heun's method [203] that aims to approximate the definite integral. It can be interpreted as a method to average the left and right Riemann sums and has the form as specified in figure 4.1 below:

$$\int_a^b f(x)\,dx \approx (b-a)\frac{f(a)+f(b)}{2}$$

Equation 4.1 - Heun's method (integral form)

During the route period where refuse collection is performed, the script based on trapezoidal approximation assumes that the vehicle is operating on a pre-defined start-stop interval (i.e. it will stop after a given distance to empty a cluster of bins). Firstly, the algorithm simulates vehicle acceleration, with a pre-set positive derivative slope coefficient applied to vehicle speed from standing, until the speed reaches a pre-defined maximum value. The coefficient used in calculations has been derived by observing vehicle driving capabilities during normal operation. Simultaneously, simulated vehicle speed and travel distance are being recorded at a data resolution of 1 second. Then, the algorithm assumes constant vehicle cruising speed driving up until the point where the remaining distance to the next collection point is just enough to complete deceleration. Finally, the algorithm simulates the deceleration stage, with a pre-set negative slope, from its max speed to 0. Similar to the acceleration stage, this has been derived from actual vehicle observation. Then, a zero-speed time interval with a set duration is added, which is meant to emulate the driver emptying the bins before repeating the same pattern until the end of a given refuse collection phase.

It must be noted that during the cruise section from one refuse collection area to another, the script assumes cruising at average speeds observed under normal operation circumstances. Therefore, the process is similar to the collection stage but with different speed and distance factor.

The outcome from the proposed algorithm is a dataset similar to a recorded dataset from an on board satellite positioning-logging GPS device. Consequentially, it can be used as the input of the energy consumption model and calculate the energy required to collect this group of addresses.

Finally, the route builder system also has a user interface (UI) that allows quick changes in emulation variables and correction factors, effectively improving the usability of the final system. This was created as a mask that encompasses the entire data processing stages.

An example of a code-generated, “emulated” driving route telemetry can be observed in Figure 4.2. Additionally, a zoomed-in version of the script-generated telemetry can be examined in figure 4.3, featuring the trapezoidal-like shapes generated by the trapezoidal approximation mathematical method.

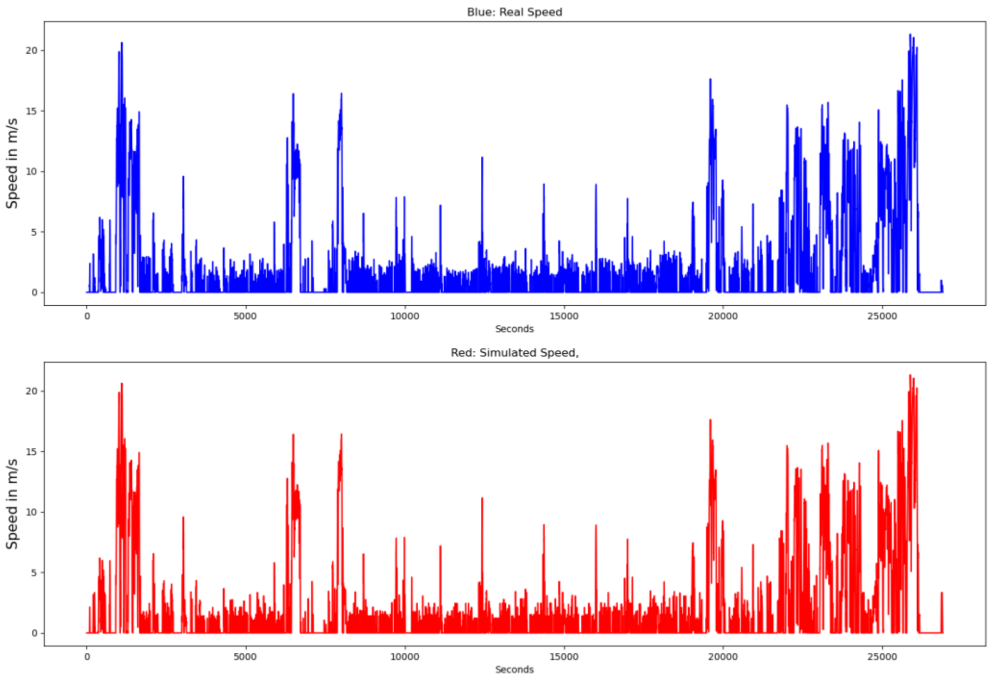


Figure 4.2 - Real driving data vs simulated cycle generated by emulation code

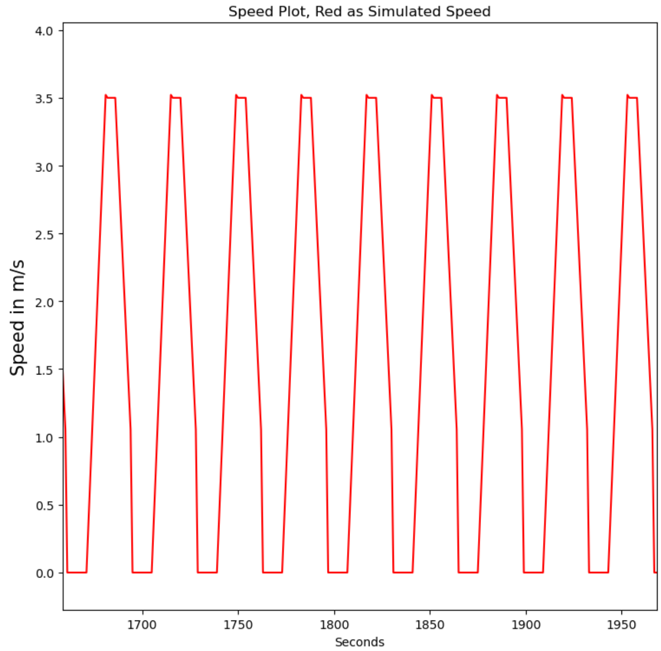


Figure 4.3 - Zoomed-in section of simulated telemetry

4.2. Validation & Testing

In order to validate the effectiveness of the chosen approach, the system was trialled in validation during the late development stages. Simulated cycles for each bin-collection sector in every dataset have been generated and fed into the model. An example of such a cycle is shown in figure 4.4., displayed as a mapped dataset, benchmarked against GPS data of a real refuse collection route, in order to better understand the route approximation script's efficacy.

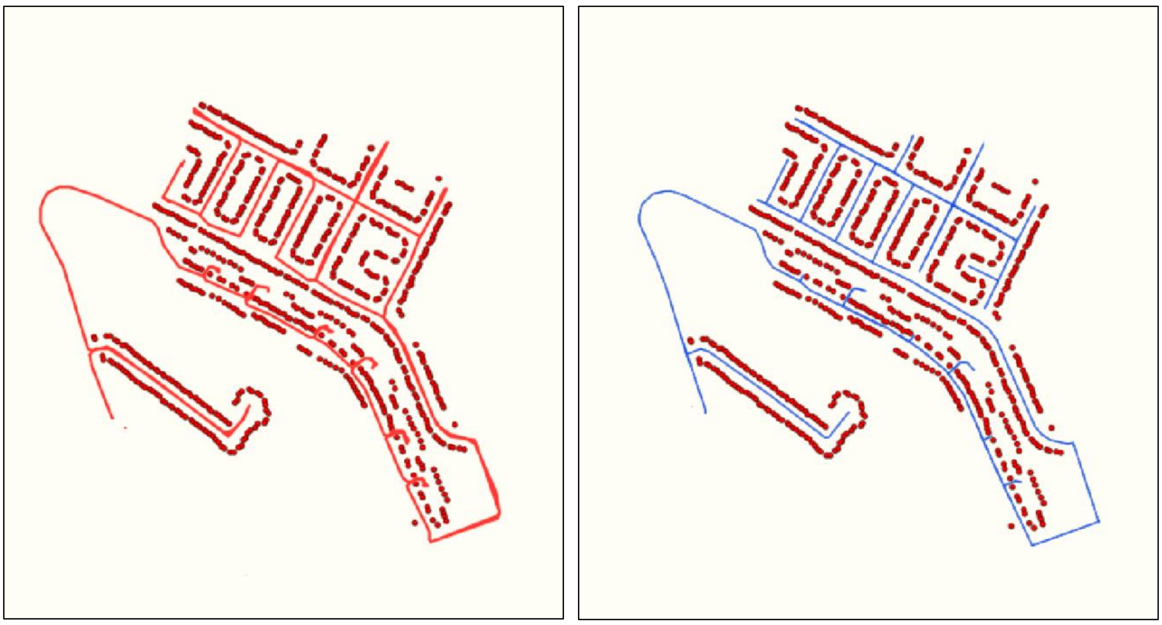


Figure 4.4 - Comparison between real (left) and simulated (right) driving route (section)

The data samples have been chosen as the "validation grounds" as it is during these simulation intervals when the EV uses most of the available energy, thanks to its stop-and-go features that require deep acceleration and braking usage with minimal room for energy regeneration through motor inertia braking. Again, the simulation performed consistently, with minimal changes to the simulation setups. It has been found that the average additional error rate in SoC prediction is 2.64%, with similar outliers compared to the 2nd testing cycle of the vehicle model.

A comparative graph showcasing the results is shown below, in figure 4.5.

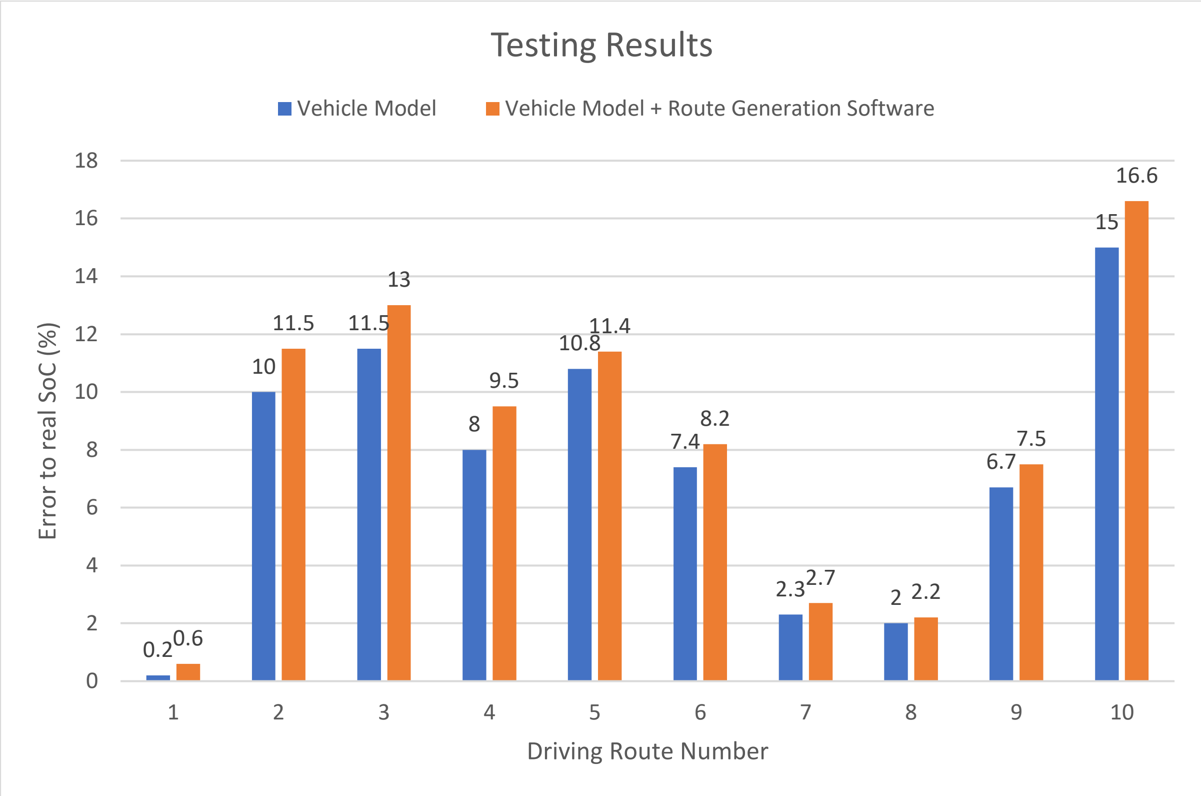


Figure 4.5 - EV model testing results - SoC estimation

However, testing the route builder system was a more complex process, with various stress tests performed in different contexts to better assess limitations and real-life performance, by benchmarking the error in absolute SoC discharge rate. Therefore, the testing process includes stress testing the model when changing extrinsic factors, such as road / route slope. Understanding the influence of such geographical factors over energy usage and prediction error is key to ensuring a low-error model performance.

4.2.1. Importance of geographical factors

4.2.1.1. Slope Effect on Energy Usage Prediction

The first stage of this testing phase included a comparison between a no-slope simulation run and a slope-enabled simulation run of the same batch of routes in order to assess the direct impact of slope on energy use. The routes in the testing batch exhibit different features, with varying degrees of slope change and length. The slope-enabled simulations have been based on a dataset with less data points implying a lower result precision, however this does not appear to significantly affect the control of the vehicle while describing a near-identical speed-distance curve.

It has been derived that the average effect of slope over the entire testing route batch on relative SoC is 3.22%, with one significant data outlier. Disregarding this, the effect drops to 1.68%.

A detailed histogram is shown below, in Figure 4.6.

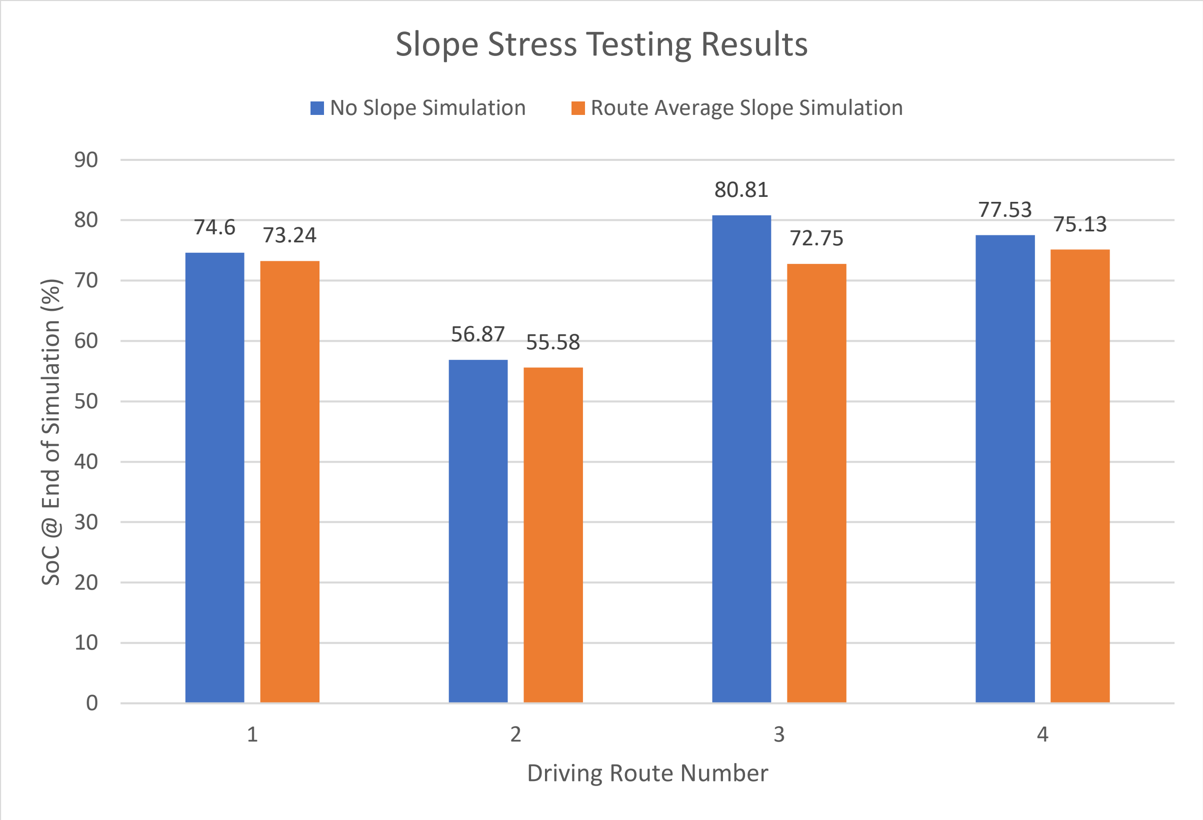


Figure 4.6 - Slope simulation testing results

4.3. Chapter 4 Summary

The featured results indicate that the route generation method performs consistently and reliably. Whilst some limitations exist concerning the slope effect on energy usage prediction exist, these are minimal, consistent, and predictable in nature, therefore easy to account for when interpreting the simulation results. Together with the EV model previously described, the system is capable of predicting energy usage robustly with minimal degrees of error. A simplified diagram outlining the functionality of the proposed model-based prediction solution is indicated in figure 4.7. for further reference.

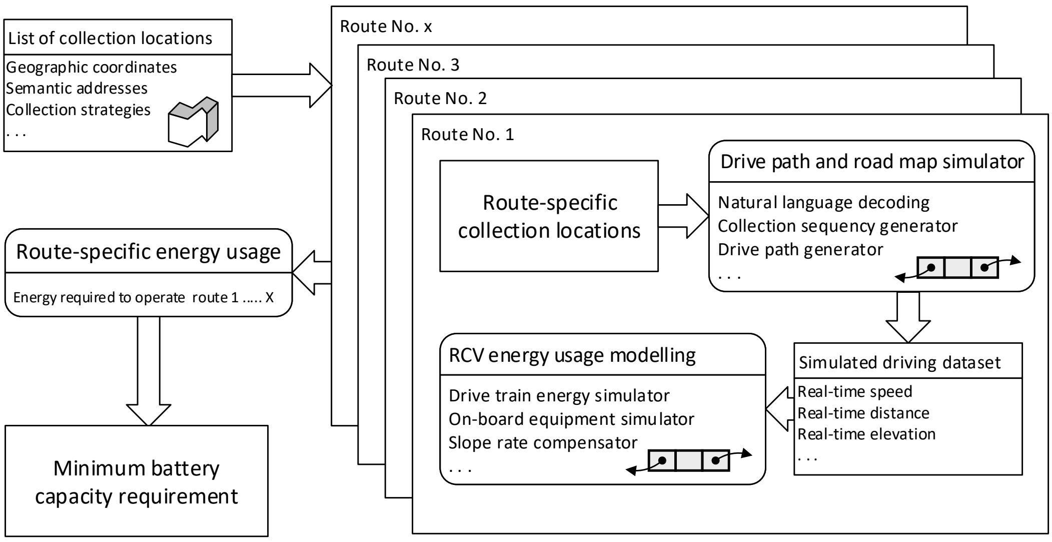


Figure 4.7 - Concept system diagram

A simpler diagram outlining the concept of the presented solution can be observed under figure 4.8.

Figure 4.8 - Simplified idea of proposed solution [204]

Finally, it must be mentioned that the work carried out towards the development of the route generation algorithm has been performed in collaboration with other researchers. Consequentially, the work presented in this thesis only concerns the research phases that have been performed collaboratively with significant input from myself.

Following the extensive validation and testing considerations presented in this section, the developed software solution has been considered to be suitable to be employed in real-life-based data applications, which will feature an in-depth analysis in chapter 5 of this work.

5. Chapter 5 – PSV Energy Usage Investigation through proposed simulation solution

Following the development, validation and testing of the basic functionalities of the proposed software model, presented in the previous chapter, the model has been considered a viable approach for electric vehicle simulation. When simulating an EV travelling over a particular route, one parameter of interest is the predicted energy use. This, in turn, is able to serve as a cornerstone for more general investigations, such as various electric vehicle fleet feasibility studies.

This section of the thesis presents the first application of the proposed model and is concerned with understanding the energy usage of public service vehicles, both at an individual vehicle level, and overall, as a fleet. Furthermore, the chapter will also demonstrate how understanding the energy usage of vehicle fleets can be a key factor in providing a carbon footprint and energy refuelling analysis for fleet feasibility studies. Examples of where this is important may be found from a study of waste management trucks (refuse collection vehicles RCV's), and buses. Additionally, an overview of the expected operating costs and CO_2 emissions produced by these vehicles will be presented. Finally, further considerations as to how energy consumption can be optimised at a low-level will be described.

5.1. Assessing eRCV fleet energy usage

5.1.1. Aims

The initial investigation employing the proposed simulation approach described earlier is based around understanding energy requirements, and other key performance characteristics of the refuse collection routes covering the areas under the administrative jurisdiction of Sheffield City Council. To achieve this study, certain information is required. Not only the eRCV parameters for the vehicles of interest, but also the bin collection routes over which the vehicles operate. The parameters in question have been obtained from the contracted company responsible for refuse collection in Sheffield (Veolia).

The aims of analysing the dataset are based around understanding energy usage if eRCVs with a given custom specification were to be deployed in order to perform refuse collection, over the same routes the contracting company is currently deploying its diesel RCV fleet. The predicted energy usage then informs recommendations as to whether routes should be managed differently based on a selection of criteria (such as collection area type, or day of week). Understanding energy usage can also provide an insight towards the feasibility of deploying a fully electric RCV fleet for refuse collection. The environmental and financial impacts of such a fleet may be further reduced through the use of other renewable sources to charge the fleet. Secondly, an analysis of the fleet's energy requirements will also give some insight into whether the vehicle batteries could be integrated into the energy grid and be used as "extra energy storage" in the form of a managed Battery Energy Storage System (BESS), that would help ease electricity grid stress during peak times. Such systems may also be used to provide long-term investment advantages, by integrating them with the energy grid so that they may be able to supply energy to the system during peak demand hours.

Finally, to efficiently simulate the entire received bin and route data, a custom-specification simulation routine parallelisation procedure has been developed.

5.1.2. Methodology

Firstly, the technical specification of the vehicle has been compiled for reference in a table (Appendix 3). Whilst most of the important vehicle specifications have been provided by Veolia, additional data related to aerodynamic and braking performance was required. This is in order to ensure robust prediction accuracy. These parameters have been obtained through publicly available technical data of similar vehicles to those deployed on the routes.

Secondly, the route information provided consists of 229 datasets of GPS coordinate logs, recorded in real-life conditions, during bin collection runs. An example of a provided GPS dataset can be seen in figure 5.1. The points represent refuse collection areas.

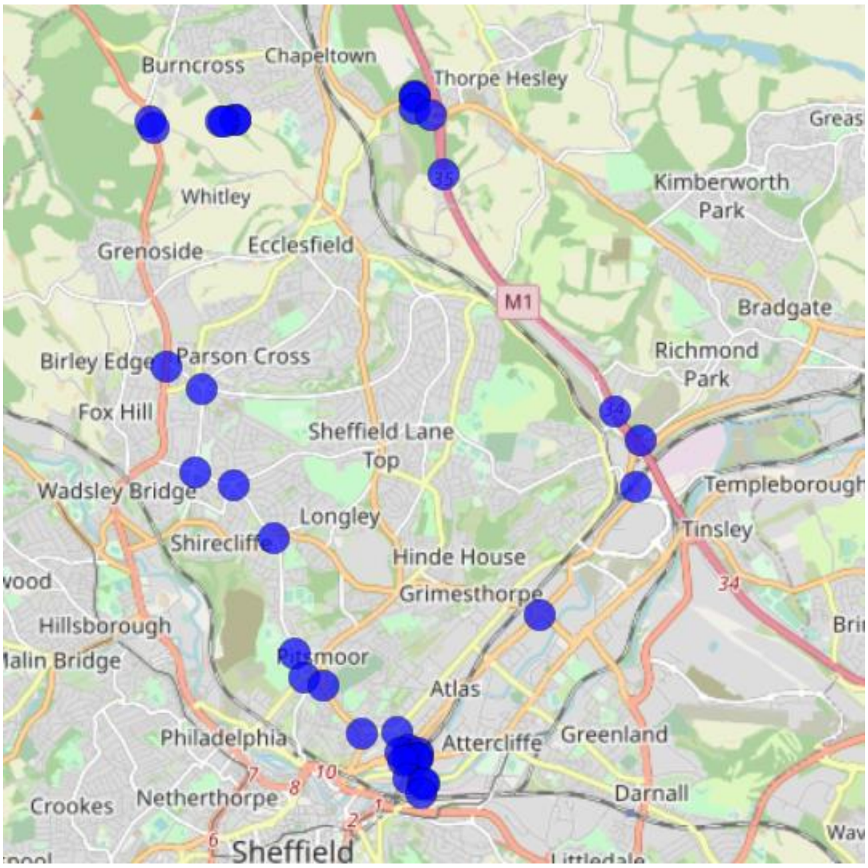


Figure 5.1 - GPS dataset log example

Each dataset has been processed employing the route builder script described in chapter 4 to emulate vehicle telemetry consisting of speed-time value pairs. This data may then be used by the proposed electric vehicle model for simulations. Therefore, the processed telemetry serving as input reference for simulation in the vehicle model consists of 229 different routes and it can be classified as a large-scale dataset. In order perform simulations over the entire dataset in a timely manner and increase overall productivity, a process parallelisation procedure that aims to significantly cut the time spent computing simulation data has been developed. This procedure consists of a runtime script which takes advantage of the Matlab environment's parallel computing capabilities and is further described in the following subsection. The bin location data was obtained through private communication with Veolia, the local company servicing refuse collection operations.

5.1.2.1. *Process Parallelisation*

By observing the model mechanics previously described in chapter 3, it can be seen that the developed EV Matlab model has a low-level “hard iterative” nature, meaning that during any simulation, a given state and its related values in the process is entirely dependent on the past states and their values (that have already been determined). Therefore, a given simulation will intrinsically be bottlenecked by how quickly simulation states can be calculated in an incremental manner.

The application of the presented model was arranged such a way as to answer energy usage questions for multiple complex systems in a relatively short time, and when simulating complex systems, it is common that many simulation factors and physical constraints must be considered. Hence, the iterative low-level design of the simulation is a slow-performing factor in determining the desired simulation outputs. However, from a high-level system perspective, simulations can be run independently from one another as long as they are relying on different input datasets from different complex systems. Therefore, the system can benefit from the application of parallel computing principles.

Parallel computing refers to the principle of simultaneous execution of many calculations or processes that are not inter-dependent, in order to achieve much higher processing speeds than a normal iterative process would output [205]. Several different forms of parallel computing exist, ranging from low-level hardware approaches such as bit or instruction level parallelism to system level concepts such as task parallelism, which is an idea of interest to be employed with the software EV model.

From a theoretical standpoint, the speed benefit offered by task parallelisation is nonlinear, and dependent on how many simulation environments are running simultaneously, in-situ on one computing machine. The theoretical potential speedup compared to the iterative, one-process-at-a-time methodology is given by Amdahl’s law[206]:

$$S_{\text{speedup}} = \frac{1}{1\text{-p}+\frac{\text{p}}{\text{s}}}$$

Equation 5.1 - Amdahl's law

where $S_{speedup}$ is the potential speedup in execution time of the whole task, s is the potential speedup of the parallelisable part of the process and p is the percentage of execution time of the whole task concerning the parallelisable part of the process before parallelisation.

By understanding the high-level system diagram of the EV model and the principle of task parallelisation, it can be noted that the simulation process can be effectively adapted to suit a parallel computing methodology. This is due to the input data of the simulations being independent from one another, hence the I/O information pipelines for each simulation can be run independently. In order to do this, the parallel computing capabilities of the simulation machine and Matlab environment have been employed, through the Matlab parallel programming toolbox.[207] This add-on consists of a suite of software functions that are able to create separate simulation environments. This is possible by taking advantage of a machine’s multi-thread capability.

Having the ability to run simulations in parallel, separate environments effectively eliminates simulation speed limitations related to software process single-thread capabilities. This means that the only remaining limitations on simulation speed are purely related to hardware capability. An example of this is reflected by the maximum supported number of simulation environments, determined by the CPU specifications. Other limitations include hardware operating frequencies, which are determined by rated specifications of RAM, but also data storage read-write speeds.

Thanks to the parallel programming toolbox, implementing parallelisation for computing results for a big dataset has been fairly straightforward, as the development process requires two steps, organising I/O information pipelines for every simulation individually by using simulation input and simulation output object variables, and effectively starting the parallelised simulation environments for simulating every input dataset throughout the EV model using the parsim [208] function.

Results of process parallelisation have been promising, with even small examples with only 10 input datasets (requiring 10 simulations) seeing a significant decrease in execution time, in relation with what was expected from the theoretical perspective, as seen in figure 5.2.

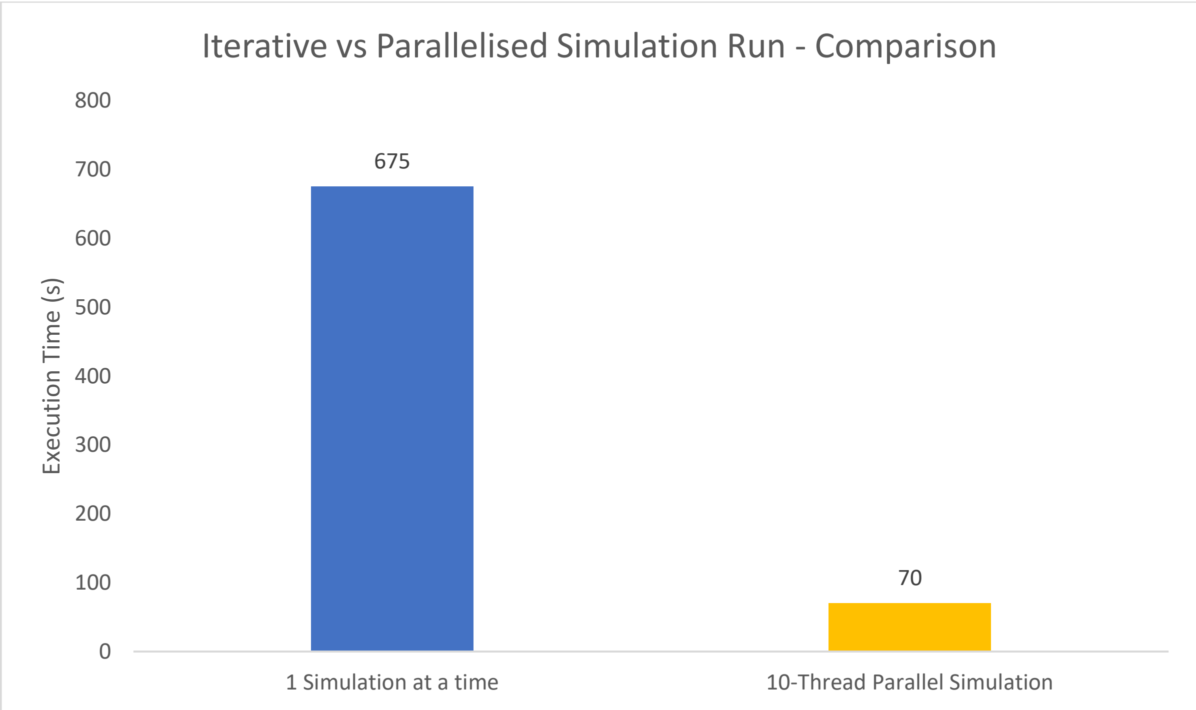


Figure 5.2 - Time execution performance

From a theoretical standpoint, 10 threads (parallel simulation environments), which is the default parallel simulation setting, should be able to simulate a given dataset 10 times quicker relative to an iterative approach. However, it can be seen that whilst the parallelised approach is by far much quicker than the conventional iterative approach, it is not in perfectly aligned with the theoretical speedup expectations. This can be attributed to a number of factors: read/write speed of the workstation storage media, the start-up procedure of the parsim function – loading the EV model, distributing this model in every simulation environment that has been created etc.).

Nevertheless, the parallelisation of the simulation process was successful, demonstrating the potential to bring significant decreases in time execution for other big data inputs, increased productivity and increasing the efficacy of the developed vehicle model when dealing with particularly large-scale datasets.

5.1.3. Simulated energy usage results & discussion

Once the parallel approach to the simulations had been decided upon, in order to provide some insight into the simulation results and provide some conclusions based on the observed energy usage, some data classification has been carried out. Firstly, routes have been grouped by the collection area type they represent (Clinical – collection of medical waste from hospitals and other care centres, Domestic – urban residential house neighbourhoods, Domestic Rural – a blend of urban and rural residential house neighbourhoods and Weekly Flats – a selection of routes that collect rubbish from a group of blocks of flats on a weekly basis).

Similarly, the routes have also been classified by the day of week on which they are performed. This has been done in order to determine an average energy usage figure throughout every day of the week independent of collection area type and should give insight related to the current route management scheduling efficiency. For every classification type, besides energy usage in absolute use (kWh), the total and average timing of every route grouping has been calculated.

Additionally, energy usage throughout the entire output dataset has been interpreted regardless of any classification factors so that a baseline energy use per bin collection route can be determined. When considering all of the 229 driving routes, the average driving cycle was 11824 seconds, and used 24.6% of a full 300 kWh battery charge (standard battery capacity supplied with the vehicle). This translates into an average energy usage of 74.38 kWh. The total energy used throughout the cycles, recorded throughout a 2-week period, is 32140 kWh and a total of 7884km was travelled. This equates to an average energy consumption figure of 2.16kWh/km, which is approximately 10 times the energy consumption expected from a regular electric passenger car. However, this correlates well with the relative difference in mileage for ICE technology (i.e. the mileage of a regular passenger car compared to the mileage of an eRCV-like vehicle – 40+ MPG vs 3-5 MPG) [29].

Finally, the complete received information consisting of 752 hours, 9 minutes and 23 seconds of effective bin collection runs was processed and simulated by the parallelised environments loaded with the Matlab EV model in 7482 seconds (a little over 2 hours).

Figure 5.3 classifies the input data with respect to what type of zone the bin is collected from, it can be seen that the share of driving routes in general is overwhelmingly represented by the urban residential cycles, accounting for over 75% of total.

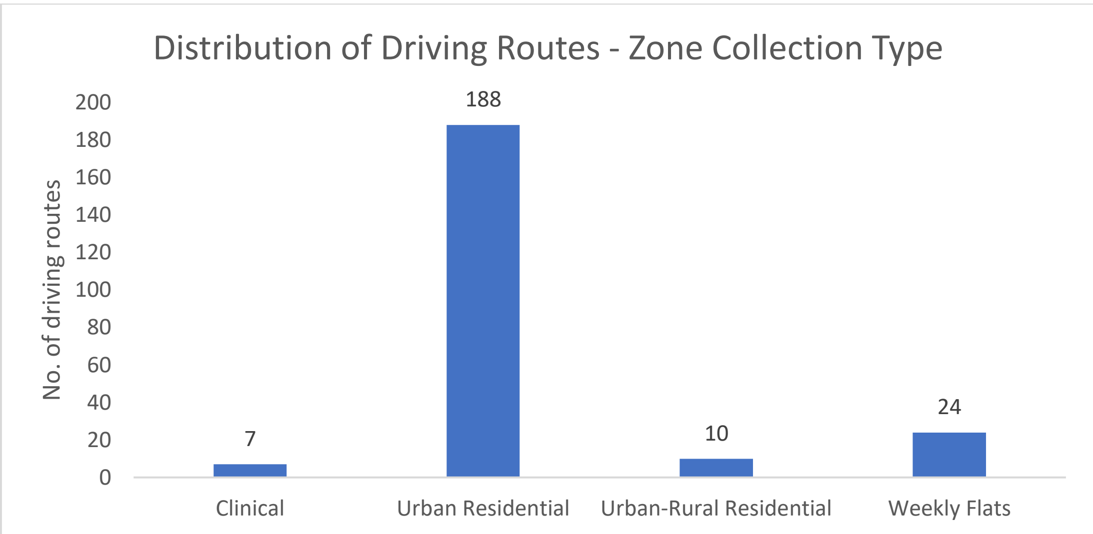


Figure 5.3 - Classification of input data by zone collection type

However, from the average energy usage figures for this classification type, shown in figure 5.4, it can be concluded that these cycles are not the most energy-hungry, the most energy demanding ones being the urban-rural residential mix driving routes, which also take the longest on average to complete, almost twice as long as the 2nd longest. Hence, if a new weekly driving schedule is to be considered, the urban-rural residential routes should be considered key routes on a daily basis throughout the week.

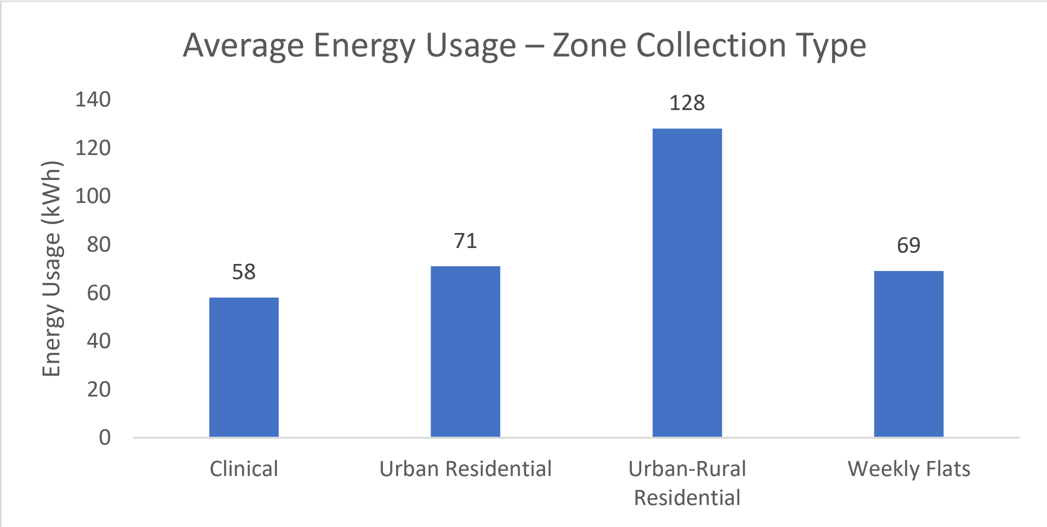


Figure 5.4 - Average energy usage - zone collection type classification

Another observation is related to the Weekly Flats and Domestic routes which appear to take longer amounts of time, especially when considering the average duration, presented in figure 5.5. This could be due to the route characteristics (plenty collection points therefore many start-stop cycles) or a general inefficient approximation of the driving style generated by the Route Builder part of the script suite.

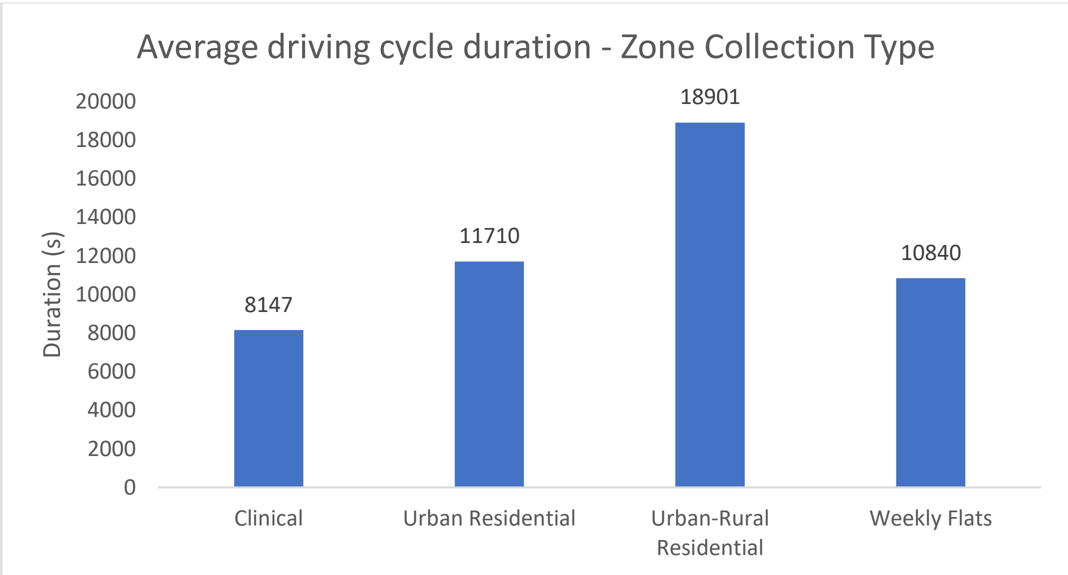


Figure 5.5 - Average driving cycle duration – zone collection type classification

Additionally, the figures related to the classification of input data by day of week, presented in figure 5.6 suggest a reasonably well distributed energy usage on average across the week, albeit this could still be further improved. Driving route durations on average vary by almost an hour of effective route collection, running between the busiest day (Wednesday) and the slackest day (Thursday), as seen in figure 5.7. This trend has a direct consequence on average energy usage, which can be observed under figure 5.8.

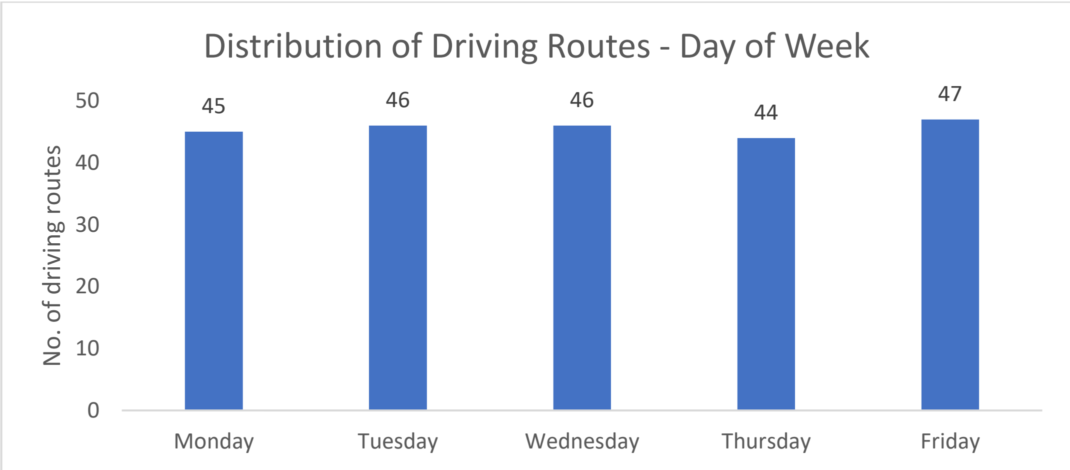


Figure 5.6 - Classification of input data by day of week. Note that input data describes a 2-week route schedule.

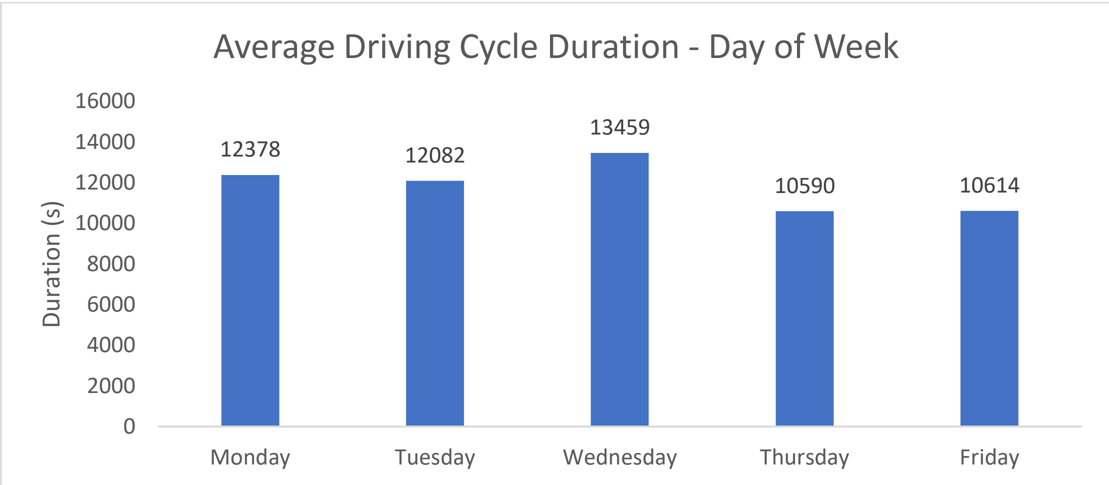


Figure 5.7 - Average driving cycle duration – day of week classification

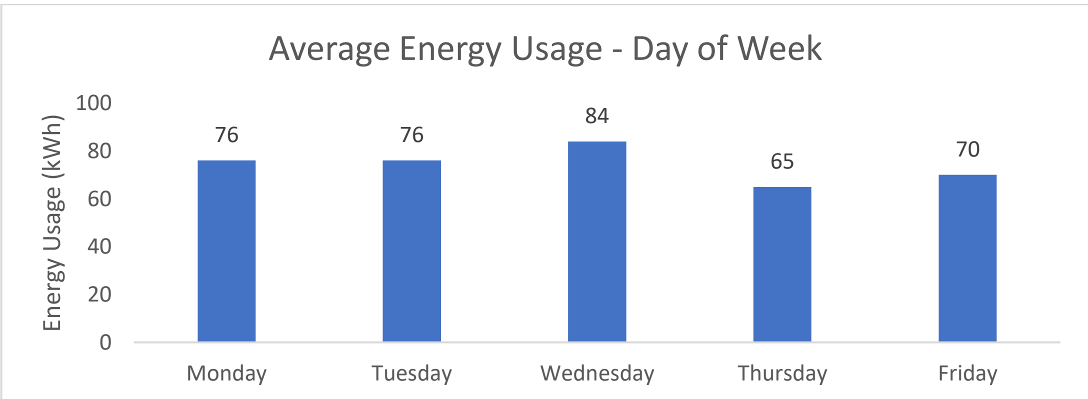


Figure 5.8 - Average energy usage – day of week classification

In order to further improve the distribution of energy usage throughout the week, driving routes could be re-organised by splitting some of the longer driving cycles into smaller sections so that the average daily usage can be more consistent regardless of the day of week.

Similarly, optimising the energy usage distribution across the entire week is a desirable concept as this simplifies the design choices (by only needing to consider one reliable energy usage figure) that may arise when conceptualising renewable energy generation options at the depot, which in turn would help reduce the charging costs of a 100% deployed eRCV fleet.

Similarly, it can be seen from the presented data that the average number of refuse collection vehicles deployed on any given day ranges from 24-26, assuming one eRCV performs one refuse collection driving cycle daily. Assuming the minimum value of 24, a summarised analysis can be performed in order to understand the daily energy use regarding a fleet of eRCVs. Assuming that every vehicle has the battery size provided by the eRCV manufacturer (300kWh), and using average energy usage and average driving cycle duration on a daily basis, together with a set start time for rubbish collection at 8AM and only one route shift, it can be shown that the rubbish collection shifts will end on average at 11:50. At this point the total, fleet-level, energy available to provide grid services would be 7000 kWh, allowing for other losses and refuse collection vehicles that fail to make it back to the depot by the average end shift time, implying an approximate total figure of 2800 kWh of energy used by all vehicles for one day. A detailed day-by-day analysis is presented in the table below, 5.1.

Day of week	Average shift end time	Available grid energy (kWh)	Number of RCVs deployed
Mon	11:26	8471	24
Tue	11:21	8394	25
Wed	11:44	7752	24
Thu	10:56	8489	24
Fri	10:57	8502	26

Table 5.1 - Energy remaining in eRCV fleet - daily results

This opens up significant opportunities in employing the vehicle battery as grid support, and other energy generators the contracted refuse collection company may have, in order to charge the eRCV fleet during low-demand hours and allow the batteries to provide grid support operations during peak energy demand hours, effectively using the vehicle batteries as a modular energy storage system that can adapt its needs and capabilities in a versatile manner.

Finally, some difficulties during the simulation process have been encountered, particularly limitations concerning the amount of simulation output data the RAM of the workstation was able to hold at one time. The parsim function is pre-programmed in such a way so that the main Matlab environment is required to hold all the processed data of all the simulations running at a given time in every generated parallel simulation environment. It has been noted that the default, 10 worker option (one simulation environment variable per CPU core) causes the data stored in the RAM memory to overflow. To avoid an OS crash due to lack of RAM memory, the Matlab environment resets the space allocated for holding the simulation data, effectively deleting the data that was stored in RAM at that time and causing data corruption on some of the collection route simulations. In order to avoid this, the number of simulation environments running in parallel has been reduced from 10 to 5, leading to a decreased speedup improvement, but nonetheless keeping a significant advantage in time execution when compared to a one-by-one simulation procedure. In order to fully utilise the CPU potential (i.e. using 10 workers at once) more RAM needs to be installed in the simulation workstation.

5.1.4. Potential Reduction in CO_2 Emissions and Fleet Costs

The contracting company that performs refuse collection currently operates a conventional, diesel-powered vehicle fleet. By utilising the simulated energy usage prediction figures, and noting the gross thermal calorific value of diesel, estimates concerning the reduction of CO_2 emission if a full-electric fleet replaces the diesel-powered vehicles may be obtained.

From the energy usage previously presented, it is noted that as an estimate, the energy usage average for all-classifications-considered is 74 kWh. Based on this figure and the estimated number of driving cycles performed daily (or number of RCVs deployed, if a 1:1 factor is attributed), it can be seen that the average energy used on a weekly basis is approximately 9200 kWh. This value can then be multiplied with the gross calorific value of Diesel [209] to calculate an estimated weekly carbon dioxide footprint. This has been found to be about 1500 Kgs of carbon dioxide emissions every week, which, if extrapolated, results in approximately 78 metric tonnes of carbon dioxide gas emitted yearly.

In reality, the carbon dioxide footprint is likely to be larger than expected, since diesel-powered powertrains have a significantly lower system efficiency, so the real energy requirement will likely be higher than that of a full-electric RCV. Furthermore, the emission estimate precision can be further improved if actual fuel consumption figures for the diesel RCVs in use are provided. However, publicly available mileage data for these types of vehicles is vague or scarce. Similarly, the methodology explained above can also provide calculation estimates for other harmful greenhouse gases (GHGs), such as NO_x. Finally, a different methodology employing refuelling data for this type of estimation has been carried out later in section 5.4.

Having discussed the energy fleet requirements, in order to fully understand the potential reduction in carbon emissions as well as the refuelling costs an electric vehicle fleet may incur, the aspect of electric vehicle fleet charging needs to be considered. To do this, 2 scenarios have been considered.

Scenario 1: Off-grid vehicle charging system. The first scenario implies an off grid charging system that works independently of the national energy grid. The contracted local waste management company currently operates a biomass refuse incinerator with a rated power output of 1MW. When comparing this figure with expected energy usage, it can be deduced that the entire fleet is realistically able to be charged from the power output of the incinerator, offering the opportunity for creating an off-grid charging system which also provides the benefit of having to consider less electric grid regulations, therefore more flexibility in terms of charging performance and lowered costs in system design and maintenance.

Finally, since the incinerator is required to operate constantly independently of the eRCV fleet, all the system energy output is “free” from the charging fleet’s perspective. Therefore, if the eRCVs were to be charged off-grid employing the incinerator-sourced electrical energy, a theoretical 100% decrease in tailpipe CO_2 emissions generated by the fleet operations may be achieved, given that the incinerator is producing the emissions anyway from the act of incinerating the waste. However, this scenario will be more prone to failure from a system design perspective since there is only one energy source for the chargers. In addition, if the fleet is not grid connected, the benefit of using the fleet batteries for grid support cannot be realised, and the additional income stream cannot be utilised.

Scenario 2: Grid connected charging system. The second possible scenario for charging the electric fleet in question is represented by having the charging energy supplied by a grid-connected system, which takes the energy from the national distribution grid. In this context, the carbon dioxide emissions can be determined by looking at the CO_2 emissions produced per kWh of energy generated across the energy grid as a whole. As of September 2022, this is currently set at 0.233 kg of CO_2 per kWh [210]. Whilst in this scenario the importance of other factors become more prevalent, such as vehicle charging efficiency, an average of at least 50% in CO_2 emission reduction is expected, relative to a Diesel-powered fleet.[211]

One benefit of this scenario is that the user can profit from energy price mechanics, such as peak/off-peak energy price variations. Therefore, a strategy involving buying energy (charging) at low price and selling vehicle leftover battery energy (supporting the grid) at high price, may be possible to produce income and support the costs of charging the fleet. This should therefore aid in quickly attenuating the higher upfront costs of switching to an electric fleet, which have been previously documented in literature[212]. Due to the fact that after every day there is a significant amount of energy left in the vehicle batteries, once the RCVs end their respective shifts, they can be connected to the grid and have the leftover capacity used as grid support BESS. This can effectively provide grid support during peak energy demand periods, thus reducing the net cost of system implementation and maintenance on the long-term, through having the ability to "sell" the available energy to the national grid during peak demand.

Similar to computing the carbon dioxide footprint reduction, charging patterns need to be considered again for indicating the incurring costs for an electric fleet. Given that one driving cycle on average depletes only 24% of the vehicle battery capacity and the shift times are reasonably predictable, with all shifts occurring during the day, it can be safely suggested that vehicles be charged overnight to benefit from the significantly lower off-peak energy costs. A full vehicle battery charge during off-peak times is predicted to cost approximately 60-70 GBP as of January 2021, accounting for a 90% charging efficiency, and can be achieved with reasonable margin during a time when there are off-peak tariffs available, and by employing 50-60 kW-rated charging stations.

Furthermore, if grid support is not required, perhaps the supplied vehicle battery capacity could be reduced, making the cost of an eRCV lower and slightly more efficient, due to the overall vehicle being lighter.

5.1.5. Summary

The presented findings suggest that both energy usage and carbon dioxide emissions can be significantly reduced by implementing an eRCV fleet for refuse collection in an urban environment. Furthermore, the financial and environmental impacts of the fleet can be further enhanced by implementing vehicle charging systems that take advantage of local energy production.

The analysis and calculations performed in this study can be further extended for larger, more complex fleets, such as bus routes. Similarly, other urban areas can also benefit from these conclusions, by using a reasonable degree of result extrapolation depending on the topography of the area in question. Such vehicle fleets may bring bigger savings in terms of maintenance and operation costs, as well as more meaningful reductions in the carbon footprint of the public logistics sector around Sheffield and beyond.

The following section is concerned with a similar analysis that has been performed on a different heavyweight vehicle fleet, buses for public transport.

5.2. Understanding eBus fleet energy usage through simulated telemetry

5.2.1. Aims

Similar to the public refuse collection vehicle fleets, understanding the emissions produced by public transport fleets is also a key factor that needs to be considered towards partial or complete transport decarbonisation. This is due to public transport comprising a significant share of the overall emissions in urban areas [213]. This section outlines the potential in carbon dioxide reduction by employing electric bus fleets by comparing the footprint of the energy required by an electric bus fleet to that generated by a conventional, diesel-powered one. Additionally, a cost analysis between these two fleets is provided. The results and suggestions generated by this study can prove to be useful insights and estimations in order to investigate the feasibility of implementing electric bus fleets on different types of public transit routes.

The investigation considers various route types as well as two different bus types. The results employ energy consumption figures generated by the software model described in chapter 3 of this thesis, tuned to emulate standard specification electric buses available on the market. This has been produced in a similar fashion to the one described in section 5.6. The technical specifications of the used vehicles may be observed in appendices 4 and 5.

The bus routes that have been chosen for the analysis are real routes that are currently being served by both conventional diesel-powered and hybrid buses. Their distances are relatively short, although their operating profiles are different, in order to accommodate a high degree of relevancy. After defining the route dataset, speed-distance value pairs that comprise artificial telemetry has been generated based on the distance between bus stops along the routes. The telemetry describes trapeziums (i.e. speed increase – constant speed cruise – speed decrease) between each stop. The increases and decreases are equivalent to the bus driver employing up to 50-75% of vehicle acceleration and deceleration performance, a behaviour that has been deemed realistic through observation. The constant speed cruise value has been set to be the bus average speed observed in urban areas.

An example of such a route, along with its simulated telemetry can be observed in figure 5.9 below. Maps of the chosen routes can be viewed in the appendix 6 for reference.

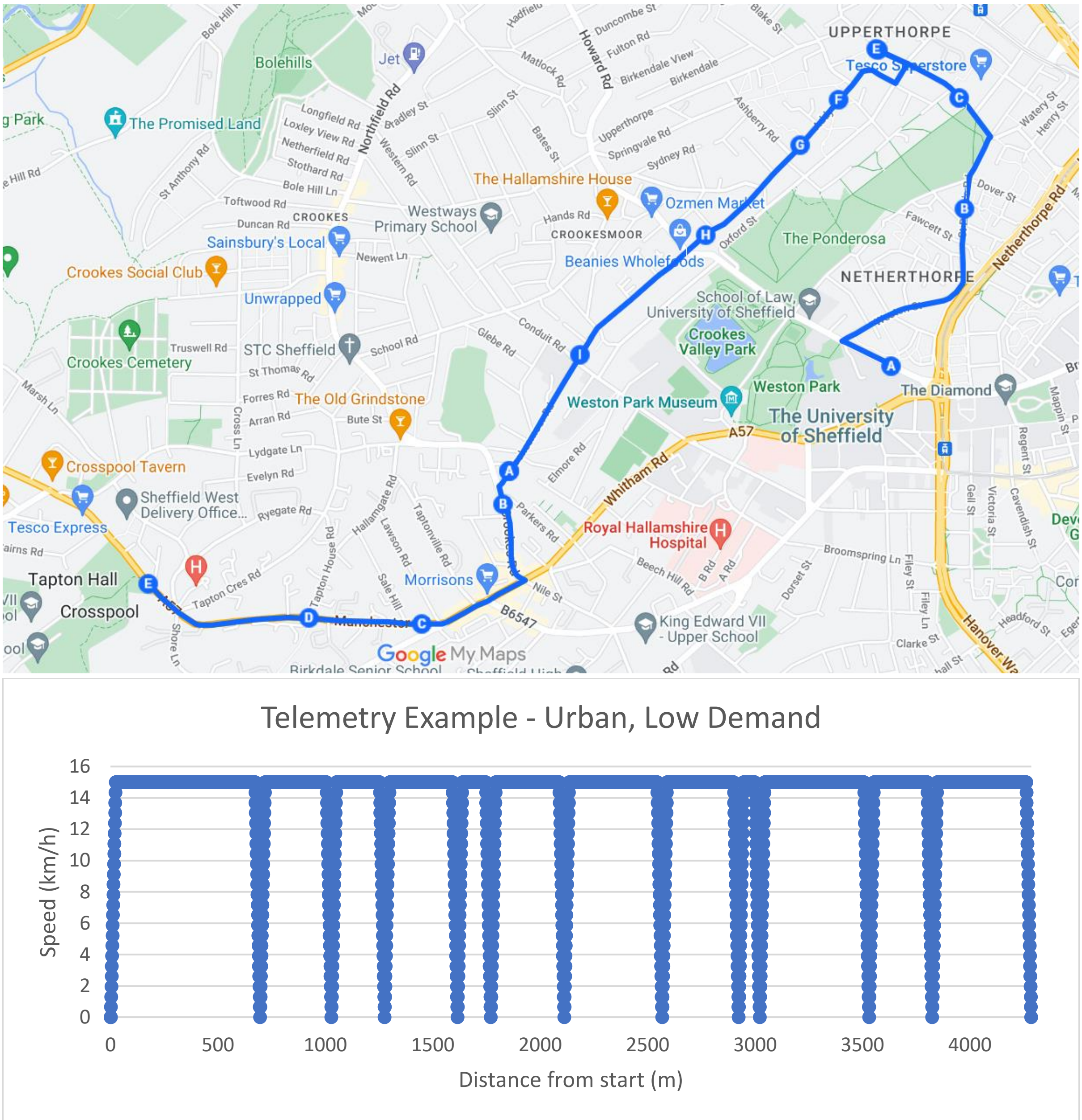


Figure 5.9 - Example of bus route and its simulated telemetry

5.2.2. Discussion & Simulation Findings

Figure 5.10 shows the energy usage prediction results benchmarked against estimated results calculated using energy consumption estimates found in literature [214]. The increased consumption in the model prediction may be attributed to higher acceleration/deceleration cycles, which are uncommon under normal circumstances. Similarly, the presence of power draw from vehicle auxiliary systems and higher drag coefficient than normally expected may also negatively affect energy usage. An important aspect that needs to be considered is represented by the energy use difference between single-deck buses, and double-deck buses. Although the kWh/km energy consumption of double-deck buses is significantly higher, they are also capable of accommodating more passengers. Moreover, if the energy consumption figure is divided by the maximum number of passengers to generate an energy consumption per passenger figure, it can be determined that a double-deck bus is more efficient than a conventional simple single-decker vehicle. Whilst this is highly dependent on the time of day (as this usually dictates how many passengers are on the bus), understanding a power to passenger weight ratio is especially important for further investigations into optimising per-route energy usage. This enables the authority that schedules the timetables flexibility over what vehicle type runs at any given time of day.

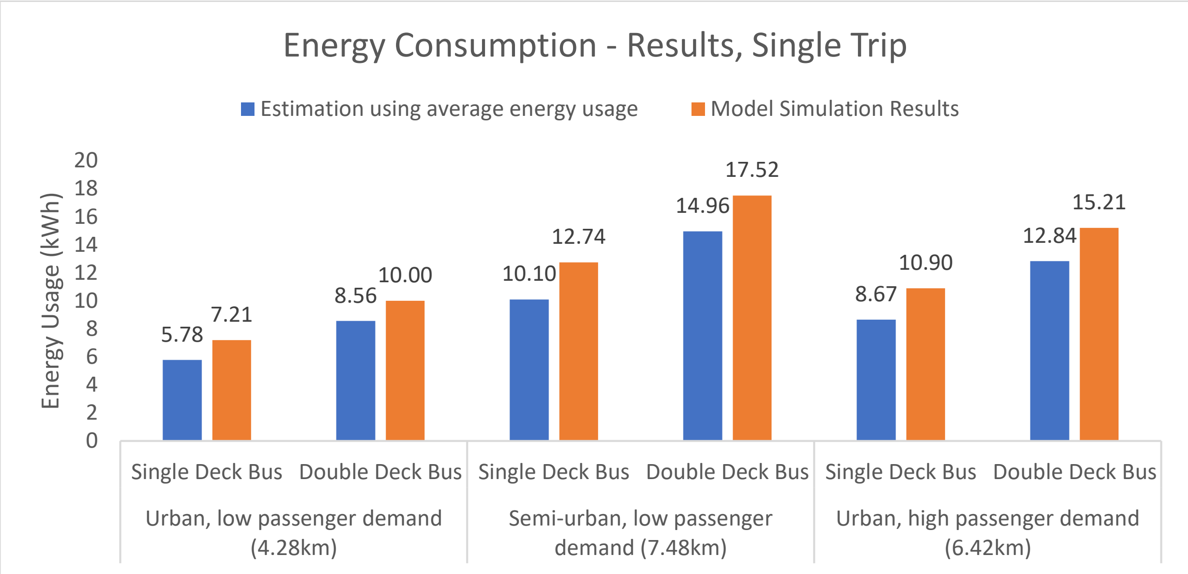


Figure 5.10 - Energy consumption results - simulated telemetry

When extrapolating the previously presented energy usage predictions to generate route service-level or fleet-level estimates, such as carbon footprint estimation and cost analysis, route scheduling must be considered. Energy demand for two of the featured route examples is relatively low, due to the small number of daily runs served by the fleet. This suggests a low passenger demand for these routes and can therefore be served by simple, single-deck buses to minimise energy requirements. The third route, which is provided in an urban area, has a schedule comprising many runs per day, indicating a high passenger demand, as observed in table 5.2. Thus, energy requirements of the bus fleet serving this route may be further minimised by employing high-capacity, double-deck buses during rush hours and single-deck buses during off-peak periods. Similarly, the same strategy may be applied when considering special route scheduling due to ongoing popular public events.

Route Type	No. of daily route runs (round trip)	Daily Energy Demand (kWh)	
		Single decker Bus	Double Decker
Urban, low passenger demand (4.28km)	8	57	80
Semi-urban, low passenger demand (7.48km)	7	89	122
Urban, high passenger demand (6.42km)	94	1024	1429

Table 5.2 - Daily energy requirements

Figure 5.11 displays estimates concerning the total carbon emissions produced daily. Estimates for a diesel-powered fleet have been computed using CO_2/km threshold standards provided by the EU's EURO certification regulations [215] for heavyweight vehicles. Whilst the difference in carbon footprint appears low on a daily basis, this adds up quickly, with monthly reductions of up to 50%. This suggests that a fully electrified fleet is able to save the average emissions equivalent to those produced by up to 30 regular passenger cars per route on a monthly basis, depending on energy requirements.

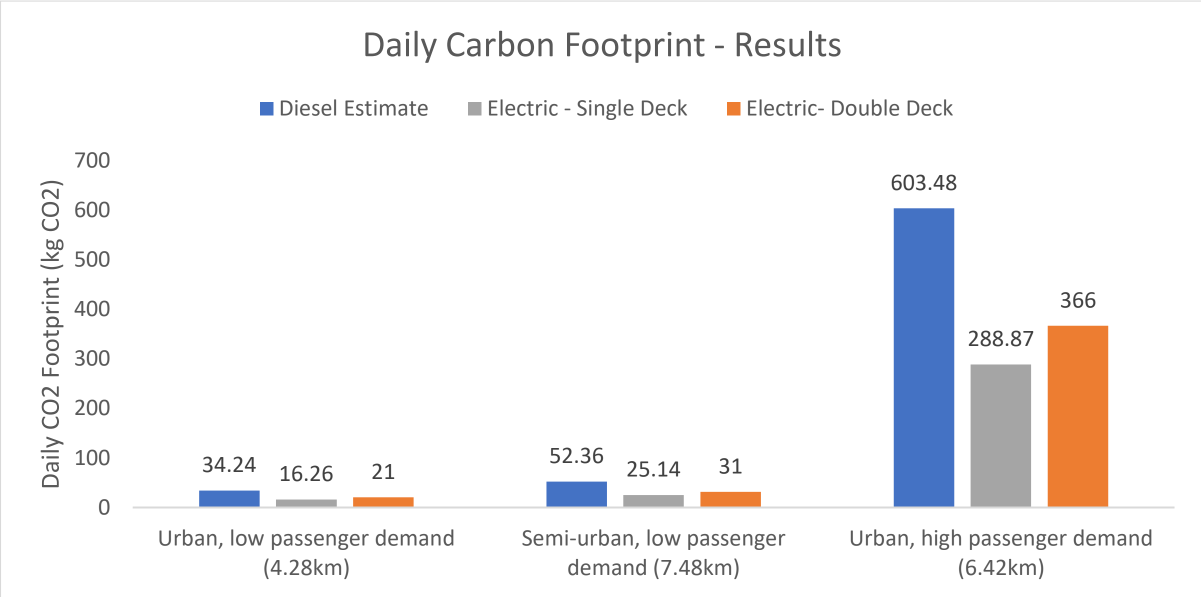


Figure 5.11 - Carbon footprint estimation

Complementing the carbon footprint estimations, a comparison between energy refuelling costs is displayed under figure 5.12. The diesel estimate has been computed employing mileage figures for currently operational Diesel buses [216]. Numbers suggest that an electric fleet is also competitive on an energy replenishment basis, although at higher upfront acquisition (capital) costs. However, with the increasing interest and technical development of renewable and nuclear energy sourcing, energy prices will likely decrease in the future, as these types of energy generation will be cheaper to run [217]. This will likely have the effect of opening up a "cost gap" that may be able to accommodate the difference in high purchase costs of electric buses, significantly reducing the period until the break-even point. This is also aided by the lower maintenance costs of electric powertrains relative to their conventional, internal combustion engine-powered counterparts. Furthermore, electric charging costs may be further reduced if the eBus fleet has access to bespoke charging systems similar to the one described the following section of this chapter.

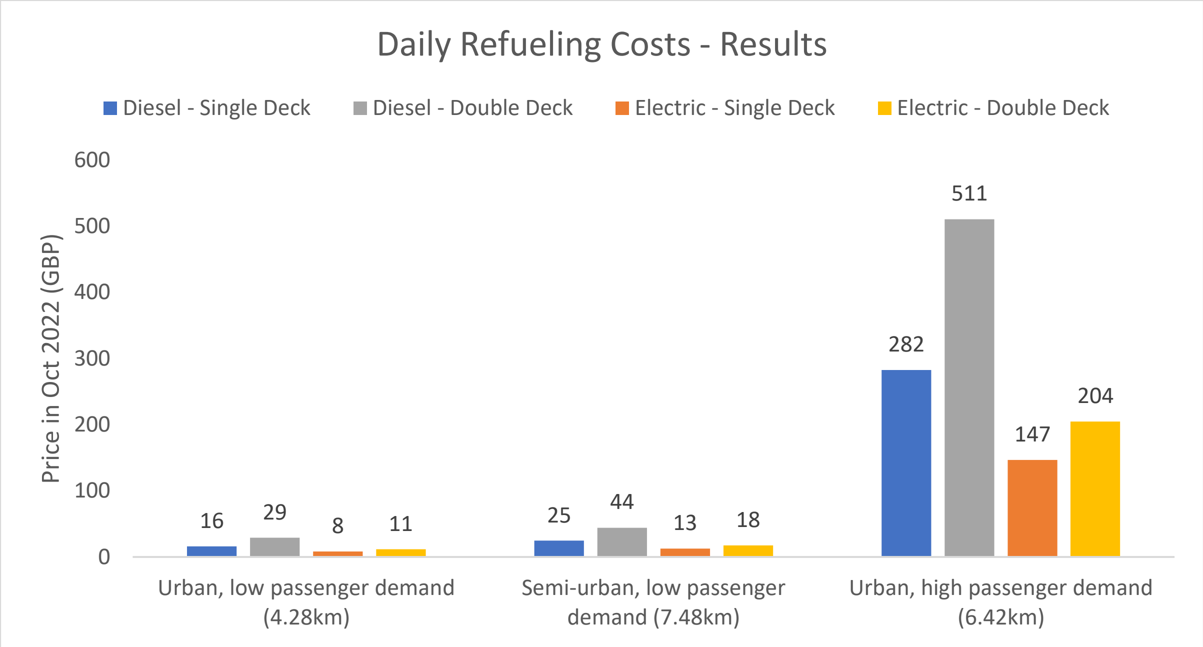


Figure 5.12 - Refuelling costs estimation

After running the initial energy use simulations with the specified parameters, the results were compared against literature in order to ensure consistency and provide some degree of validation. Whilst energy usage figures initially appear over exaggerated, this could be attributed to multiple factors.

Firstly, it has been observed that electric bus specifications are not consistent both in literature, and manufacturing companies' press releases. Consequentially, getting an accurate estimate of used energy based purely on linear energy consumption figures, such as kWh/km and kWh/mi is difficult. Literature suggests a large variation of consumption figures for models with similar technical specifications [218].

Additionally, another aspect that has to be considered is represented by the aspects extrinsic to the electric vehicle performance. In addition to the electrical energy employed for vehicle movement, there are other auxiliary systems that draw energy from the electric vehicle battery. Whilst some of these have a negligible energy demand, such as radio systems, in-vehicle lighting and other electronic monitoring systems, others may have a significant impact on energy consumption and consequentially vehicle range. One of the most energy-taxing systems is represented by electrical heat pumps, which are commonly used in all electric vehicle designs. Previous studies [219] indicate electrical heat pumps have a negative impact on vehicle range of up to 50%. Moreover, many studies and technical specifications present in press releases do not normally specify whether their energy usage estimations account for such factors [214][220] .

Another aspect that can lead to a high degree of variability in energy consumption is represented by variable environment conditions, such as traffic and the large changes in vehicle mass due to passengers boarding and alighting. As stated in the previous section, and supported by recent studies [221], traffic is highly unpredictable and difficult to emulate in a virtual environment. This negatively affects the precision of energy usage simulations disproportionately, with higher error rates present in simulations predicting higher intervals of time or distance [222].

In order to address the uncertainty factors presented above and alleviate the possibility of various inconsistencies in error, the software model has been adjusted such that it reflects a "barebones" model, with the sole add-on represented by small-scale vehicle energy consumers. Therefore, the presented results may slightly underestimate the real-life requirements. Nonetheless, the predictions generated by the model are consistent relative to estimations computed employing literature figures for average energy consumption. This confirms that the predictions are usable for further investigations.

5.2.3. Simulated Telemetry Energy Usage Outcomes

The electric bus investigation presented previously suggests that conventional bus fleet replacement with zero carbon emission electric alternatives is feasible, especially for short-length routes. Additionally, it offers another application that validates the flexibility of the vehicle model presented in this thesis, indicating its ability to accommodate any type of vehicle.

The next section is concerned with extending the findings presented in the past section with employing real-life telemetry in order to provide a better energy consumption estimate of eBuses.

5.3. Assessing Energy Use of Electric Buses through real-life telemetry data

Following the results and findings outlined in the previous section (5.2) concerned with estimating electric bus energy usage through employing simulated telemetry, the research has also been extended to utilising real-life telemetry data. Although the research featured in this section is strongly related to the previously presented results, having similar objectives and aims, it can successfully be presented as a separate, standalone investigation. This is particularly due to the significant differences in the complexity of the methodology employed.

5.3.1. Investigation Objectives

As previously stated, the research that will be presented in this section serves as an extension to previous energy usage simulation utilising simulated telemetry data. As such, the results presented in this section aim to complement previous findings related to understanding energy usage of various types of electric buses. Similarly, the data employed in this section should also give a better understanding as to how simulated telemetry datasets can be further refined to better reflect realistic driving conditions. However, the energy usage estimations presented in this section are likely to better reflect realistic consumption. This is because the input speed telemetry features various driving manoeuvres, such as prolonged, intensive acceleration and pseudo-random start-stop cycles, that should better reflect real-life conditions.

In order to facilitate a comparison process with previously presented results, the telemetry of buses driving on four bus routes with similar passenger demand and urban/rural profile have been recorded. Each of the chosen routes feature telemetry for full, return journeys. An example of recorded telemetry, as well as the mapped routed upon which it was recorded can be observed under figure 5.13.

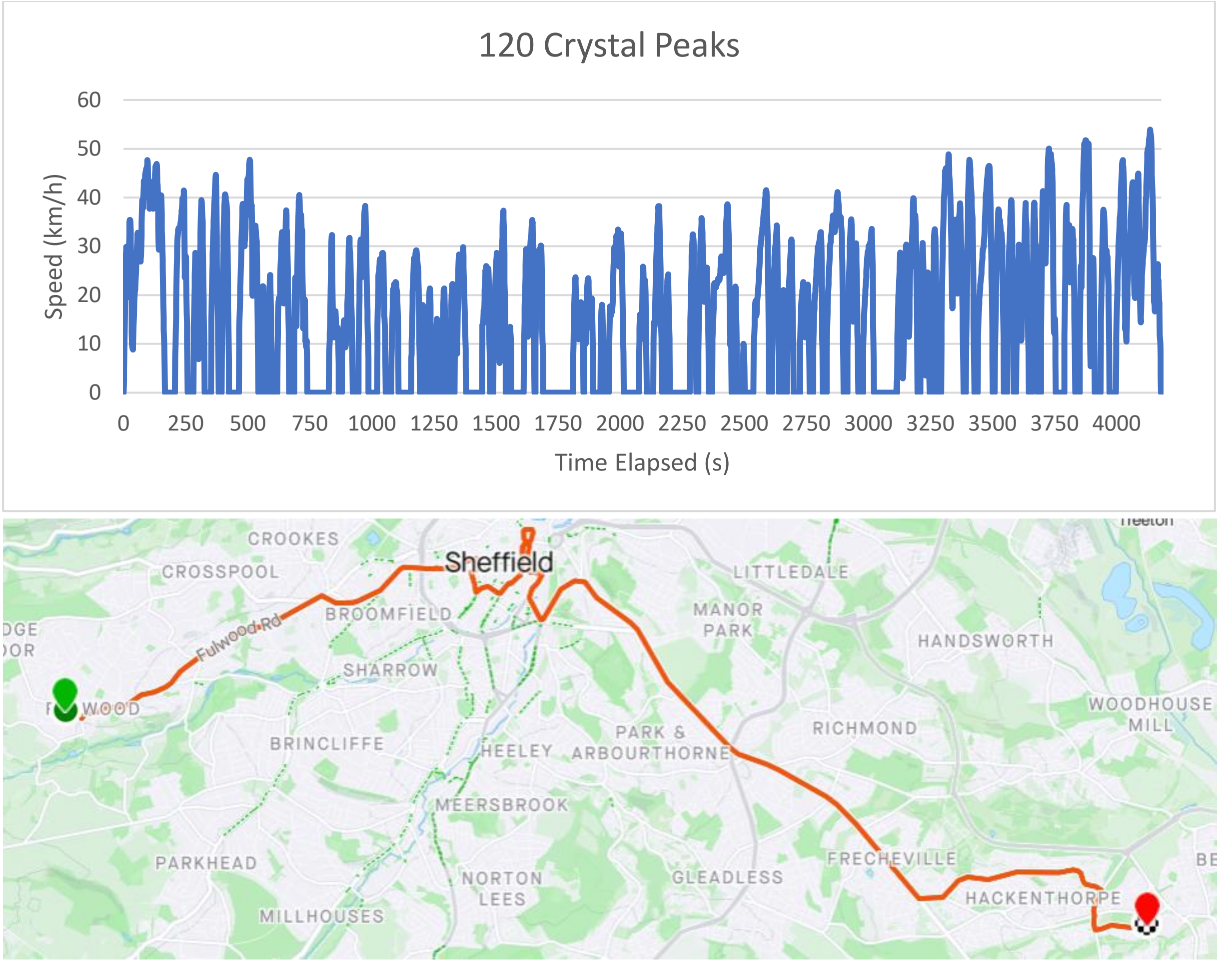


Figure 5.13 - Example of recorded bus telemetry

5.3.2. Acquiring and processing the real-life telemetry data

The telemetry data employed as input datasets for this investigation consists of speed-time key value pairs, which are then manipulated by the vehicle model described in chapter 3 and utilised as reference data for the model control system. In order to ensure input dataset reliability, two methods of obtaining the final input telemetry data have been used.

Firstly, the speed-time value pairs may be obtained through time-based recordings of global positioning system (GPS) datasets [223]. These conventionally consist of entries of value sets comprised by recording time, altitude, latitude, and longitude. The data resolution, which is usually linked with the frequency at which GPS data is being recorded, is usually bounded to time. For the purposes of this investigation, a data resolution of 1s has been utilised.

In order to record time-based GPS data, two different devices have been used. Firstly, GPS data has been recorded using a Garmin eTrex 10 GPS logger [224], configured for registering data every second. Secondly, in order to ensure data acquisition reliability, the telemetry has also been recorded through the mobile-supported Strava app [225]. This software, which is popular in the fields of running and cycling, thanks to its ability to record high-resolution detailed data with relative ease, utilises the mobile phone's GPS sensor upon which it was installed. Finally, both the solutions used for recording time-based GPS data are able to export the logs as GPX files, which have then been processed as raw CSV files using the Garmin BaseCamp [226] software.

Following the GPX to CSV file conversion process, in order to obtain speed-time value pairs, the distance between the coordinates of the log entries must be calculated. However, in this scenario, conventional mathematical systems cannot be used straightforwardly, as the latitude/longitude values are referenced against a sphere (the Earth surface). Consequentially, in order to determine the linear (i.e., as the crow flies) distance between the entry logs, a mathematical conversion of distance from spherical to flat spaces must be employed. Several conventional solutions exist, however, the Haversine formula [227] has been used due to its high conversion accuracy, as described in equation set 5.2 below, with φ values being the latitudes and λ values the longitudes of the entries in radians (1,2 denoting which is the origin and destination point), R is the Earth's radius in metres, d is the final linear distance in metres and a and c being annotations to simplify the displayed equation set.

$$a = sin^2 \frac{\Delta\varphi}{2} + \cos\varphi_1 * \cos\varphi_2 * sin^2 \frac{\Delta\lambda}{2}$$

$$c = 2 * arctan(\sqrt{a}, \sqrt{1-a})$$

$$d = R * c$$

Equation 5.2 (set) - Spherical (Great Circle) to linear distance conversion using the Haversine formula

Following the distance conversion, the speed is then effectively the distance (now expressed in metres) between the point entries. This is because these distances are recorded every second, meaning that the distance is also the speed (expressed in m/s) between two points. Finally, a conversion from m/s to km/h is carried out by applying the 3.6 constant to all values (1 m/s = 3.6 km/h). An example of telemetry section generated employing this method can be viewed under figure 5.14, in blue.

The second method used for recording real-life telemetry data is also based on information logged by the mobile-supported Strava app. Besides recording time-based GPS data, this software also uses in-app computation to calculate its own speed metrics, recorded as enhanced speed. The advantage of this recording method is that it convolutes location-based information with readings logged by the mobile phone's integrated accelerometer. This has a beneficial effect on the recorded telemetry accuracy, as it eliminates positional inaccuracies in the GPS readings due to bad signal. This is especially important when the vehicle is stationary, as low satellite signal has been observed to have a significant effect on the time-based GPS entry logs, frequently recording false, small changes in vehicle position and generating false speed telemetry readings produced using the first method.

In order to acquire the Strava app enhanced speed data readings, the information is exported as Strava's proprietary format, FIT files. These are then parsed using the FitParse Python library [228], which decodes the format. The speed-related information is then extracted using Python-based basic control flow statements and written in a CSV file. The code concerned with data extraction has been attached in appendix 7 of this document. An example of a telemetry portion generated using this method can be observed under figure 5.14, in red.

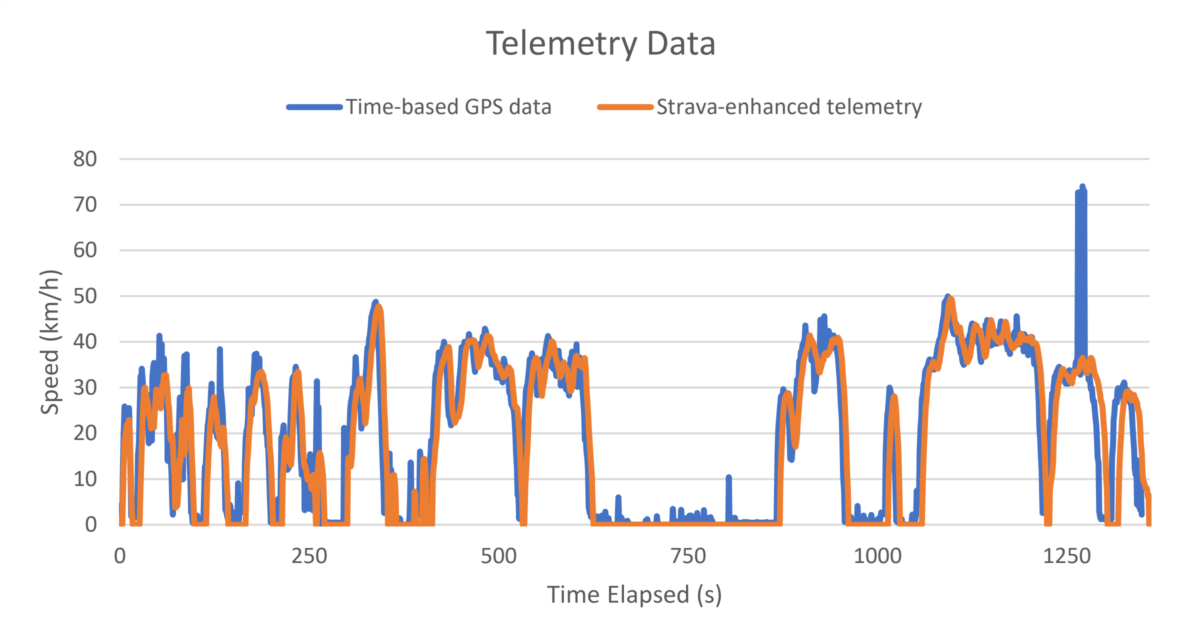


Figure 5.14 - Example of telemetry produced using Strava's proprietary enhanced speed calculation method and the conventional time-based GPS approach. Note the vehicle idling periods set to zero and the "cleaner" telemetry aspect of the Strava solution (red) relative to the GPS-only information (blue)

Finally, during the telemetry recording process, it has been observed that the time-based GPS data logged using the Garmin GPS logger has occasionally missed logs. Whilst this does not have a significant effect on small portions, the impact of these missing entries may add up, resulting in significantly incorrect telemetry data. Due to this, but also the improved accuracy of the enhanced speed calculations computed by Strava, the telemetries generated using the second method have been chosen for simulation work.

5.3.3. Simulation Findings

As previously stated, in order to ensure a consistent comparison to the previous simulated telemetry research, bus routes having similar features were chosen for telemetry recording. Figure 5.15 shows the energy usage prediction of 3 of the recorded routes. The estimated consumption using literature figures [214] is also displayed, for reference.

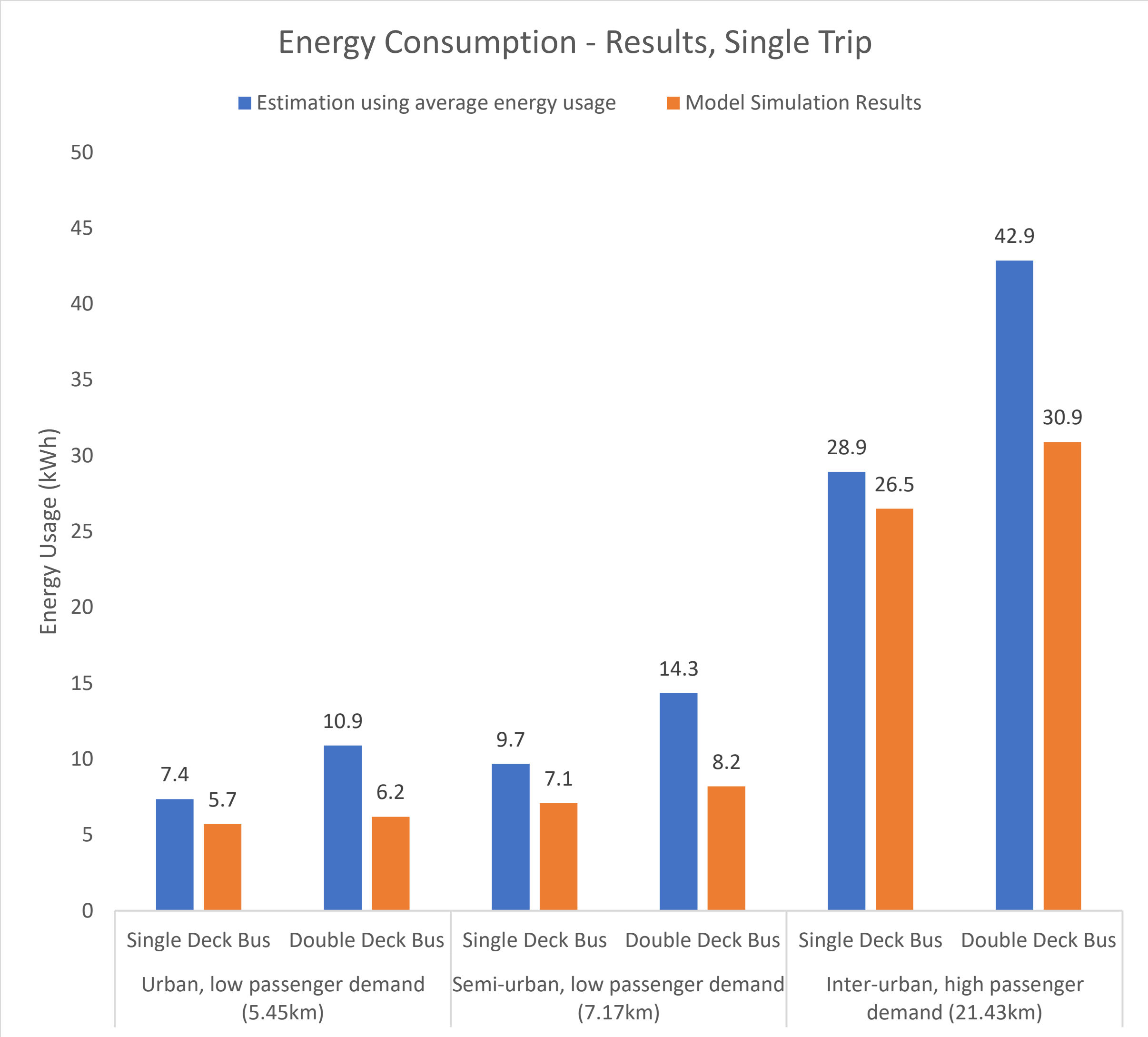


Figure 5.15 – Simulation results – real-life telemetry

Whilst the distance of the routes is somewhat different to the ones analysed by the simulated telemetry approach in 5.3, the energy usage can be normalised, computing a kWh/km figure, which is a standard performance metric that can be understood with relative ease. These can be viewed in figure 5.16, along with kWh/km figures produced by the simulation of the artificial telemetries and estimations using literature figures [214] previously presented.

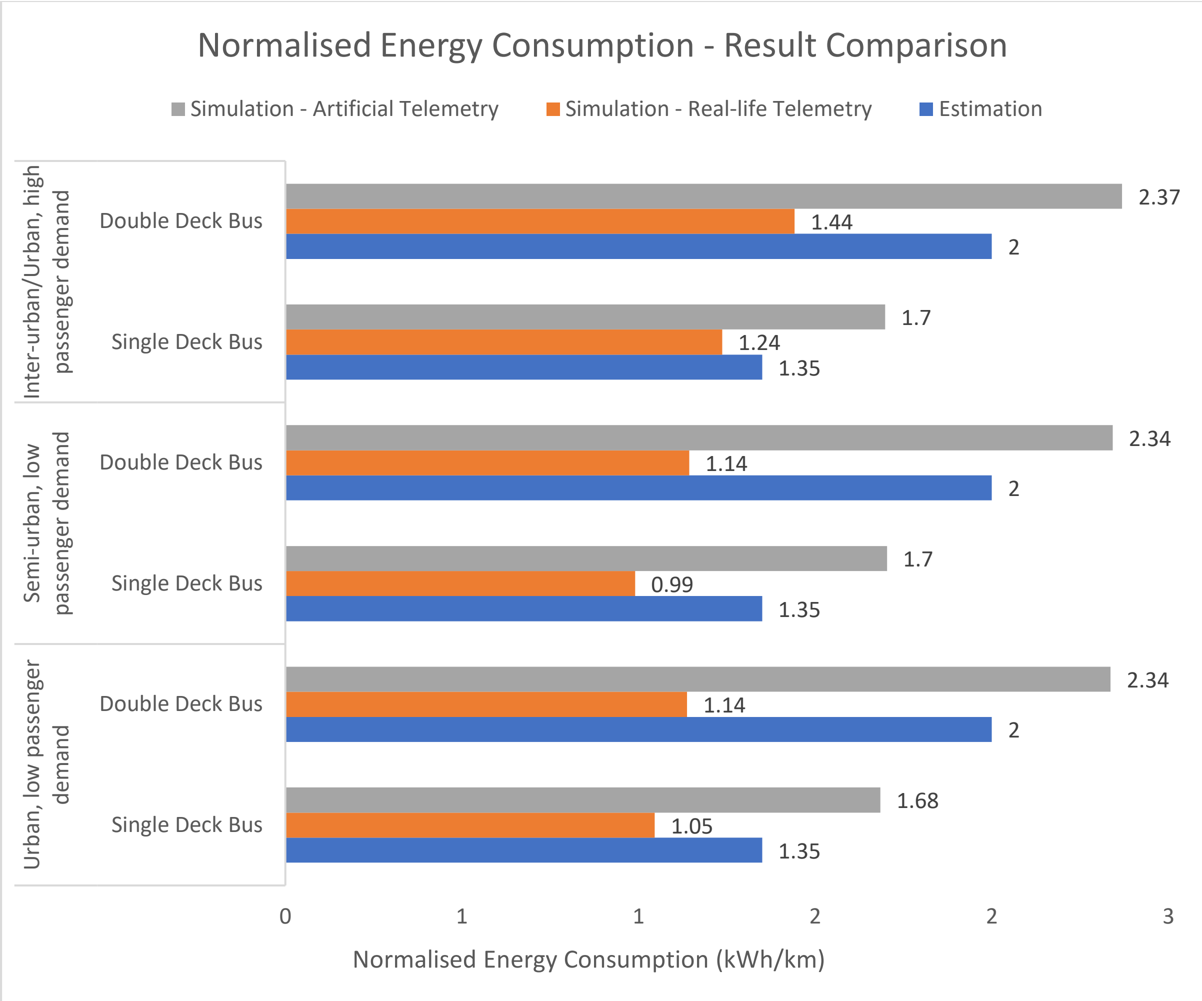


Figure 5.16 - Comparison between energy consumption rates

It can be observed that whilst the energy consumption is predicted to be somewhat smaller than the initial simulations based on artificial telemetry, the variation appears consistent throughout the routes and bus types. Additionally, the decreased consumption may be attributed to several factors, for example the driving style. The artificial telemetry data describe frequent, aggressive accelerations and decelerations, whereas the real-life data has portions of slow-steady deceleration, allowing the bus to recover some energy through regeneration.

Additionally, it can be shown that, if the simulated telemetry speed values are scaled down by 33%, as presented in figure 5.17, the energy usage of simulated telemetry drops significantly, shown in figure 5.18, bringing the values closer to those stated in the literature [214] and real-life energy figures. This is due to lower target speeds and most importantly, smoother acceleration/deceleration.

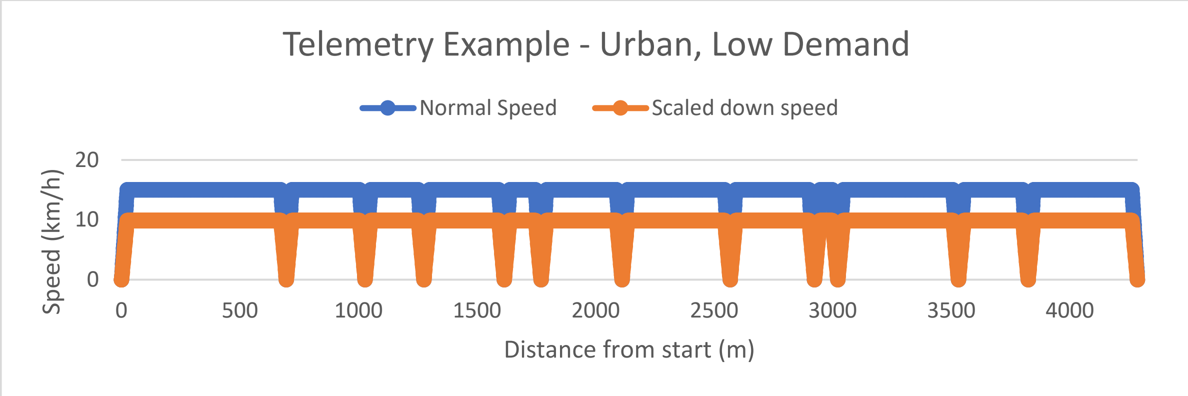


Figure 5.17 - Scaled-down simulated telemetry example

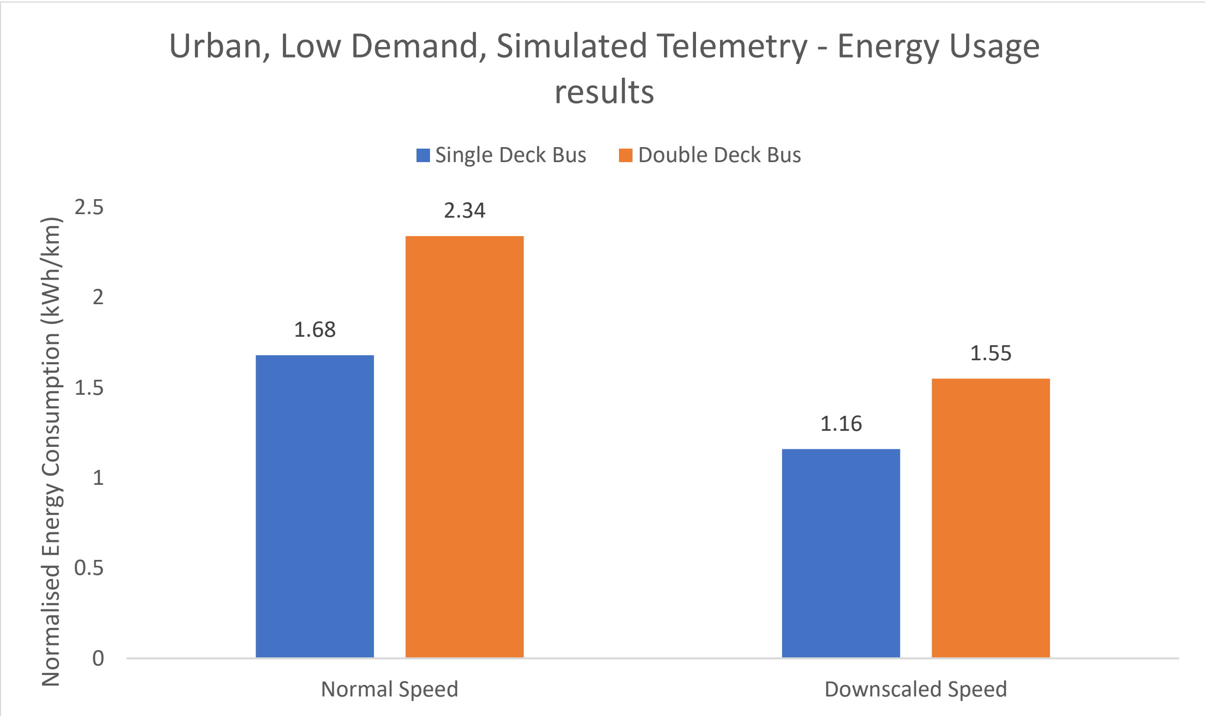


Figure 5.18 - Energy usage (normalised) comparison between normal simulated telemetry and downscaled version

Moreover, the frequency of stops in real-life circumstances appears to be lower relative to simulated telemetry, which also leads to less start-stop cycles, effectively ensuring steady driving for longer periods of time, which is less wasteful in terms of energy consumption. To that end, the recorded routes have been predominantly logged during off-peak traffic hours (before 9am and past 6pm). Therefore, energy consumption during peak times will likely be significantly higher.

Finally, vehicle mass variation also must be considered. The logged routes were recorded during off peak times due to inconsistencies in route availability and timetabling, thus it has been observed that the vehicle was mostly empty during the route runs. This suggests a lower-than-normal energy consumption due to the vehicle being lighter, which is consistent with figures seen previously in literature [214]. Consequentially, a proportional increase of energy consumption with higher passenger traffic is expected.

5.3.4. Analysis Outcomes & Future Work

The conclusions suggested by the recorded data, based on real-life bus telemetry, further backs up the argument made in section 5.3 regarding the feasibility of electric bus fleets in urban, semi-urban and inter-urban environments. eBus technology has the potential to be significantly greener than conventional ICE solutions, whilst also being more economical [42] in the long run.

The presented results further validate the idea that the carbon dioxide footprint and energy refuelling costs of an electric vehicle bus fleet are still expected to be lower than a diesel-based transportation solution. An effort to estimate a daily energy demand has been attempted – however, the timetables have large periods of time throughout the day that do not specify the exact schedule, making it difficult to estimate how many runs are carried out during that period.

Future work related to this investigation may be focused on several areas. Firstly, acquisition of more telemetry data may be beneficial, especially if it is focused on recording routes with similar telemetry characteristics in different contexts (e.g., many passengers onboard, telemetry logged during peak hours etc.). The additional telemetry data will reflect different vehicle weight values, which will affect energy consumption and driving attitude (which will also affect energy consumption). Additionally, the research may benefit from developing a more detailed model, through more refined vehicle technical specifications, to be used in the simulation workflow. Finally, the original time-based GPS data may benefit from some data clean-up in order to minimise the effect of inaccurate positional recordings due to erroneous telemetry recordings.

5.4. Comparing CO_2 emissions and costs of heavyweight fleets in urban areas

Having examined the energy usage of multiple types of electric heavyweight vehicle fleets, in order to better understand the benefits of electric alternatives to public service vehicle fleets, a high-level examination of the current carbon footprint and energy refuelling costs of these vehicles is necessary. A robust insight into this may be offered when considering the monthly energy requirements of a typical council within the UK.

To this end, an analysis into several aspects of the vehicle fleet managed by Ashfield Council, UK has been carried out. This data has been obtained through private communication with the council in question. By inspecting the refuelling logbooks, which contain information concerned with the amount of fuel put into the vehicle tank and the price of this, it can be observed that the council currently operates fleets of vehicles to service many of its public operations, ranging from refuse collection to housing support, many of which are predominantly traditional, ICE-powered vehicles. However, the operating fleet size varies significantly between the categories, consequentially the carbon footprint share of each category has some variation attached to it.

Figure 5.19 shows a pie chart indicating the relative share of the emissions grouped by fleet category in Ashfield Council for the month of April 2022. By cumulating the total amount of purchased fuel and multiplying it by the amount of emitted CO_2 of diesel fuel per litre, it can be determined that the total carbon footprint during that period of time has been calculated to be 92.7 tonnes of CO_2. This equates, on average, to the emissions produced by approximately 240 ICE-powered private passenger cars on a monthly basis [229].

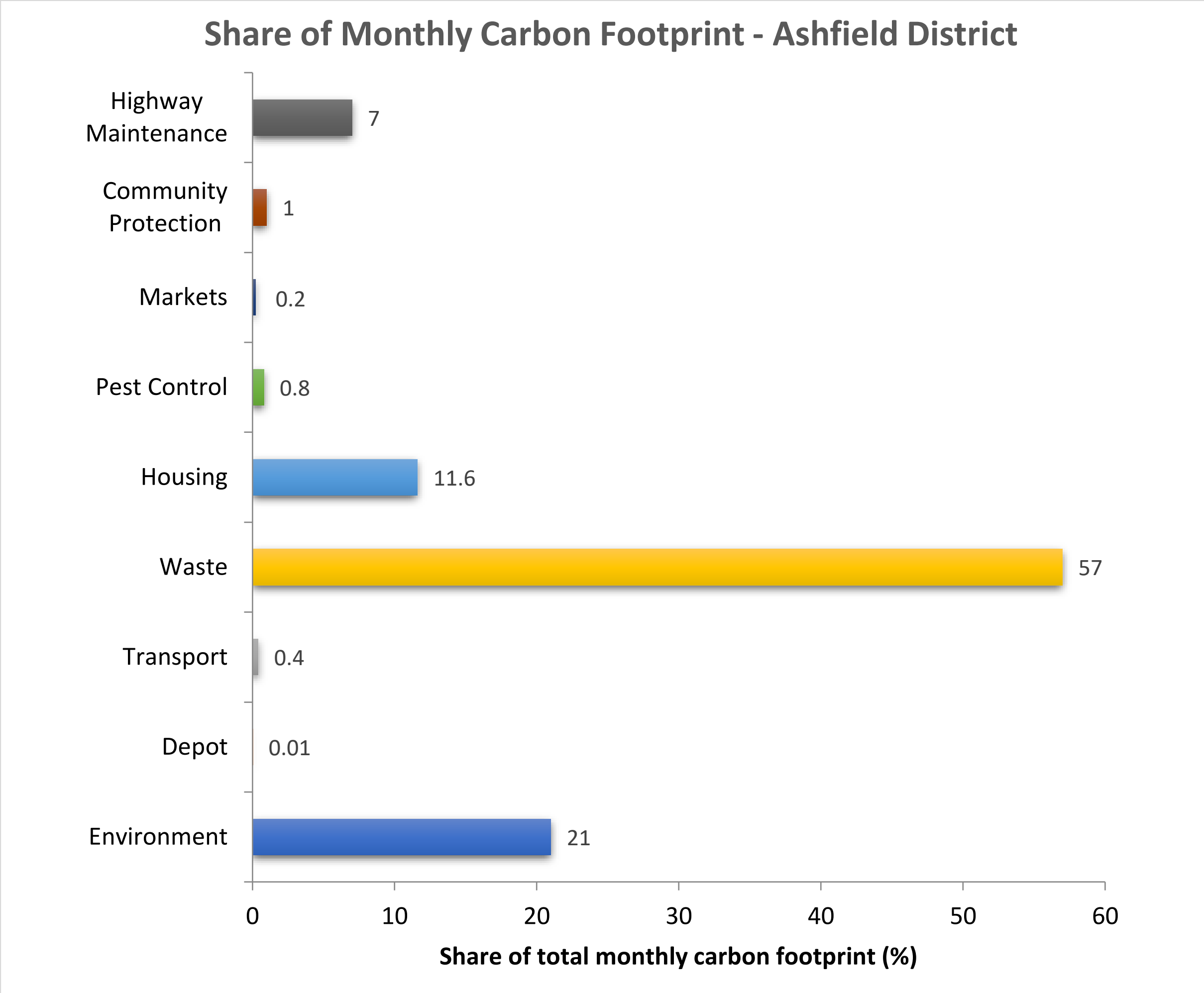


Figure 5.19 - Share of Carbon Footprint – Monthly

Fleet	Vehicle Composition
Environment	1 gator, 5 sweepers, 1 excavator, 1 JCB, 10 mowers, 2 quad bike, 2 tractors, 22 vans
Depot	1 unidentified small vehicle
Transport	1 4x4 vehicle, 1 van
Waste	19 refuse collection vehicles, 2 vans
Housing	34 vans
Pest Control	2 vans
Markets	1 van
Community Protection	3 vans
Highway Maintenance	10 vans

Table 5.3 - Fleet composition

As can be seen, the relative share in total carbon footprint (92.7 metric tonnes) indicates that fleets incorporating a majority of heavyweight powertrain vehicles have significantly larger emissions than fleets comprised of lighter vehicles, such as electric vans and regular passenger vehicles. Whilst vehicle fleet sizing plays a significant role in this, the major carbon emitters, except the "Waste" fleet, have similarly sized fleets in terms of vehicle numbers. This effectively proves the previous remark related to larger vehicles having higher emissions. Furthermore, the idea is backed by other studies, predictions and experiments described in literature [230]. The full vehicle composition of each of the fleets is stated in table 5.3 above for reference.

Having determined the fleet types that are the largest pollution and cost source, an investigation concerned with estimating the amount of emissions and required costs for energy refuelling has been carried out. The findings have then been correlated with the results of the investigation concerning eRCV energy usage in section 5.2.

In order to compare the current emissions of these vehicle fleets to those which may be generated by an alternative, electric-powered fleet, electric charging of the vehicles needs to be considered. In order to showcase the potential in carbon footprint reduction of electric fleets, two types of scenarios may be considered. Firstly, assuming the electric fleets were to be charged from a grid connected system, carbon footprint estimations have to consider the current average emission per kWh present in the energy grid, currently set at 0.233 kg CO_2/kWh [210]. Additionally, the diesel-related estimations from the Sheffield fleet of eRCV's have been estimated by utilising and linking to the fuel logs and distances covered of the Ashfield fleet.

When observing the computed estimations, it has been seen that an eRCV heavyweight electric vehicle fleet operating in the Ashfield area, coupled with on-grid charging would lead to a carbon footprint reduction of 65-66%. This figure has been observed to be consistent with the eRCV fleet operating in Sheffield area, as shown in figure 5.20.

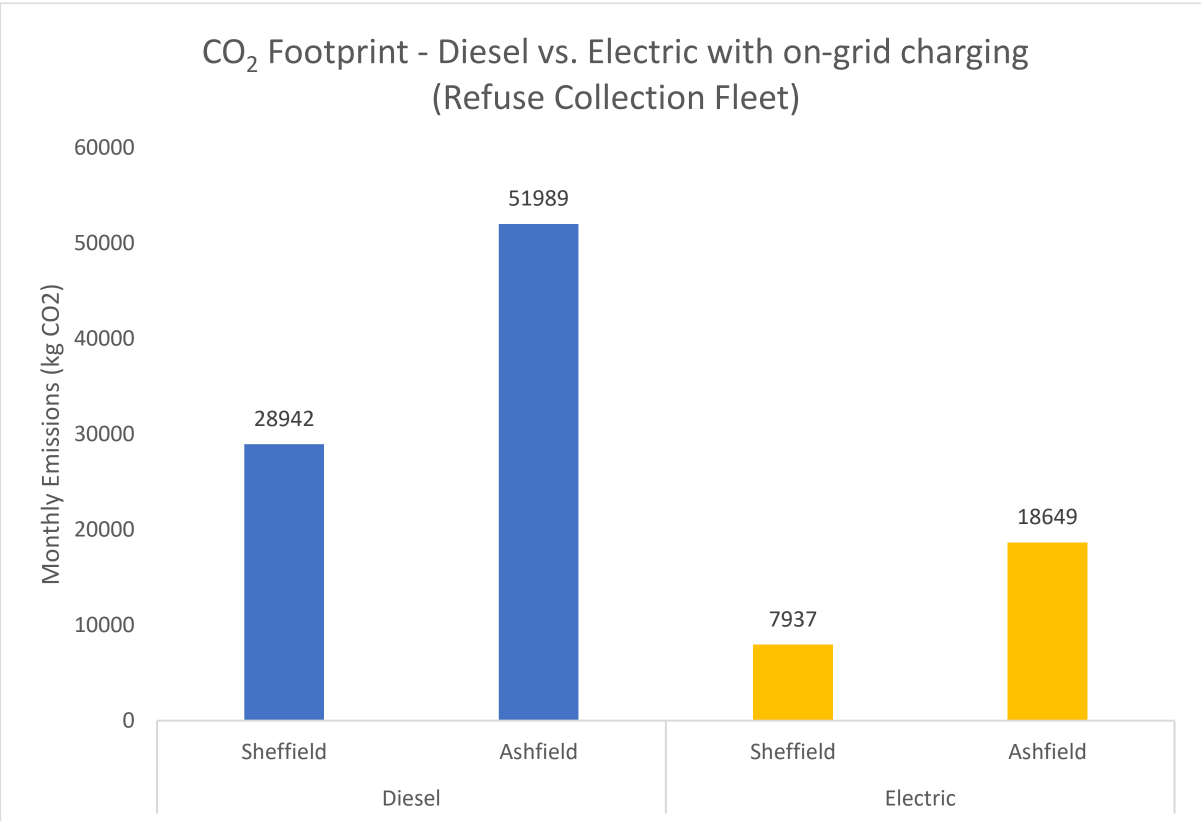


Figure 5.20 - Carbon dioxide footprint comparison

Furthermore, if the operating fleets were to have access to biowaste burning systems that are coupled to heat-extracting energy generators, the tailpipe carbon dioxide emissions of the vehicles would be reduced by 100% as such incinerators produce emissions whether or not the energy produced supplies a vehicle fleet. The capabilities of such a system have been previously described further under section 5.2.

When considering costs related to energy refuelling, similar trends relative to the carbon footprint estimations appear. It must be noted that in this scenario, the costs of an electric fleet that is being charged via an on-grid system are more difficult to estimate, since such an installation can profit from selling surplus energy back to the grid at times of high grid demand, earning revenue from grid services. However, this is likely to have a significant beneficial impact on overall cost reduction. For the purposes of comparison, the estimation calculation takes into account a more simplistic scenario, where energy is being bought from the grid at the average business tariff pricing. The results can be seen in figure 5.21.

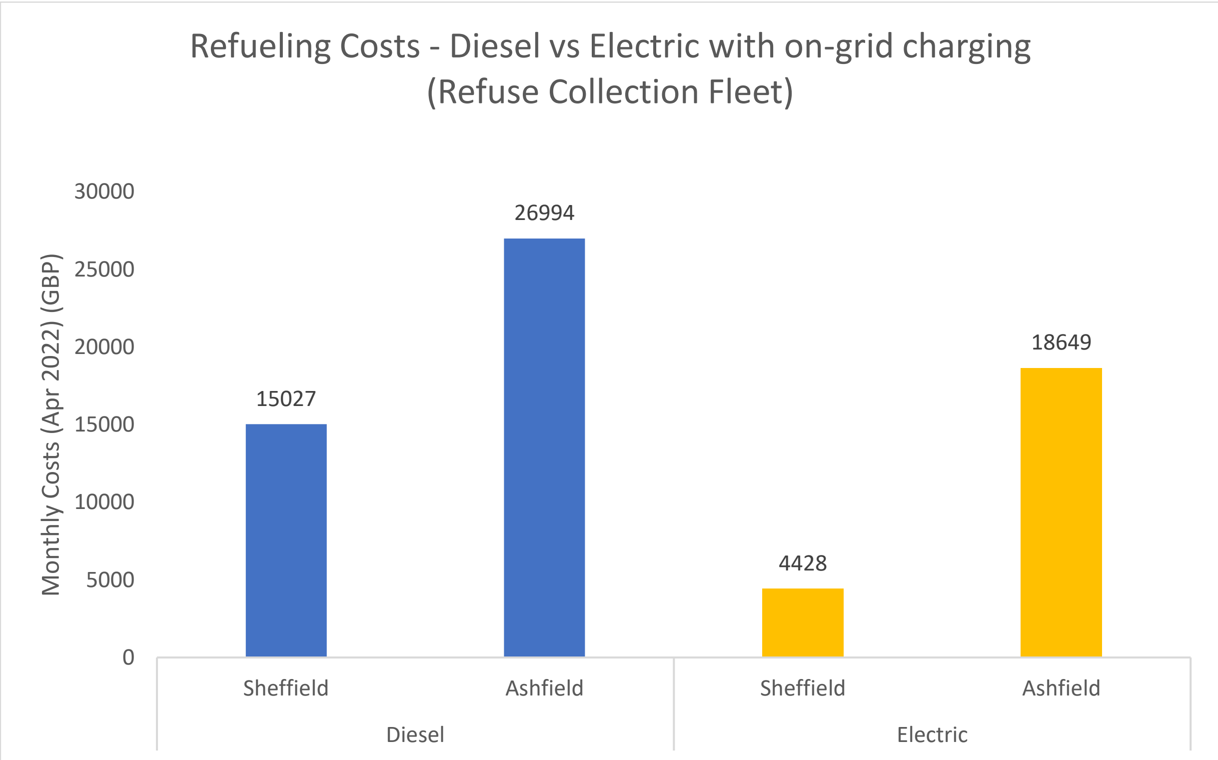


Figure 5.21 - Energy refuelling cost comparison

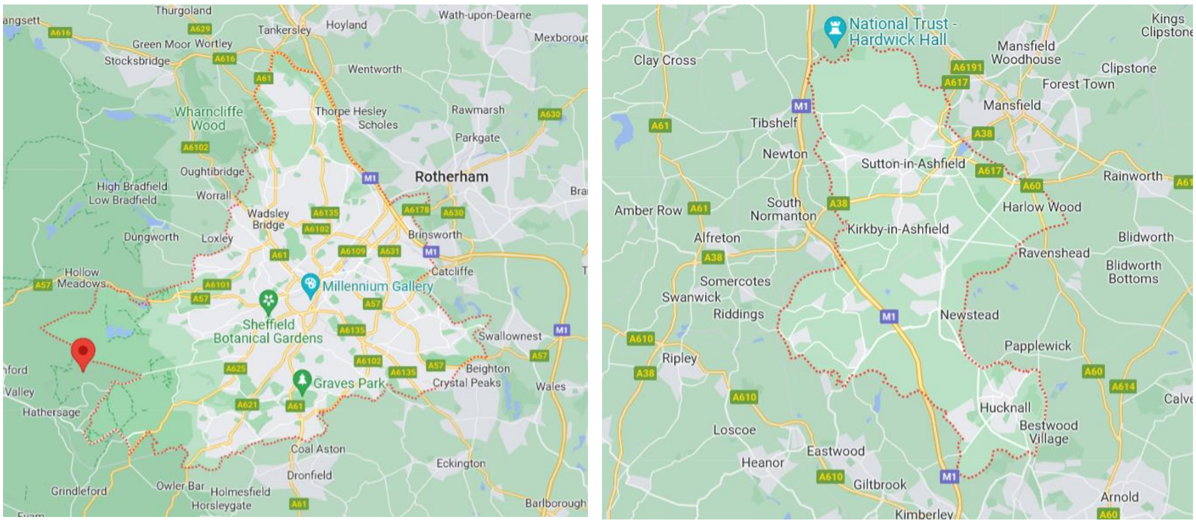
Furthermore, the overall savings offered by deploying an electric fleet will likely be pushed significantly lower. This is due to maintenance costs being smaller for electric vehicles relative to conventional ones [231], due to the smaller number of moving parts in the powertrain.

It must be observed that whilst the reduction is consistent, there appears to be a big difference in the CO_2 footprint and refuelling costs of the analysed fleets. This is mainly due to the difference in the distance that these fleets cover on a monthly basis, as shown in table 5.4.

Parameter	Location	
	Sheffield	Ashfield
Distance Travelled (mi)	9796	23000
Est. Energy Consumption (kWh/mi)	3.48	
Required Energy (kWh)	**32140**	**80040**

Table 5.4 - Fleet energy requirements

There are a number of factors that may explain the reason behind the difference in covered distance. Firstly, the surface area and population density of the areas served by the refuse collection fleets. It can be observed that the population density of the Sheffield area (figure 5.22a) is significantly higher than the one calculated for Ashfield (figure 5.22b), as indicated by table 5.5. Areas with higher, more dense population have been shown to generate more refuse per a given surface area [232][233]. This, in turn, has a significant influence on the number of collection points and the distance between them.



a b

Figure 5.22 - Districts of interest

Parameter	Location	
	Sheffield	Ashfield
Population	557039	127900
Surface Area (km^2)	122.5	109.6
Population Density (persons/km^2)	**4547**	**1166**
Normalised CO_2 Footprint (kg CO_2/km^2) - Diesel	**236.2**	**474.3**

Table 5.5 - Population/area-related information

Moreover, another important factor to consider is represented by the data employed for this analysis. Whilst data concerning the Sheffield eRCV fleet precisely describes telemetry of vehicles performing scheduled refuse collection, the data in Ashfield is based on refuelling logs. Therefore, the odometer readings present in the logs of the latter fleet may also include mileage that has not contributed to refuse collection, for example testing runs, vehicle refuse unloading etc. A more detailed analysis of the consumption figures of the fleet servicing the Sheffield area has been presented in section 5.2.

Additionally, the analysis presented above has also been performed for the other fleets that service the Ashfield council. Reduction trends are even higher in relative terms for the other fleets, although they are smaller in absolute values, due to the significantly shorter distances covered. Moreover, the energy consumption figures used in these investigations have been taken from press releases of electric alternatives to the vehicles currently being used [234]. These are likely to be optimistic, with higher energy consumption figures likely in real-life scenarios. Therefore, the estimated reduction in emissions and costs when deploying an electric fleet may have a significant degree of error.

Example analyses of CO_2 emissions for two other major fleets can be observed under figure 5.23. Similar trends have been observed with energy refuelling estimations.

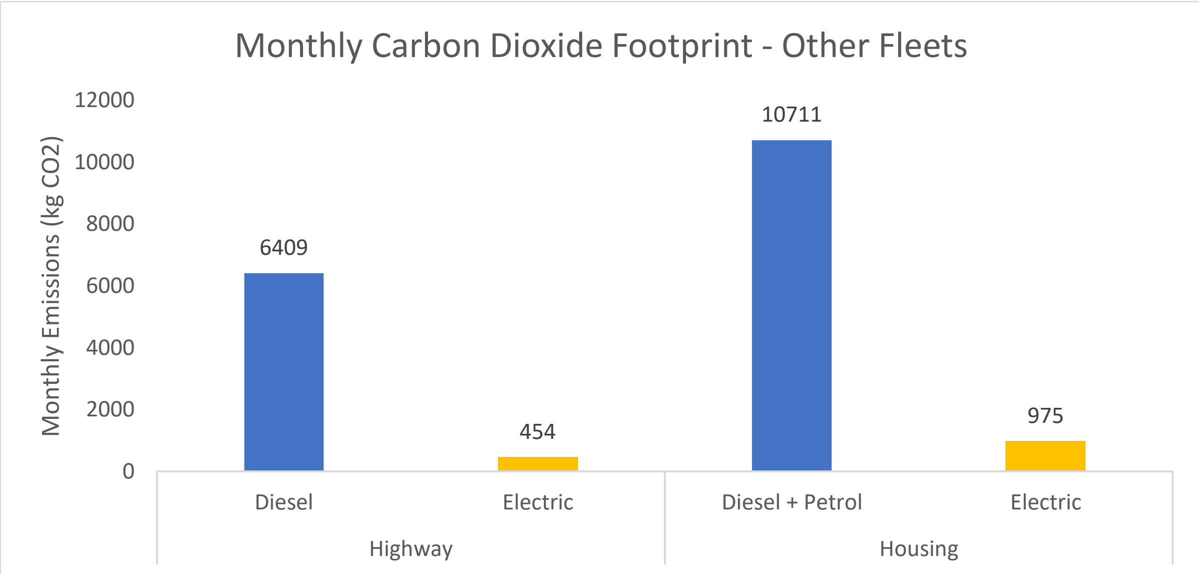


Figure 5.23 - CO2 emission estimation for other fleets

Finally, the previously presented analysis of carbon footprint and refuelling costs indicates that electric alternatives to heavyweight public service vehicle fleets may be a significant step forward towards local and place-based decarbonisation. Moreover, the cost calculations suggest that this may also be performed in a financially sustainable way, with the lower operating costs of electric powertrains capable of shortening the period to the break-even point.

Having discussed the capabilities of heavyweight PSV vehicles, at both low-level and high-level perspectives, the following section is concerned with presenting findings related to energy consumption of such vehicles over short distances with varying numbers of start-stop cycles.

5.5. Understanding Energy Usage at Street-level for heavyweight powertrains

The findings of the investigations performed on various heavyweight public service vehicles presented previously has generated further interest into investigating the effect of start-stop speed variations on energy usage in a more localised, small-scale environment.

5.5.1. Objectives

This chapter section presents another application of the software prediction model, which is concerned with understanding the energy usage of heavyweight powertrains undergoing frequent stops at a street-level. Whilst the simulations in this section have been set up to predict the energy usage of an eRCV, a similar argument may be made for other similar vehicles, such as electric buses, although the suitability of such a model to integration into traffic is yet to be explored.

In addition to assessing the predicted energy use depending on geographical features and number of stops, key aspects related to finding an optimum number of stops per street for refuse collection are also studied. The purpose of optimisation in this case is to minimise vehicle energy use during normal collection operations. Finally, conclusions arising from the application of the model will be provided, in addition to some key recommendations regarding operation optimisation of such eRCV fleets that complement existing findings in waste management research. It is expected that, if applied correctly, these recommendations will significantly impact electric vehicle energy use in a positive way.

5.5.2. Methodology

In order to allow the presented software model to simulate the scenarios of interest in this investigation, a specific style of input data had to be produced in the format supported by the simulation environment. The modelled input data has been created to reflect normal refuse collection operations covering a set street length. After observing real-life operation of traditional ICE-powered RCV fleets when collecting refuse bins in the Sheffield City Region, UK, several approaches were considered that generated different modelling datasets, which are discussed below.

After considering the requirements of the simulation environment and correlating these with the aims of the simulation results (i.e. energy usage prediction), two input data modelling approaches have been identified.

The first modelling approach considered is one based on an input dataset that consists of speed-time value pairs. The main advantage of this approach is that it represents the intuitiveness of reading the energy usage predictions, which will be generated as a time-based prediction. However, the main problem of this approach arises when attempting to model the input dataset. Since, as in this context, there is no direct causality link between distance and time, it is very hard to estimate the amount of distance travelled using solely the speed-time value pairs and first-order approximation principles. Therefore, maintaining control over elapsed distance and ensuring equal distance values over many datasets can prove difficult.

The second modelling approach employs an input dataset that is composed of speed-distance value pairs. The advantage of this technique is that it allows for complete control over the amount of distance travelled by the vehicle during the simulation, which in turn signifcantly simplifies the process of creating the input dataset. The main drawback of this method can be traced back to the lack of causality issue described previously. A speed-distance set of value pairs do not contain any information related to time, therefore the energy usage predictions would not be able to account for any time-dependent energy use during potential periods when the vehicle was stationary, such as heating, radio etc.

While this may pose a significant accuracy-related problem in a driving contexts with a high degree of randomness, where the energy usage predictions may be affected due to traffic and high, inconsistent speed variations, the lack of causality is not a significant issue on refuse collection sections, as traffic is rarely a problem in a single street during bin collection. It has been observed that under normal refuse bin collection operation, the vehicle usually operates in a continuous fashion and the vehicle speed is usually maintained at a low level. This low speed has been determined to be, on average, similar to a human walking speed in order to facilitate the actual bin collection by the workers. Therefore, it can be assumed that the lack of correlation between the two approaches presented above and a real-life context is expected to be minimal. Consequentially, the speed versus distance approach has been deemed suitable for the purposes of this case study, because of its degree of intuitiveness when modelling.

Two different methods of input data generation have been developed employing the speed versus distance approach, with the second one being an evolved iteration of the first.

5.5.2.1. Modelling Approach 1: "Ideal Cycle" – Simple approximation, speed vs distance

The first method developed, using the speed versus distance approach, employs a triangular approximation method to "emulate" a given driving pattern. This involves creating triangle-like vehicle driving patterns (for acceleration/deceleration) between an assumed number of evenly-spaced collection stops, over a fixed and predefined distance. This method produces driving patterns that strike a good compromise between refuse collection efficiency and vehicle energy usage.

Each triangle pattern in the final output aims to describe a period of acceleration, followed immediately by a period of deceleration, from one cluster of bins to the next. It is worth noting that the acceleration and deceleration points on the final driving cycle are predetermined by the assumed number of stops, the only variable factor being the acceleration and deceleration slopes that connect these points.

The method is a 4-step process that can be described as presented below. The justification behind employing powers of two in the chosen values and calculations is that an exponential trend can be assumed when creating the number of start stop cycles (i.e. a 4-stop cycle may be generated from a 2-stop cycle and so on).

1. Set the desired street length (set at 512m, for ease of calculation, and successive division allows a wide variation in number of stops within the street)
2. Set the number of stops required (used multiples of 2^n+1, sole exception being 2 stop)
3. Divide to discover distance between each stop
4. Assume acceleration until mid-point of each start-stop cycle such that at the mid-point the vehicle will have a set speed, then decelerate untill the end of the cycle, such that the vehicle will have 0kph at the 'stop' position.

A driving pattern example generated by this approach can be seen in figure 5.24. Acceleration and deceleration slopes are assumed identical for ease of calculation and pattern smoothing.

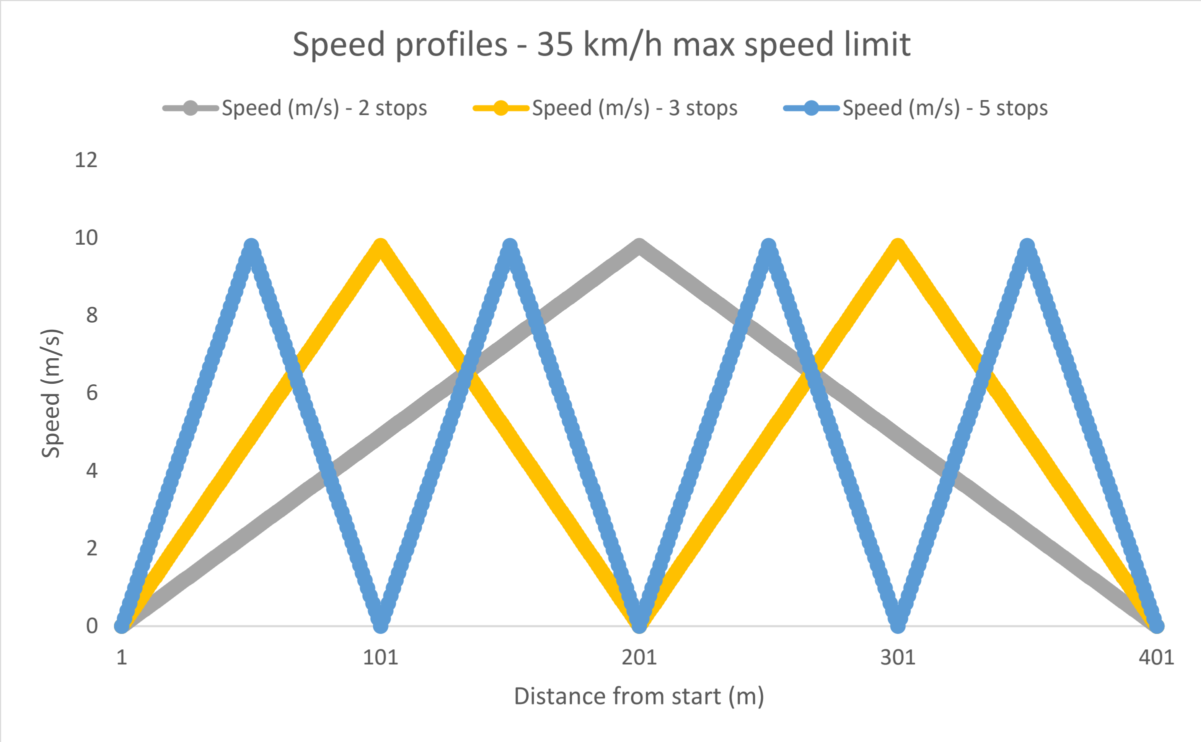


Figure 5.24 - Ideal cycle driving patterns, example

From the process described above, it can be seen that the shapes of the driving patterns will not change regardless of the maximum set speed, the only change being the rates subject to various acceleration/deceleration slopes.

However, whilst this triangular approximation-based method provides a good statistical starting point, it does have several drawbacks. Firstly, it can be observed that the driving patterns require a high degree of precision and driving predictability to accurately follow. This can cause inconsistencies in accurate energy usage prediction, since it has been concluded that the driving styles of eRCV operators have a high degree of variability. Furthermore, in the case of generated driving patterns that feature a high number of start-stop cycles, the method may assume acceleration and deceleration deltas that may be unachievable by the vehicle under normal operation in real-life, effectively presuming performance capabilities beyond the vehicle's technical specifications. This is bound to significantly reduce the relevancy of such simulations.

5.5.2.2. Modelling Approach 2 "Realistic Cycle" – Custom-conditional approximation, speed vs distance

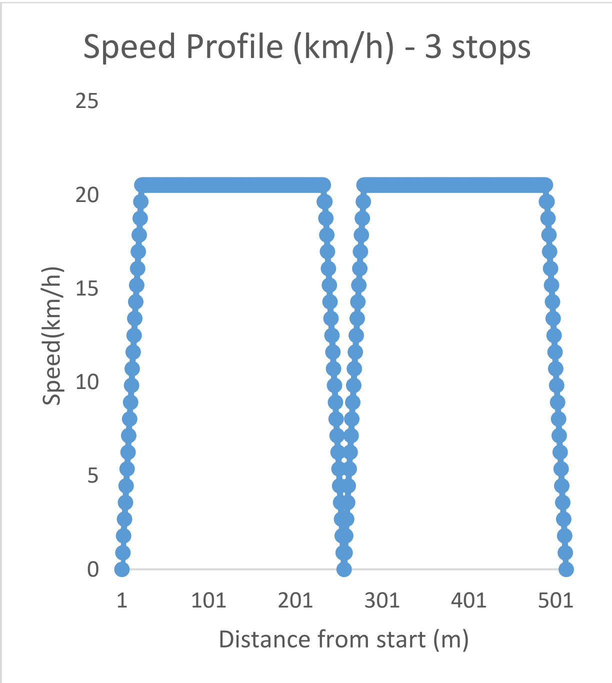
Following careful consideration, it was determined that the first method is unsuitable to give a realistic energy usage estimation. This is mainly due to drawbacks related to being unable to accommodate a wide range of driving styles and lack of correlation with the vehicle's technical specification. An improved method has been developed that adds a layer of conditional complexity on top of the first approach described in the previous subsection. The added complexity will generate different driving shapes depending on the imposed speed limit set for a given set of generated driving patterns, and should better reflect various driving styles, increasing the relevancy of energy usage prediction to real-life applications.

As previously, the acceleration and deceleration slopes are equal for ease of pattern generation. The approach is presented below. The assumptions taken when setting the analysis values are similar to the approach described in the previous subsection.

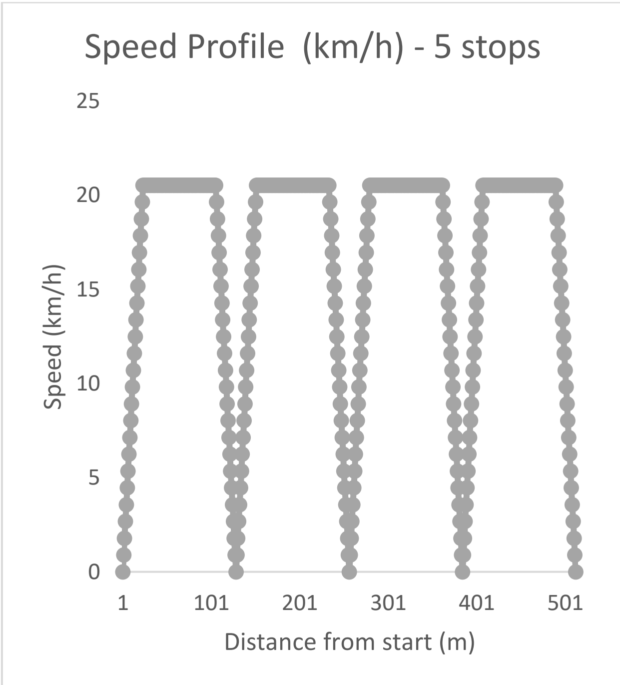
1. Set the desired street length (set at 512m, for ease of calculation)
2. Set the number of stops required (used multiples of 2^n+1)
3. Divide the desired street length by a set number of stops to find out length of each start-stop cycle
4. At the start of every start-stop cycle, the driver will begin to accelerate at a maximum specified rate. The acceleration/deceleration rates have been directly derived from actual vehicle physical performance specifications.
5. If a maximum set speed is reached before the midpoint, the driver will stop accelerating and maintain that set speed for several meters before the end of the cycle, then will decelerate.
6. If the maximum speed is not reached before midpoint, the driver will decelerate from midpoint to 0.

It can be observed that by adding this conditional complexity layer that takes into account an imposed speed limit, the driving pattern shapes on a speed versus distance graph can vary from a triangle to a trapezoid shape. Consequentially, this technique features a more refined approach in terms of acceleration control. Therefore, this method has been successfully applied to a wide range of driving cycle patterns with various conditions (variable acceleration intensity, variable road slope, various set limit speeds etc.).

Examples of generated driving patterns using this method can be seen in figures 5.25 and 5.26.



a)



b)

Figure 5.25 - Realistic cycle driving patterns. a) 3 stops, 512m street, 20kph limited, b) 5 stops, 512m street, 20kph limited

Figure 5.26 - Realistic cycle driving patterns. 33 & 17 stops, 512m street, 20kph limited

5.5.3. Results

Following the methodological development phase, different test cycles have been created by employing the mathematical construction approaches presented previously. The aims of these tests are particularly concerned with understanding vehicle energy usage related to various vehicle driving styles. Another important aim is related to quantifying the potential improvements in energy saving by using lower vehicle operation speeds and taking advantage of the energy re-harvesting capabilities of the vehicle, such as through regenerative braking.

5.5.3.1. Ideal Cycles – Triangle approximations for each start-stop cycle

The “ideal cycle” approach described previously has been deemed restrictive in its ability to emulate real-life driving behaviours because of its large acceleration-braking invervals. However, the results of the simulations related to this approach are nontheless useful for determining a reference set of baseline energy figures. This is meant to serve as a guideline for comparison relative to other simulations and provide understanding of the energy-saving potential in driving pattern scenarios that strike a good balance between time efficiency and energy usage.

The simulation sets, based on the “ideal cycle”, compare energy usage at different target maximum speeds and number of stops. It has been found that regardless of the set target maximum speed, an inverse exponential correlation exisits between enegy usage and different numbers of start-stop cycles. This happens because cycles with a high number of start-stop cycles prevent the vehicle from reaching higher speeds at which energy consumption is more significant. Additionally, simulation results suggest that intense acceleration up to low speeds is more economical than steady acceleration up to higher speeds. One of the potential reasons behind this behaviour may lie with use of a single gear, which may have an unsuitable gear ratio for higher speeds, effectively pushing the motor into a low-efficiency, high-RPM performance zone. This is highlighted by the energy usage comparisons present in figure 5.27. This evolution is expected since energy usage is tightly correlated with vehicle acceleration. This correlation is further amplified in heavyweight powertrains.

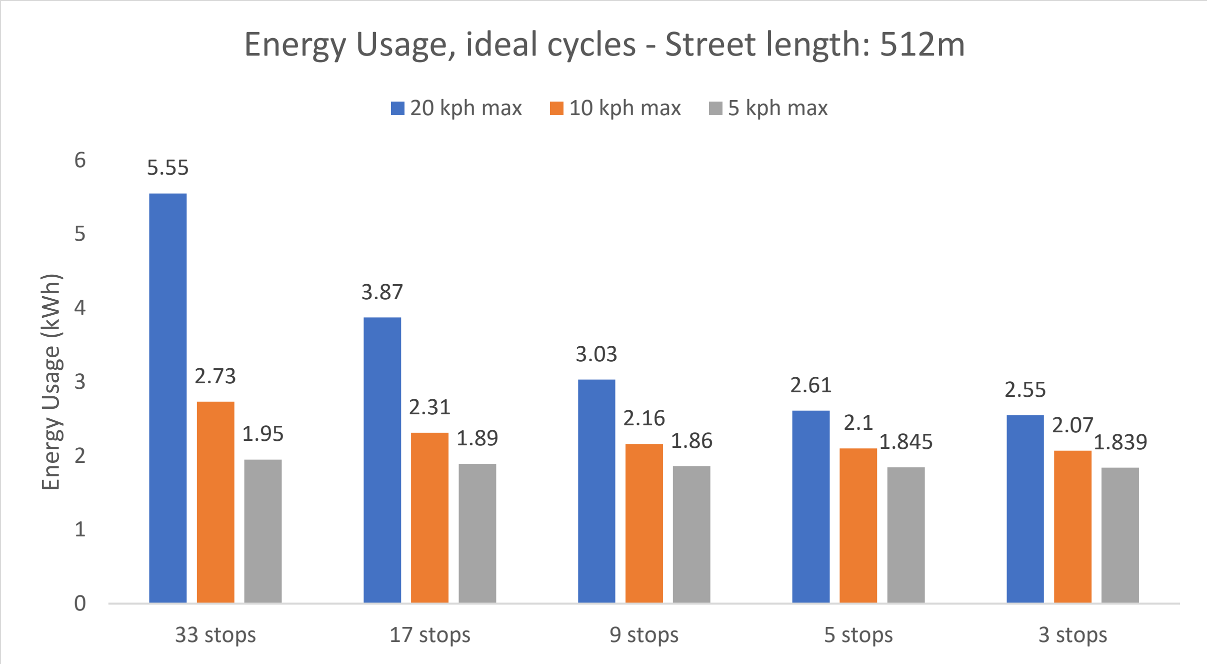


Figure 5.27 - Energy usage – ideal cycle comparison

5.5.3.2. Realistic Cycles – Triangle/Trapezoidal approximation for each start-stop cycle

Since the "realistic cycle" driving cycle mathematical construction approach has been deemed more representative of real-life eRCV driving styles, and should therefore maintain a higher degree of relevancy, the analysis of the simulations carried out is more comprehensive. Comparisons focusing on energy use have been made by changing several of the primary factors that affect the energy demand, including various set limit speeds, acceleration intensities and road inclination.

It was determined that for an imposed speed limit, energy usage decreases with respect to an increase in the number of start-stop cycles in a test-driving pattern, as seen in figure 5.29. This correlates well with the conclusions presented by the analysis of the "ideal cycle" related simulations presented previously, regarding the acceleration effect on energy usage. On a similar note, the increased energy usage for the driving patterns featuring small numbers of start-stop cycles (2-9) may be attributed to the higher average speed, and a vehicle cruising at a high speed can consume significantly more energy when compared to accelerating up to a certain much lower speed.

The energy usage figures and the inverse exponential trendlines regarding energy usage can be seen under figure 5.28.

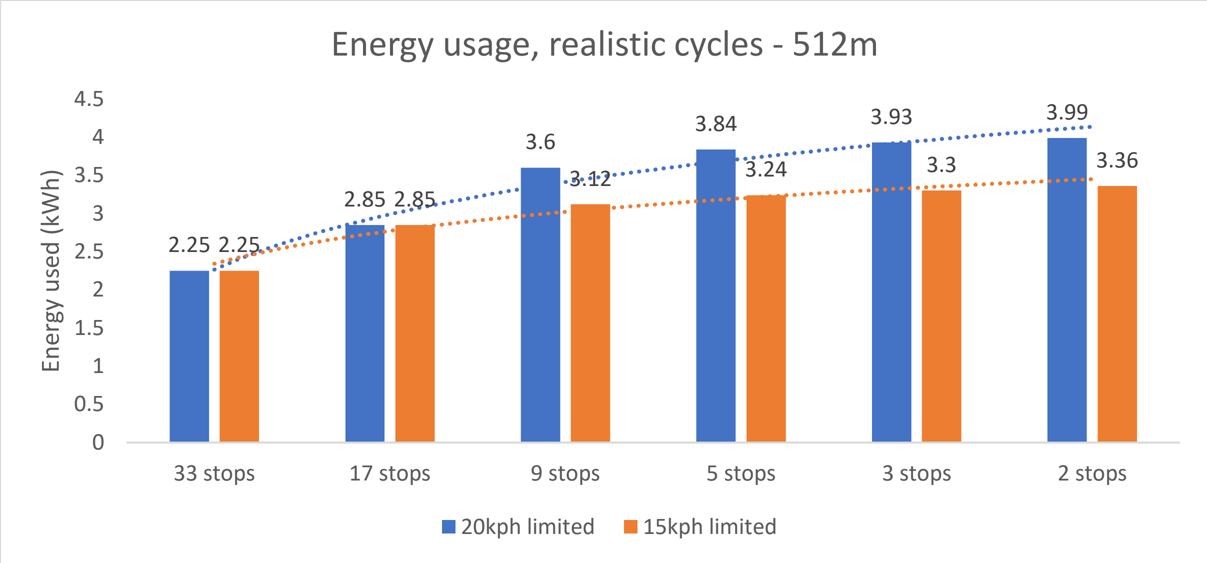


Figure 5.28 - Realistic cycle driving pattern comparison

Similarly, simulations have been carried out with a fixed set speed limit, with various acceleration levels, focusing on values between 50% and 100% of the maximum acceleration available. The justification behind these simulation comparisons is related to the remarks regarding eRCV driving styles. It has been observed that drivers rarely use the full capability of the vehicle's acceleration, the exact level being highly variable and related to road conditions and other external factors. Therefore, understanding the correlation between vehicle energy use and acceleration applied during acceleration phases is critical towards determining reliable energy figures for further analysis.

Simulation results show that although decreased acceleration will generate slower collection times, they can significantly reduce overall energy demand, as seen in figure 5.29. It can be observed that the energy saving is further accentuated by the higher the number of start-stop cycles in an emulated driving pattern. In these specific contexts, a potential energy saving of almost 30% can be observed, relative to 100% acceleration intensity used during acceleration phases.

This interpretation relies on data gathered from different 'set' speed limits that show similar trends, confirming the conclusion, and are presented in figure 5.29.

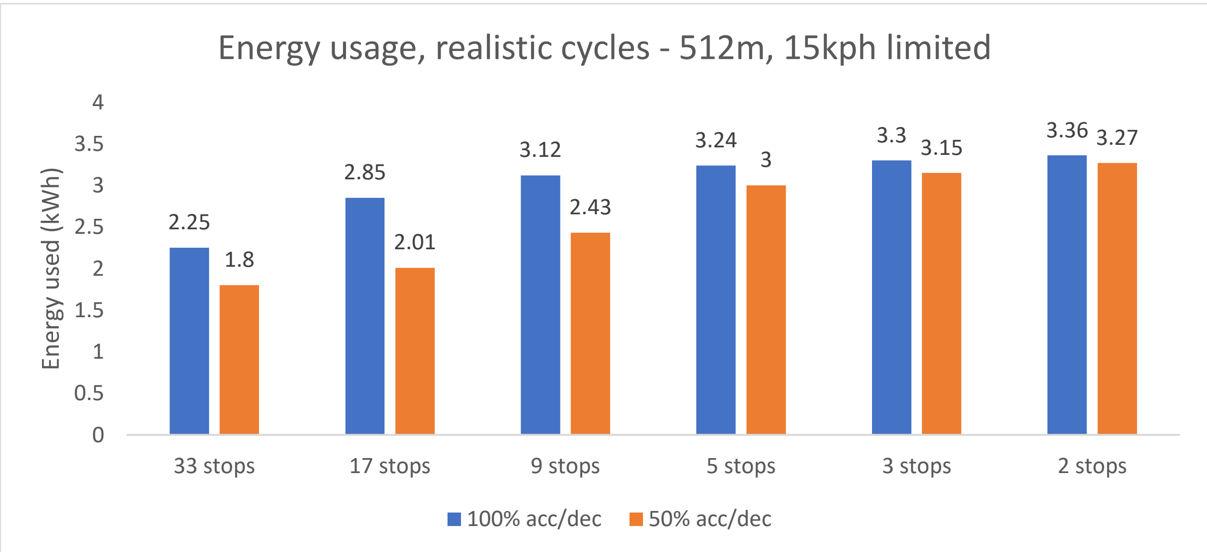


Figure 5.29 - Realistic cycle driving pattern comparison, various acceleration intensities

5.5.3.3. *Road slope effect on street-level energy usage*

Previous work on energy usage simulation of such heavyweight powertrains suggest that road slope / incline together with acceleration generally have the biggest impacts on energy consumption [235]. Furthermore, analysing the slope effect on energy usage is especially important for cities with mixed topographical features, such as is the case of the City of Sheffield in the UK and its surrounding area.

Since it is expected that eRCV drivers will only collect refuse while facing downhill in the UK, due to standard health and safety procedures, and given that uphill refuse collection is guaranteed to significantly affect energy consumption in a negative manner, simulations with various degrees of negative relative slopes have been carried out using the generated realistic cycle patterns. By analysing the simulation results, it is noted that a negative road slope has a significant contribution to energy savings, given that the vehicle is able to use its own gravitatonal pull for propulsion, as seen in figure 5.31. For simulations with a positive road slope, energy usage is significantly increased when compared to the neutral road slope simulation sets, presented under figure 5.30, blue bars. This indicates that road slope has a significant effect on average energy usage and should be carefully considered when estimating vehicle energy requirements, especially at fleet-level.

In order to further increase the precision of energy usage predictions, the set road slope used in the simulation should be correlated with real topographical data for a given refuse collection operating area.

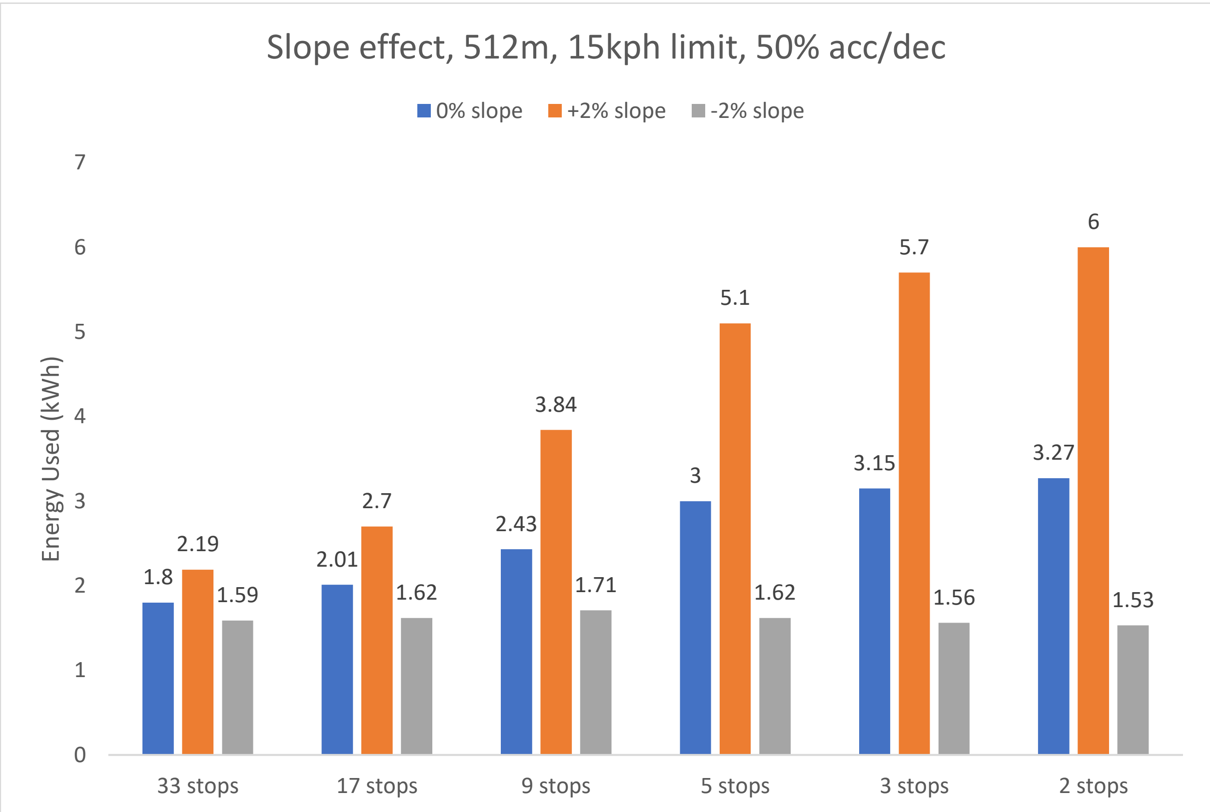


Figure 5.30 - Realistic cycle driving pattern comparison, various number of stops and slope variations

5.5.4. Extending the realistic cycle method to real-life datasets

After reading into the results of the previous investigation that were concerned with energy usage on a set-length simulated street, the methodology has then been further applied to more realistic data, which has been previously used in section 5.2. The aims behind these simulations are to further increase the relevancy of the energy usage predictions for a real-life scenario.

In order to create a more realistic dataset, real-life refuse collection routes have been observed. The route characteristics that were of particular interest are related to the route length and road slope (point-by-point and averaged).

Refuse collection telemetry from two separate cities have been acquired. The collected data consists of several tens of collection routes that cover the entire refuse collection scheduling for a 2-week period. In order to prevent a bias in simulation analysis and accuracy, a set of 5 routes have been chosen at random from both cities refuse collection datasets. An example of such mapped route can be observed in figure 5.31, along with the route telemetry data. The dataset of each of the 5 routes has been inspected to determine the simulation timestamp intervals in which the refuse collection operation is being performed. This can be determined by observing the maximum speeds achieved on a given period, which are smaller relative to when the vehicle is being driven between collection zones or back to the depot.

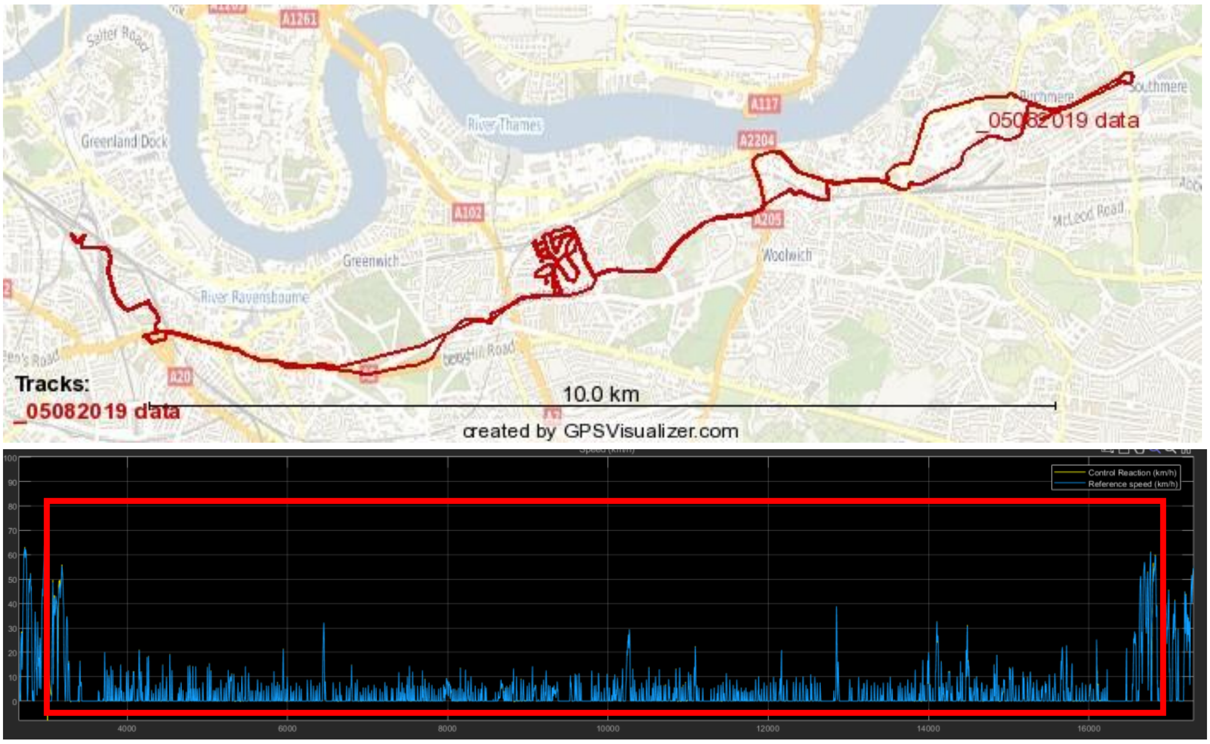


Figure 5.31 - Route Example 1. Telemetry route of interest highlighted with red rectangle

After creating the 5-route randomised dataset and inspecting the relevant telemetry periods, emulated speed profiles have been created for each of the routes. Although the methodology of creating these has remained unchanged relative to the one described previously in chapter 4, the way the start-stop features are employed has been changed, due to the variability in route length. Therefore, the stops have been placed relative to a set interval length, regardless of the overall route length. This may slightly affect the overall prediction accuracy, particularly due to the lack of correlation that may happen at the end of the routes, where the emulated speed profile may not be reflective of the driver's behaviour in a real-life scenario.

Figure 5.32 shows the energy usage variation between the emulated speed profiles for the refuse collection routes presented in figure 5.31. The results show a similar trend line to the one that has been observed in the previous set-length street analysis described in the previous section. This further confirms that the simulation approach is robust and exhibits a low degree of uncertainty regardless of the input data. The absolute energy usage values appear to be in line with the energy consumption (kWh/mi or kWh/km) expectations for this type of vehicle mass [236]. Additionally, the energy usage results vary in a linear fashion relative to the route length, which is to be expected on average. A change in energy usage at different speed limits is also observed, which is more potent in estimations concerning a bigger distance interval between the number of stops. This correlates well with the findings observed in the set-length street simulations and indicates that vehicle energy usage is significantly affected by higher speeds.

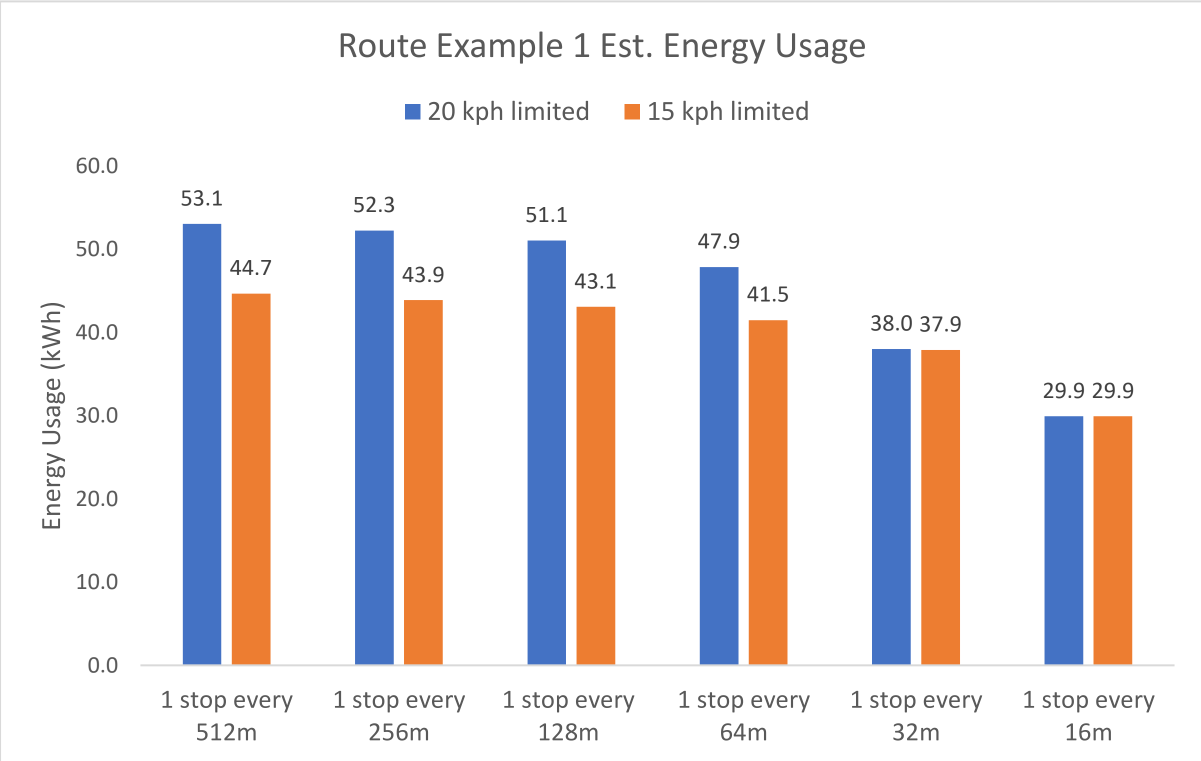


Figure 5.32 - Estimated energy usage results

5.5.5. Produced estimation interpretation & applied discussion

The presented results show that the process of picking a meaningful energy use baseline figure may not be as straightforward as initially thought. The decision should not only be dependent on several technical parameters, such as vehicle performance features and vehicle mass, but also on environmental factors, such as the local topography. Moreover, some factors that may influence energy use go beyond the scope of the factors considered in this thesis, for example events having a high degree of randomness from a simulation perspective, such as street crowdedness. This opens up potential improvement avenues to the conclusions of this case study, particularly in the field of traffic congestion modelling related to time of day and other social influences.

When choosing an energy use baseline, it is important to maintain a good compromise between realism and practicality, as for example 33-stops on a 512m street would imply the eRCV is constrained to stop for bin collection every 15m, which has rarely been observed under normal conditions. Similar choices should be considered for the other classifications presented in this paper, such as road slope and level of acceleration.

However, the more realistic analysis presented in section 5 of this paper shows an apparent "knee point" between energy usage and the distance interval between stops. This appears to be consistent regardless the input data and happens around a distance interval between 8 and 16 metres. This may be an important indication for vehicle manufacturers as well as public services administrators in order to maximise energy saving, productivity and overall refuse collection efficiency.

While the number of stops or distance interval between stops on a given route is highly situational and largely at the liberty of the driver, the presented case study is still able to offer a set of reliable baseline energy figures. These could prove useful to be considered when starting the engineering and operation design process of an eRCV fleet. A specific scenario that can be valid for a given collection area can be chosen if situational approximations are carefully considered.

Additionally, the presented research findings may aid the design process of routing algorithms that aim to create optimised routes for energy-efficient, low-emissions travelling for a wide range of vehicle types. The field, which is related to the theory of combinatorial optimisation [237], has seen a significant increase in research communities worldwide. The theoretical approach has been successfully applied to products, some of them being in the final development stages before launching as consumer-ready products [238]. The energy usage figures presented in this research should prove useful to further optimise the algorithms designed to minimise energy use. The findings may prove particularly useful for conventional graph colouring based algorithms [239] that are specifically tailored for electric heavyweight powertrain vehicles.

Similarly, the presented figures and discussion may help heavyweight powertrain manufacturers and users better understand how to further optimise operation scheduling of these vehicles to prevent or minimise the adverse psychological aspects of driving such vehicles, for example range anxiety. Whilst the range anxiety concept has been extensively researched for electric passenger cars [240] [113], there is little progress into investigating how this idea applies to public service purposed heavier vehicles such as eRCVs.

When extending the realistic approach to a dataset that emulates an entire route rather than just a simple linear street, it must be noted that some additional limitations exist. Firstly, considering multi-street routes involves a higher degree of uncertainty, due to the multiple complex factors that may appear in traffic. Some of them are predictable, such as traffic lights and their scheduling, whilst others are harder to account for, for example road accidents and unexpected traffic due to road conditions. These are bound to somewhat increase the error in energy usage prediction relative to real-life conditions. Moreover, the unpredictability factors are even more important in the case of simulations with a high distance interval between stops, as one unexpected stop in such simulations due to random factors has a higher importance due to the low number of stops. However, the uncertainty component of the simulation is likely to represent a relatively small proportion of the error relative to real-life results over many route iterations. It should be expected that most of the error rate present in the predictions is due other factors, such as inconsistent technical specifications or unsuitable simulation solver configurations.

Public service vehicles have been observed to be driven differently when compared to consumer / passenger cars. Telemetry data indicates that PSVs tend to have a much higher number of start-stop cycles compared to the more lightweight powertrain vehicles. Moreover, they are being driven at significantly lower average speeds than smaller electric vehicles. Another factor that has a different impact on range, and consequentially on range anxiety, is represented by the vehicle mass. While passenger cars tend to carry a stable average mass throughout their journey, PSVs have significant vehicle mass variations during operation.

For example, the vehicle mass of an eRCV increases in an almost linear way throughout the duration of a collection route. Similarly, electric buses exhibit a fluctuating increase and decreases in mass, subject to the numbers of passengers embarking and disembarking along the route. However, in the case of eBuses the trend is dependent on a wide suite of factors, ranging from time of day (peak/off-peak) to location relative to bus stops. Central bus stations are associated with higher variations of passenger numbers and vehicle mass compared to bus stations closer to the ends of the routes [241][242], but this is situational and varies depending on whether the route ties residential/outer city zones to city centres.

Finally, the presented energy performance indicators show that in general, PSV drivers and route planners should aim to optimise vehicle energy usage by maximising the number of stops, and minimise the maximum speed reached between route stops, while also ensuring smooth acceleration and deceleration. This should help with maximising energy regeneration, if such vehicle capabilities exist.

5.5.6. Investigation Summary

The results and interpretations presented in this section aim to provide meaningful insight that should assist engineering, public administration and other service provider entities in designing eRCV fleets that operate in an energy-efficient fashion.

Furthermore, the findings related to the relationship between speed and energy consumption integrate well with existing research [243] and may serve as a cornerstone for future, more advanced investigation concerning the topic of energy usage optimisation. The results should also prove to be useful guidance for meaningful implementation of public policies concerning the complete electrification of the automotive sector, such as the UK’s Road to Zero [145].

5.6. Chapter 5 Summary

Having discussed the capabilities of the proposed software solution regarding electric vehicle energy prediction for public service vehicles, it can be concluded that the findings offered by the simulations may provide robust and accurate information for feasibility analyses. Similarly, it has been observed that the developed model is able to successfully accommodate these types of vehicles. Moreover, replacement of traditional, ICE-powered public service vehicle fleets with electric alternatives have been shown to offer significant benefits in terms of gas emissions reduction, as well as costs related to energy refuelling [218].

The following chapter presents similar investigations applied to a different category of vehicles, namely lightweight powertrains, such as motorbikes. This aims to complete the picture concerning the requirements and benefits of transport sector decarbonisation through comprehensive vehicle electrification.

6. Chapter 6 – Second Application of Model – Understanding Energy Usage of electric two-wheel, two-axle vehicles

Following the assessment of energy usage in heavyweight vehicles purposed for transport in urban areas, a new study is now proposed for observing the energy requirements of a different vehicle category. This chapter examines the estimation of energy requirements of electric motorbikes in various contexts.

As it is difficult to acquire relevant telemetry data for analysis, an unconventional procedure to gather the required data from video information is described. Whilst this has only been employed for obtaining a dataset limited to motorbike telemetry, the methodology described can successfully be applied in a multitude of circumstances, for example gathering data for prediction of use in commercial vehicles where in-cab video recordings are commonplace.

Two wheeled vehicles, such as scooters, motorbikes and mopeds, on average make up over 10% of urban traffic worldwide [244]. This share rises to 74% in certain regions of the world [245], predominantly south-east Asia. Moreover, these types of vehicles have increasingly grown in popularity for short-distance commutes as well as being a favoured means of transport for certain types of services brought about by the gig-based economy, such as food delivery [246]. This is mainly due to the vehicles' sizing, having the ability to flow through traffic much easier than heavier and bigger powertrains. It is therefore important to grasp the capabilities of the electric alternatives to these vehicles in order to complete the picture of a fully decarbonised transport sector.

Finally, some of the research material presented in this chapter has been presented in a number of publications [247][248].

6.1. Acquiring Telemetry Data through Dashcam Video Imaging

When simulating vehicle behaviour in a software environment emulating real-life conditions, one of the hardest challenges to overcome is acquiring relevant data that can be employed as a reference input for the simulation. A similar situation may be considered in the context of the investigations presented in this thesis, which can only be undertaken with reliable speed-related telemetry values.

This subsection presents a novel approach to acquiring vehicle telemetry that aims to provide speed/time-based simulations with a much larger and more accessible data pool. This is made possible by applying optical character recognition (OCR) technology to video graphical overlays that display instantaneous speed at a reasonably high data resolution. OCR engines for text recognition have been studied using several approaches and have gained significant interest in recent years, thanks to advances in computational science [6][7][8][9]. In the proposed solution described below, a state-of-the-art OCR engine, Tesseract [253], is employed as the OCR agent that identifies the digits in the extracted and enhanced images. This serves as a novel application of this technology in the transportation field, having the ability to provide significant amounts of telemetry data for bespoke simulations, including the proposed solution in chapter 3.

To date, this procedure has only been employed in order to acquire telemetry data from unconventional sources for the purposes of assessing energy usage of high-performance motorbikes. The results of this investigation will be presented in subsection 6.2. However, because the process is independent of vehicle specifications, the principles may be successfully applied to an extensive range of simulations and investigations, beyond the purposes covered in this thesis.

6.1.1. Dashcam Video Telemetry Extraction Process

The script applying the proposed procedure has been developed in order to extract telemetry from Phase Alternating Line (PAL) encoded videos. For the purposes of demonstrating the capability of the proposed solution, a video publicly available on the Youtube platform has been chosen. This shows dashcam footage of a motorbike performing qualifying laps around the Isle of Man Racecourse. The analysed video has a resolution of 1280*720 pixels, captured at 25 frames per second. The start of the telemetry extraction process begins with harvesting the video frames numbered as multiples of 25 to generate datapoints on a second-by-second interval, along with 6 adjacent frames. The adjacent frames will aid in increasing the confidence in digit prediction of the OCR system in the case of excessive image blurring on the sampled data point. This phenomenon often happens due to inter-frame compression or bitrate limitation. The target frames are detected using a model function as described by equation set 6.1.

$$
\begin{aligned}
&f(0)^* = 0 \\
&f(t)^* = [25t - 3, 25t + 3], 1 < t < \tau - 1 \\
&f(\tau)^* = [25\tau,],
\end{aligned}
$$

Equation 6.1 (set) - Image data mathematical modelling

Where t is time in seconds and τ is the length of the target video (in seconds) until the last whole second. An important remark is that the dashcam video typically starts and ends with the vehicle stationary and at a fixed location, therefore the first and last frame group contain only one single frame. Finally, the frames are then cropped using a pre-defined area mask that targets the area of interest (i.e. the graphical speed overlay). A trimmed frame group example is shown in figure 6.1.

Figure 6.1 - An example of trimmed frame group

Additionally, figure 6.1 above illustrates the two issues that need to be addressed before an OCR algorithm can be utilised to identify the desired numerical values. Firstly, the information is overlaid onto the video with a semi-transparent background, which changes the quality of the image edges. This in turn affects the quality of foreground characters and reduces contrast. Secondly, the foreground characters can be heavily distorted due to inter-frame video compression. Consequentially, the recognition rate for these original frames has been evaluated at less than 15 per cent, which confirms the necessity to perform image enhancements in advance of the OCR progress.

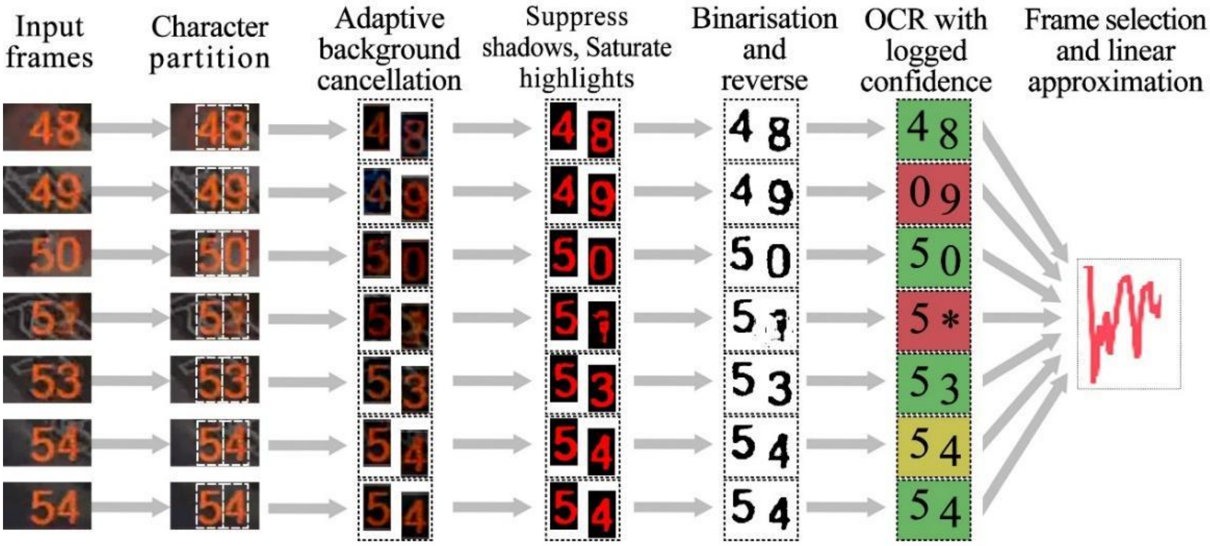


Figure 6.2 - Proposed image processing procedure. Example shows a typical input frame group and its related OCR results with the level of prediction confidence coloured in Green (high), Lime Green (average) and Red (low)

In order to address the above-mentioned issues, a multi-progress frame enhancement algorithm with inter-frame approximation is employed. This will help with improving the recognisability and reducing the instability of the produced telemetry. As shown in figure 6.2, data is processed as frame groups. Firstly, pre-defined cropping masks are applied to the input frames where each frame are separated into individual primitives containing a single character or number. However, as observed in figure 6.3, the significance of the desired foreground object (in this case the digit '4') could be affected by the erratic background. In order to alleviate this effect, an adaptive background cancellation image filter is employed.

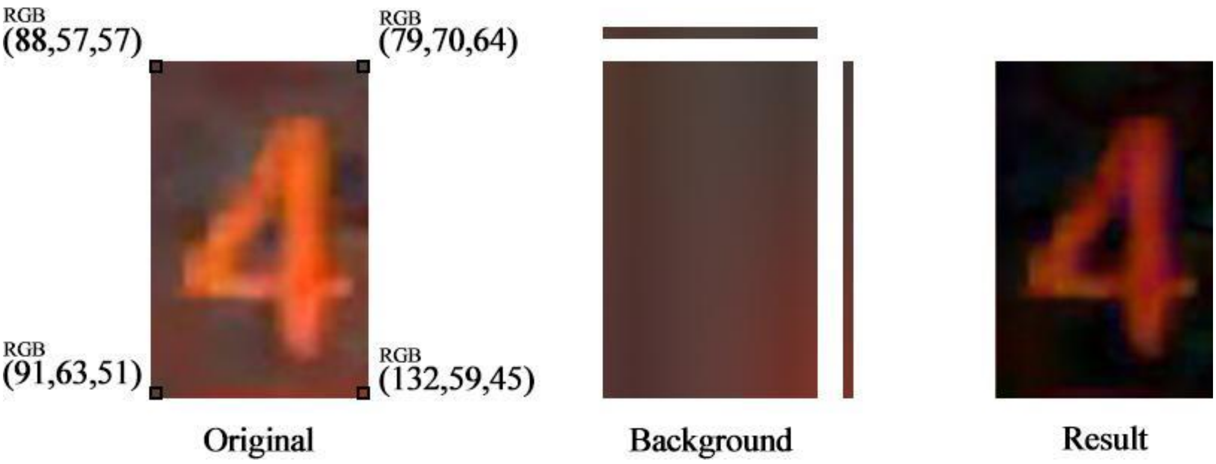


Figure 6.3 - Background noise cancellation employing a virtual background with its colour established from corner pixels

As observed in figure 6.3 above, the corner pixels of every image are targeted in order to obtain the colour properties encoded using the Red-Green-Blue (RGB) format. Colour gradients are then established such that the computed interpolations will fill the image background with intermediate pixels. This has the effect of replacing the original background with a mono-coloured one. Finally, a filter is applied with the purpose of saturating the bright pixels and further reducing the shadows. The enhanced images are then filtered and reversed in order to be passed through OCR engine identification.

Following that, both the OCR result and its corresponding confidence metric are recorded. A variable polynomial approximation algorithm is then deployed depending on the original confidence metric on OCR frames labelled as ‘average’ or ‘low’. Finally, using the example shown in Figure 6.2, four out of the seven OCR frames are obtained with high confidence and will be used in computing the polynomial equation of the approximation. The result for the reference frame can then be calculated, as presented in figure 6.4.

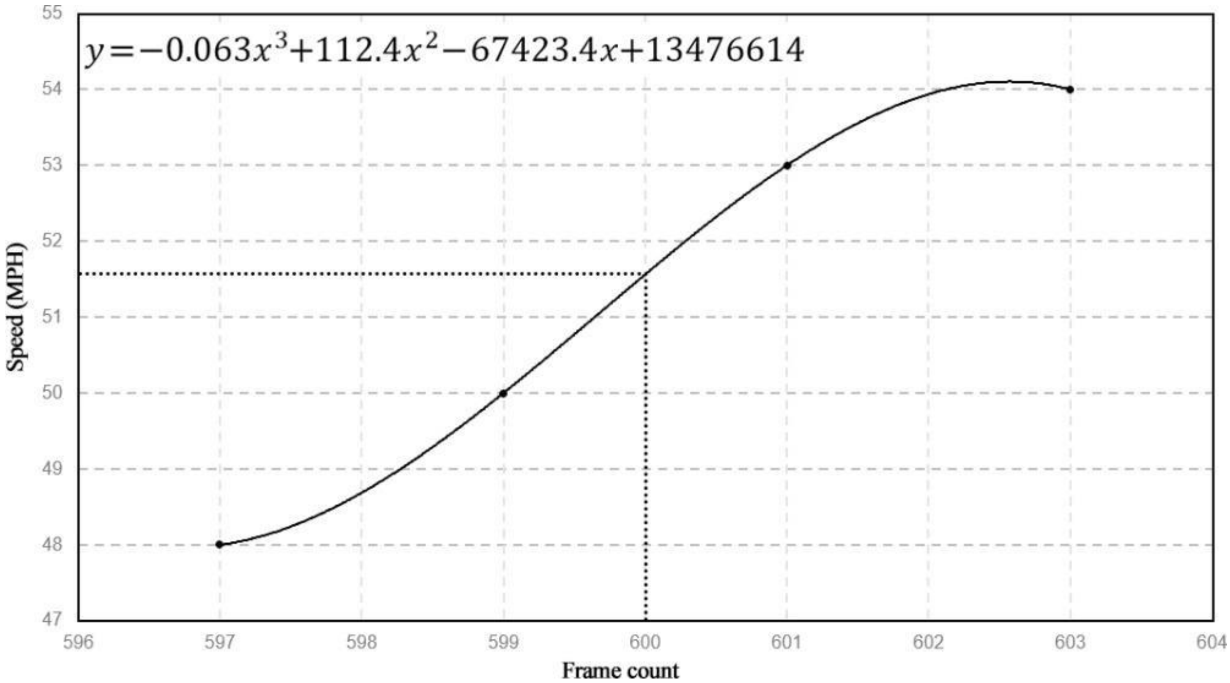


Figure 6.4 - A plot of the polynomial approximation for OCR results of the frame group presented in figure 6.5. The mathematical equation described by the curve is shown on the top-left side of the image

Following the procedure presented previously, each frame group is processed, and its OCR result obtained. If the OCR engine is unable to generate a robust result for an entire frame-group, the polynomial approximation will be employed in order to increase the accuracy prediction. Finally, the results are then linked together in order to obtain a speed profile that can be utilised as vehicle telemetry.

6.1.2. Accuracy of Findings & Discussion

In order to test the accuracy capability of the proposed procedure, a publicly available dashcam video containing motorbike dashcam footage was used. The chosen video is publicly available in order to avoid issues related to commercially sensitive data and is shown in figure 6.5. This evaluation aims to verify the methodology of the proposed dashcam video-based information extraction approach. Therefore, the specific video chosen and the difference in vehicle type should have a negligible effect on the evaluation result. Further information concerned with the chosen dashcam footage video is outlined in table 6.1.

Figure 6.5 - An example snapshot of the dashcam video used for acquiring telemetry

Based on the bitrate and file size values under table 6.1, it can be determined that the video is significantly compressed. A further pixelation effect can be observed in figure 6.5. This has been done in order to accelerate the OCR processing phase and avoid identifying digits in other areas of the video.

Parameter	Value
Resolution	1280x720
Frame rate	25
Data of interest	Vehicle speed in Miles Per Hour (MPH)
Total frames of the original file	115382
Video codec	H.264
Average bitrate of the original file	481 kb/s
File size of the original file	266MB

Table 6.1 - Information about the proposed dashcam video used in the evaluation

As previously stated in the methodology section, seven frames are extracted as a frame group. The middle frame, which is also the reference frame is extracted as the last frame captured every second. Following the harvesting, a manually defined cropping mask of 112*60 pixels is applied to the image, as suggested by the dotted area in figure 6.5. The cropped result is then further broken down into three 34*60-pixel areas where the digit values will be displayed. These primitives are then further enhanced using the process shown in figure 6.2. The resulting images are then fed into the Tesseract engine, which analyses the information and performs OCR computation on it. Figure 6.6 shows the overall confidence prediction classified as digit type (hundreds, tens, ones).

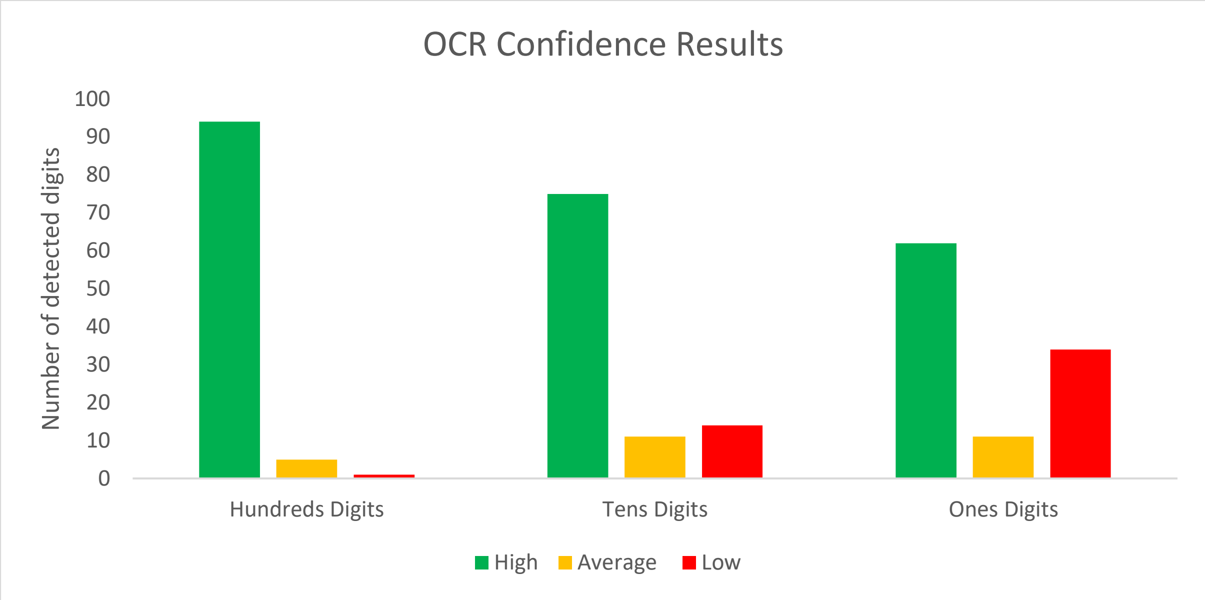


Figure 6.6 - Distribution of OCR confidence metrics. High confidence range: 70-100% accuracy, Medium: 50-70%, Low: 0-50%

Using these OCR results, a speed-time profile can be produced through data concatenation, as shown in figure 6.7. The readings have been converted from the original dashcam video values displayed as miles per hour (mph), as presented under table 6.1, to kilometres per hour (km/h) to ensure consistency with the metric measurement system.

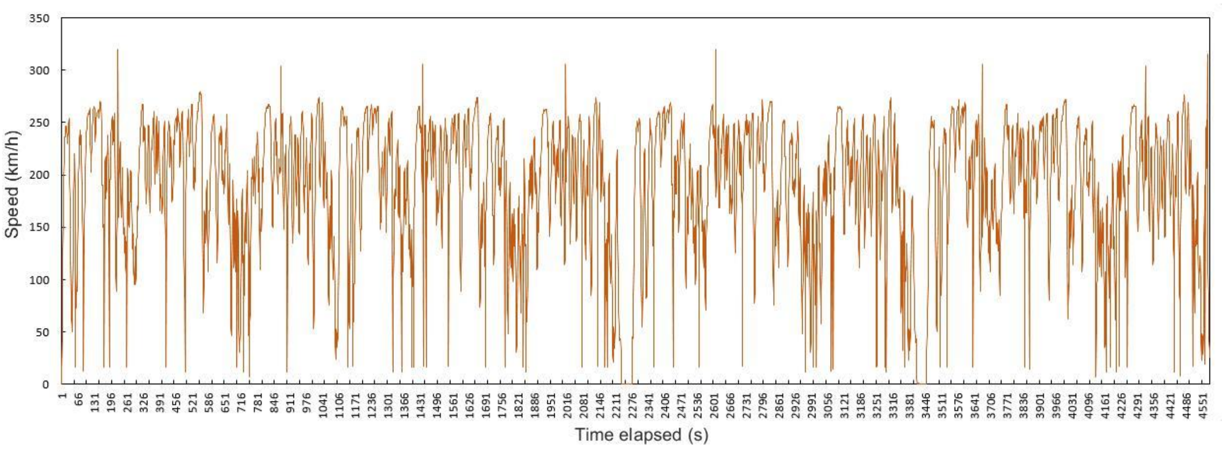


Figure 6.7 - Speed profile generated from sample dashcam video

However, some limitations in terms of raw data-driven results must be noted. The dataset upon which the methodology was built does not have a direct comparison based on conventional telemetry recorded via standard vehicle data loggers. This is due to data loggers having a much better accuracy in reflecting telemetry data relative to OCR readings. Consequentially, at this stage, the dataset featured in the presented methodology does not have a clear benchmark in order to measure the efficacy and other key performance indicators of the solution. Similarly, the potential sources of error that may have an effect on the overall accuracy of the presented concept have been identified within the image processing stages of the methodology. These are represented by the signal-to-noise (SNR) ratio of the captured image and the accuracy percentage of the trained OCR algorithm.

6.1.3. Result Implications and Next Steps

The first section of this chapter has presented a novel approach to harvesting video data to produce vehicle telemetry. The proposed methodology for creating vehicle telemetry is based solely on using data gathered from publicly available dashcam videos. The produced telemetry has been achieved using an improved OCR algorithm and other image enhancement methods. Utilising the proposed image processing and OCR technology, textual information is retrieved and re-organised to create speed-time profiles.

The proposed solution demonstrates that vehicle telemetry data can successfully be extracted from a dashcam video captured from a given vehicle on a given route through modern OCR technology. This data may then be fed into a purpose-built model in order to predict various parameters, such as energy usage for electric vehicles. The presented results have successfully demonstrated the consistency and accuracy of the proposed methodology. Finally, the presented methodology adds a significant amount of data (previously unsuitable for simulation work) to the already existing telemetry data that is employed for analysing various vehicle performance characteristics. This is likely to become a key supporting factor for feasibility investigations, such as urban planning and logistics management decisions. This will be even more important for situations where vehicle telemetry is difficult to acquire.

The presented methodological approach may be expanded to other areas of interest that rely on telemetry data, such as assessing the impact of replacing an entire conventional ICE-engine vehicle fleet with an electric vehicle fleet. Therefore, to further improve the accuracy of the produced telemetry, future work may be directed to implementing enhancements to the method that increase the identification prediction. Moreover, the telemetry acquisition through OCR may be improved by employing better trained algorithms, as well as applying other unconventional algorithms, such as AI-based neural networks [254]. Some work in this regard already exists and potential applications can be built on top of existing research [255][256].

6.2. Applying OCR-generated Telemetry to Assess Energy Usage of a high-performance eBike

The first proposed investigation in understanding energy usage of electric motorbikes is concerned with the energy usage of a high-performance, electric motorbike undertaking high-speed laps around the Isle of Man TT racecourse [257], shown in figure 6.8. This example is used to highlight the adaptability of the Matlab-based vehicle software model described in chapter 3 to adapt to various diverse powertrains. The input telemetry data used for energy usage simulation is produced using the solution proposed under section 6.1.

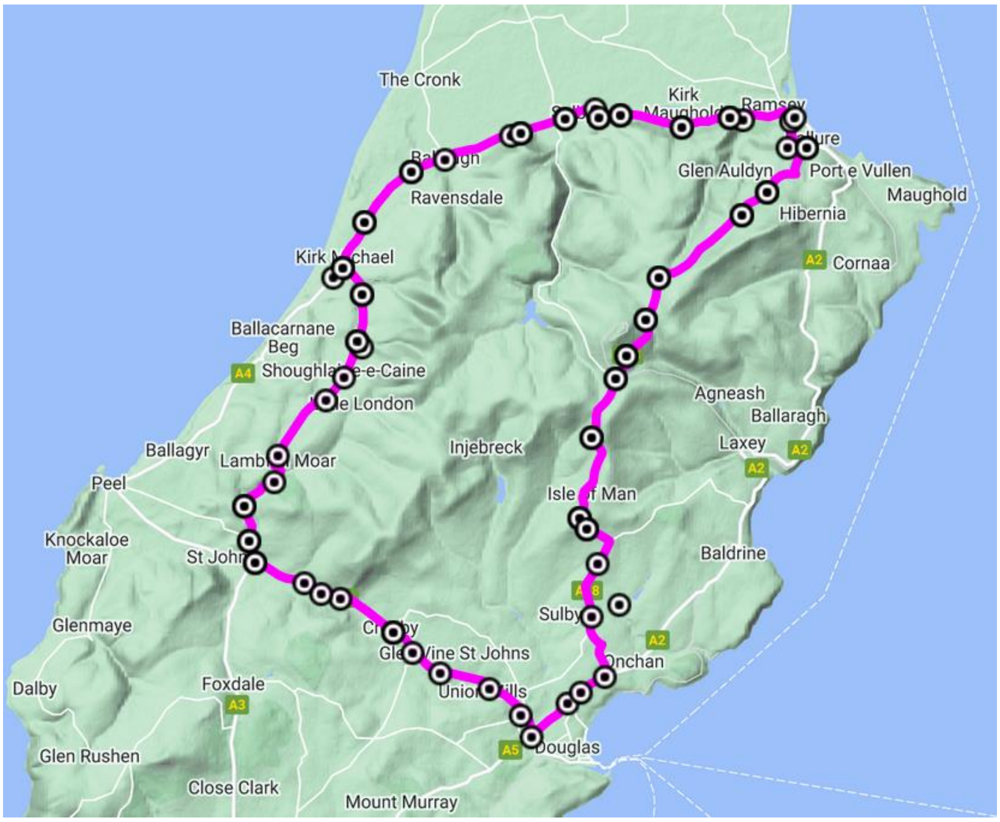


Figure 6.8 - Isle of Man TT racecourse

The aims of the investigation presented in this chapter are concerned with estimating energy usage of an electric motorbike under high-speed driving around the Isle of Man TT Racecourse. However, due to the limited availability of motorsport-purposed vehicle telemetry data, the objective of this research is to provide a ballpark figure rather than a precise estimate. This is because lack of technical data makes the simulation results difficult to fully correlate with a real-life scenario. Similarly, validating the results of this investigation may prove difficult. This is due to the lack of availability of relevant validation data, whilst currently existing data is uncorrelatable due to large differences in vehicle specification and driving styles. However, this investigation will also help in understanding the limitations of the vehicle model through stress testing the simulation environment capabilities.

This research builds up on the telemetry extraction solution previously presented under section 6.1, through employing the OCR-produced video dashcam telemetry.

6.2.1. Simulation Requirements and Limitations

Given that the initial aim of the model in its development stages was to accurately simulate an electric heavyweight vehicle, some structural changes had to be made to the model topology in order to adapt to the new technical specification. The aerodynamic model has been changed in order to reflect the characteristics of a high-performance motorbike, but also the mechanical structure of the vehicle. As such, only one wheel per axle has been employed, as well as separate brake sources of each axle since the braking force of this vehicle is higher than the one used by other, heavier vehicles relative to its mass. Additionally, aerodynamic values for the motorbike chassis are based on similar and representative values from conventional motorbikes. Similarly, powertrain performance values have been updated in order to reflect the real-life characteristics of such a vehicle. These have been based on one of the 2019 Isle of Man TT vehicle competitors, the Mugen Shinden Hachi [258] (the vehicle specification is provided in appendix 8). Finally, the simulation's mathematical solver values have also been changed to allow for a higher flexibility in solving the simulation states by setting a higher relative tolerance, while decreasing the minimum iteration step size and increasing the number of such consecutive steps. This will ensure minimised ambiguity in results through increasing the number of computation iterations performed per step, albeit at a higher computation cost.

Similar to the investigations performed in chapter 4, in order for the model to perform a simulation, an input dataset consisting of speed-time value pairs are required. However, the route emulation solution previously presented is unsuitable, since motorsport-purposed vehicle telemetry data is difficult to obtain, due to the confidentiality aspects of this competitive field.

A robust source for acquiring this data has been found in publicly available videos that show replays of different competitors lapping around the Isle of Man racecourse. Some of these videos also feature a graphical video overlay that indicates the live vehicle speed. Through employing OCR (optical character recognition) technology and other filtering techniques a speed-time telemetry dataset can be obtained. This has been carried out by employing a novel image processing algorithm and has been previously described in detail under section 6.1.

Unfortunately, no on-board data recordings of electric powertrain motorbikes were found, therefore the only candidate selection criterion was the OCR algorithm confidence accuracy. While a robust ICE-powered motorbike recording candidate was found and high-accuracy speed-time telemetry has been harvested from the recording, the speeds achieved in the video were significantly higher than the performance capabilities of the EV motorbike described in the previous section. This has led to the inability of the control system in the model to adapt to the required speeds, leading to simulation crashes. In order to address this, but also establish some degree of relevancy, the speed values in the speed-time telemetry have been scaled down with a constant scaling factor. This constant has been determined by dividing the maximum speed achieved in the telemetry data harvested from the recording to the maximum approximate speed observed in telemetries of previous research materials.

However, the downscaling of the speed figures implies that the travelled distance will also be scaled down, hence the final energy usage figures will have to be scaled back by multiplying the values with the inverse of the scaling factor used. The main drawback of this approach is the under-estimation of air resistance at the higher speeds.

Finally, the acquired telemetry data used as input information for the electric motorbike model consists of approximately 4 laps of the course. There is no clear delimitation between all the laps that can be derived from the speed-time information alone, but a clear one-lap telemetry has been identified by visual inspection of the video.

6.2.2. Energy Usage Results

The telemetry of one lap may be determined by observing similar patterns of zero-speed idling in the telemetry graph. Based on this observation, the telemetry of one lap can be clearly identified between simulation time 2277s and 3388s (equating to approximately 18m 31s). By extrapolating this difference to the energy usage graph in figure 6.10, bottom right of the power information figure, it can be determined that throughout the small-scale lap approximately 11.1 kWh were used. When this value is scaled back up by multiplying by the inverse of the scaling factor to account for the distance travelled, it can be estimated that the real energy usage throughout a 1:1 lap is estimated at approximately 20.8 kWh. Although the extrapolation method may not be consistently precise in estimating energy usage, applying a more refined estimation method is currently unsuitable, as it requires an accurate vehicle specification. This is difficult to obtain, given the limited availability of data due to the confidential nature of motorsport.

Speed analysis and power information are presented in the figures 6.9 and 6.10 below.

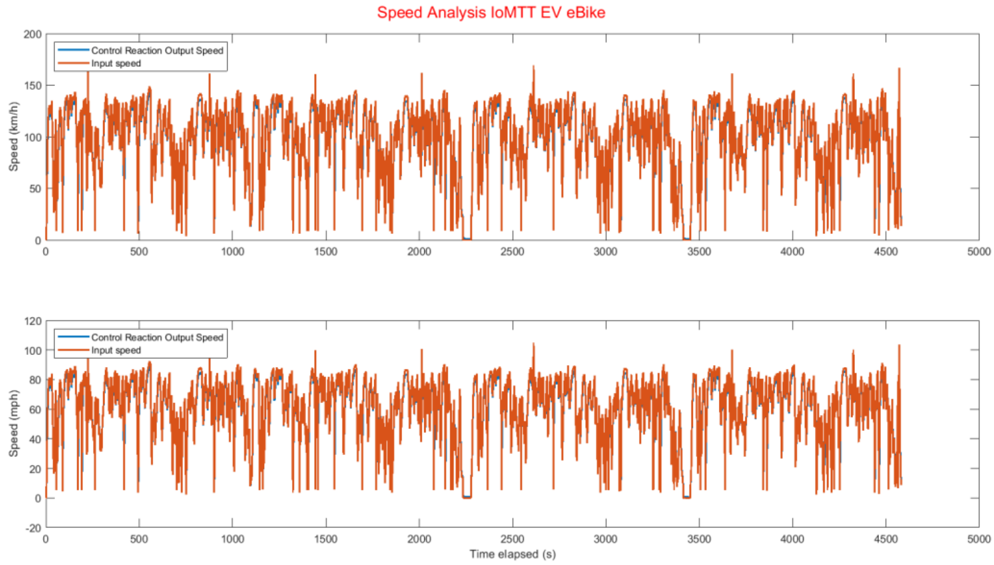


Figure 6.9 - Speed Analysis – Isle of Man TT eBike

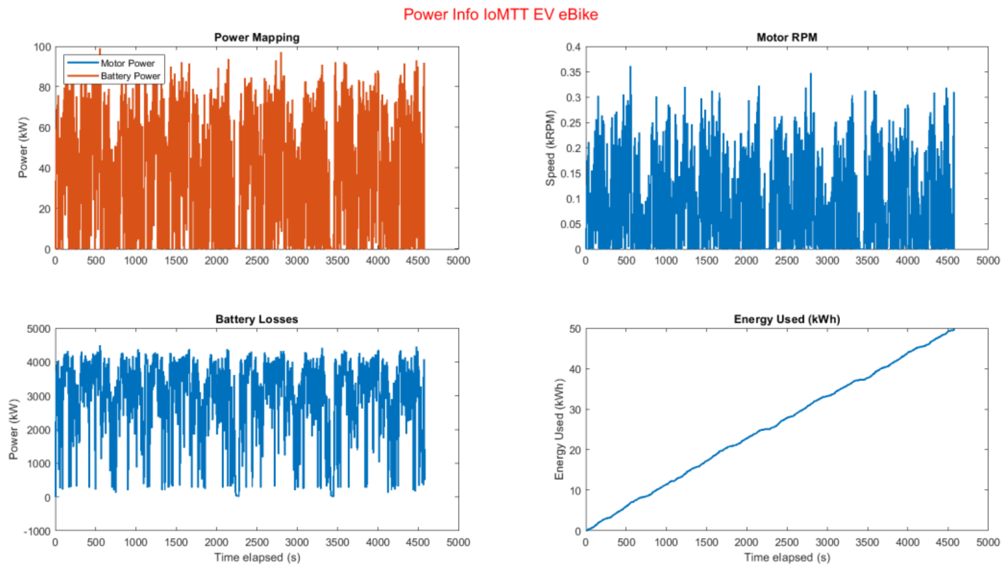


Figure 6.10 - Power Info – Isle of Man TT eBike

The simulation of the harvested telemetry data had a runtime of 278.4 seconds. Some minor control issues have been observed, similar to the ones exhibited by the model when simulating an eRCV, where the control module fails to adjust the system response so that the model can accurately match the speed in the input data. This could be due to a lack of finer tuning of the model's controller response, namely the proportional and integral values of the PID controller. However, the speed delta between the input and the system response is small, hence it does not make a significant difference in energy usage.

Similarly, it has been noted that energy regeneration through braking cannot achieve a sufficient energy saving that would decrease overall net energy usage. Whilst some regeneration is observed, it is small and within the simulation tolerance, therefore cannot be considered as meaningful. One possible reason for this could be the aggressive acceleration-braking scheduling described by the telemetry, which is not conducive to braking through motor inertia. This factor is intrinsic to the performance of the vehicle producing the input telemetry, therefore cannot be changed. Indeed, if race operation is required, there is little opportunity for slow, regenerative 'engine' braking. Another potential reason may lie with the technical parameters of the vehicle and the approximations considered for the missing parameters, as these might describe a vehicle incapable of performing energy generation through motor braking.

When comparing the energy use with other figures present in literature [259], the simulation results appear robust in nature. Additionally, it is expected that the observed error is likely to be close to the percentage errors observed when testing the model adapted for an eRCV, where input data and technical specs were of a much better quality and clear correlation exists. Another factor that influences the increased energy usage lies with the lap times – the telemetry data pointing a significantly lower lap time than those achieved in literature [259].

However, system control-related observations indicate that the model simulation is robust and did not fail or exhibit major errors in simulation. This validates the presented approach, showing its flexibility and that it can be successfully employed to simulate multiple powertrains. Additionally, the accuracy is expected to be significantly increased if highly representative technical parameters and input data are available.

6.2.3. Limitations of proposed solution and results

Due to the lack of correlation in data, there are many limitations to this model accuracy related to both real-life and simulation results accuracy. Similar research [260] presents detailed sets of physical constraints to serve as a reference for building a vehicle model, however these may prove unfit for describing an electric powered motorbike, as they are focused on describing dual-axle, 4-wheel vehicles. This leads to the inability to consistently match the specifications of the ICE vehicle on which the telemetry was logged with the capabilities of the electric motorbike model.

Given that technical parameters and input data aren't strongly correlated between each other, many sources of error arise from these. In addition to the technical parameter inconsistencies, another major potential source of error is the telemetry data and the harvesting process itself – it has been observed that in the harvested telemetry data from the video several sudden spikes in speed maps appear, with very steep deltas between the immediate past value and the next value.

Additionally, previous research [259] employs more detailed vehicle models, which allow greater accuracy in simulating aerodynamic parameters. This is especially important as, in a motorsport context, the vehicle will be driven aggressively in an effort to minimise the lap time. The model presented in this material does not include such an accurate representation of aerodynamic constraints and as such the results accuracy is expected to be lower.

6.2.4. Investigation Summary

Whilst a meaningful conclusion is yet to be reached regarding the usability of the presented model in a motorsport context, the robustness of the simulations in the presented investigation validates the model's flexibility. Furthermore, the proposed solution has the potential to present itself as a viable, cheap, and productive alternative for designing optimised high-performance motorsport eBike vehicles through understanding energy usage and system component sizing, but also in offering predictions concerning the expected lifetime of certain powertrain components, such as the battery and the electric motor.

6.3. Understanding energy usage of road-legal electric motorbikes in urban areas

Following the success in validating the flexibility of the proposed software solution applied to high-performance motorbikes, an investigation has been launched into assessing the energy requirements of electric motorbikes in urban settings. This section presents the aims, methodology and findings of the energy usage simulations for road-legal electric motorbikes in urban areas.

The target findings of this investigation are mainly concerned with understanding the energy usage of road-spec electric motorbikes and comparing them against their traditional, ICE-powered counterparts. Furthermore, estimations regarding carbon emission footprint reduction, as well as cost implications will be presented. The presented findings are expected to complete the picture when considering the decarbonisation of the transport sector for motorbikes.

6.3.1. Acquiring energy usage estimations - Method

The methodology the investigation has adhered to is very similar to the ones presented in the investigations on energy usage of heavyweight powertrains, featured in the previous chapter 5. However, some changes concerning the vehicle technical specification exist.

Firstly, data concerning the technical vehicle specification has been obtained from a privately-owned enterprise through private communications. To this end, the data obtained includes aerodynamic specifications, as well as a detailed torque-speed curve of the proposed electric motor design. This should greatly increase the prediction accuracy, as the motor data exhibits a high resolution, therefore offering the ability to map power requirements with minimal estimation. However, it has been observed that the original motor spec implied that the design is able to develop more than 14kW of power at peak capacity. This has been considered over exaggerated and will lead to thermal issues in practice; therefore, the motor power has been limited at 10kW, which appears to be in line with the power capabilities shown by existing vehicle designs. In the context of the mechanical side of a motor, power is described as seen in equation 6.2.

$$P = \omega * T$$

Equation 6.2 - Power in angular mechanics

where P is power expressed in W, ω is the motor angular speed expressed in rad/s and T is the motor torque in Nm.

Therefore, some power limitation has been carried out by observing the maximum torque-speed product point, then proportionally downscaling the rest of the torque values in the torque-speed set values, as observed in figure 6.11.

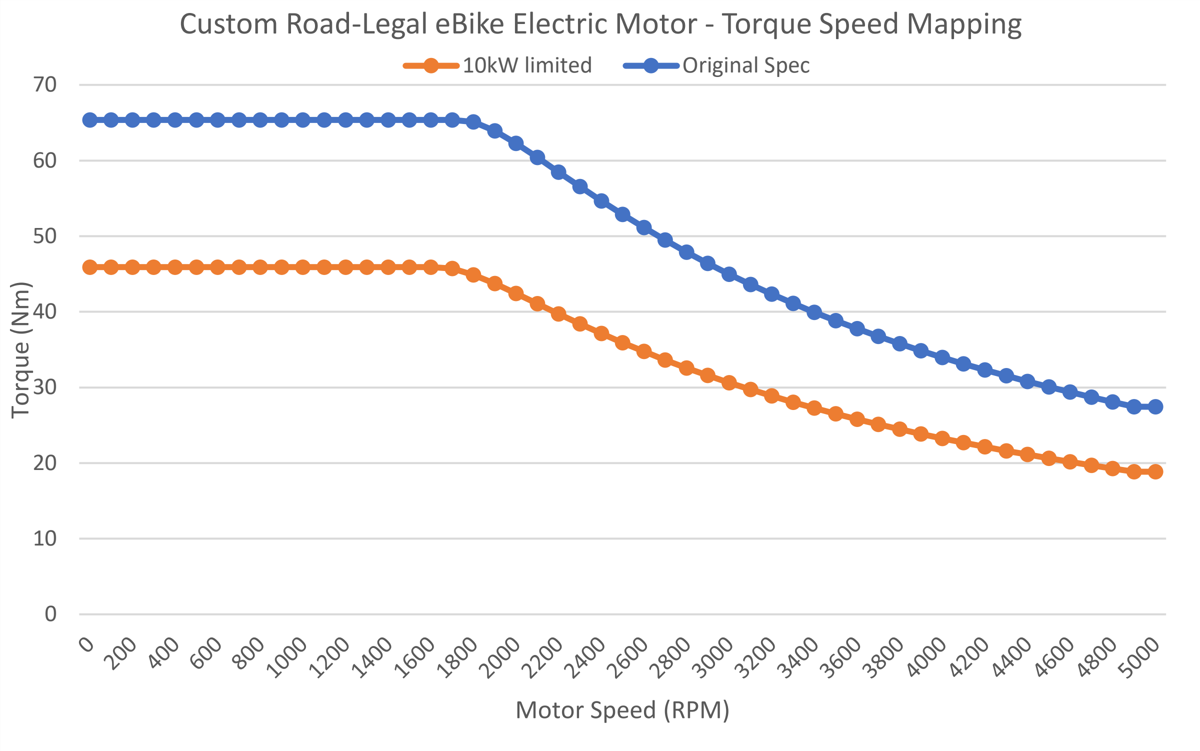


Figure 6.11 - Torque-speed map of presented motor spec

Secondly, the input telemetry data used for this study consists of publicly available emission-testing driving cycles, referenced under table 6.2. The rest of the employed vehicle specification can be found under appendix 9 for reference. Whilst the purpose of this data is different to that of this investigation, the information describes normal urban driving through speed-time value pairs. Therefore, the obtained data is highly relevant to the aims of the investigation. In order to ensure prediction consistency in the simulation estimations, five driving cycles purposed for urban emission testing of lightweight powertrains have been chosen. Additionally, the chosen data has been generated from studies carried out across the world, looking at urban driving in various geographical locations, therefore exhibiting significantly different driving styles. This will ensure minimised data bias in the simulation results.

The telemetry of one driving cycle included in the dataset is displayed in figure 6.12 for reference. Additionally, the regulating agency source as well as the purpose for each driving cycle is shown in table 6.2.

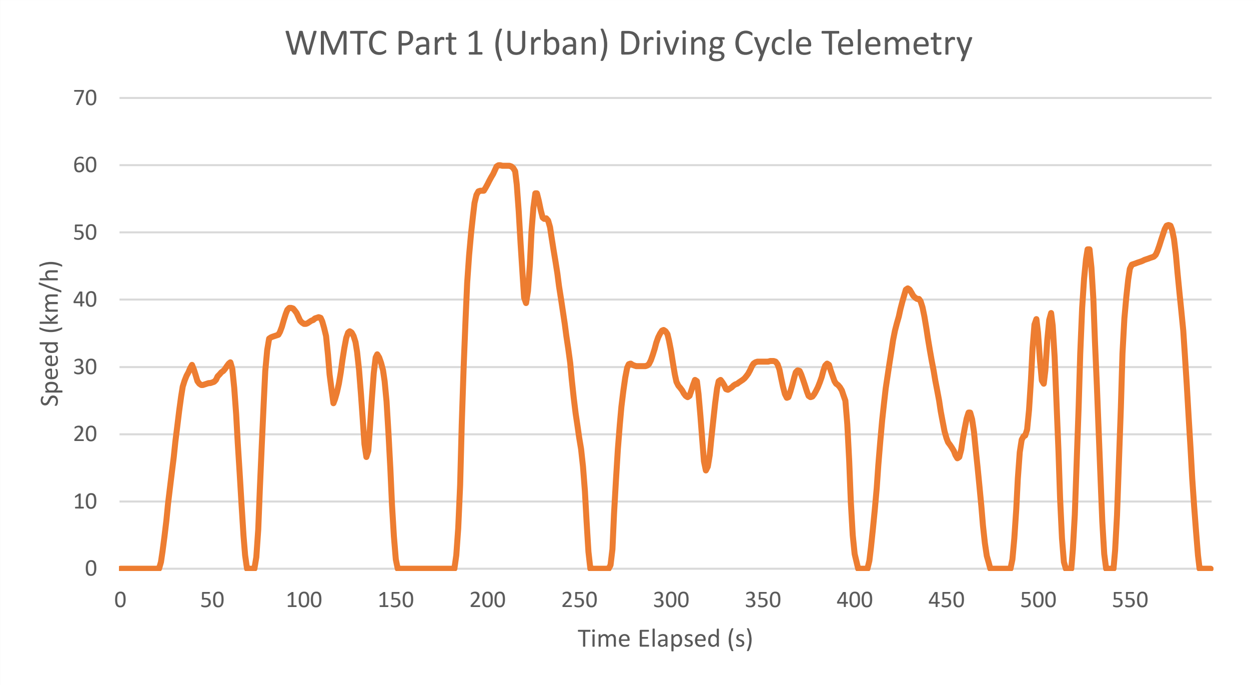


Figure 6.12 - WMTC telemetry

Cycle Name	Source	Purpose/Observations
WMTC Part 1 [261]	UNECE Transport Division	UN-regulated driving cycle. Used as reference for emission testing worldwide. Part 1 has been chosen as it reflects urban driving.
Artemis Urban [262]	European Statistical Study	Study has examined a large number of typical driving styles within Europe, generating driving cycles that accurately reflect real-life situations. The Urban cycle has been chosen for analysis.
NEDC ECE [263]	European Union	Old emission testing reference cycle for homologating EURO6 certification.
WLTP Class 3 Low [264]	Worldwide Convention (EU + Japan + India)	Standard emission testing driving cycle. Class 3 has been chosen as the vehicle spec describes a vehicle with a power-to-mass ratio higher than 34.
FTP Motorcycle [265]	US EPA	Emission testing driving cycle created for assessing motorbike emission performance.

Table 6.2 - Input dataset description

6.3.2. Estimated Energy Consumption for urban eBike use & Discussion

The simulation process carried out with the previously presented dataset detailed under table 6.2 has shown no inconsistencies over several iterations. The simulated energy usage results may be observed under figure 6.13.

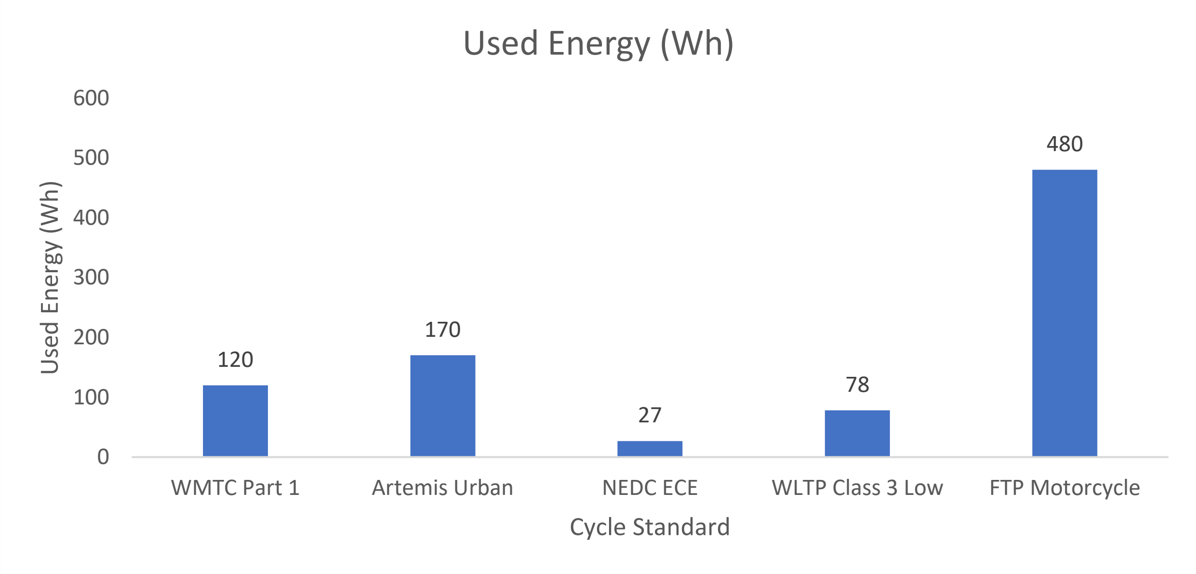


Figure 6.13 - Energy usage results

It can be seen that there is a high variation in used energy throughout the driving cycle components in the dataset. This is to be expected, as the distance covered by each of the testing cycles varies largely, as observed in figure 6.14.

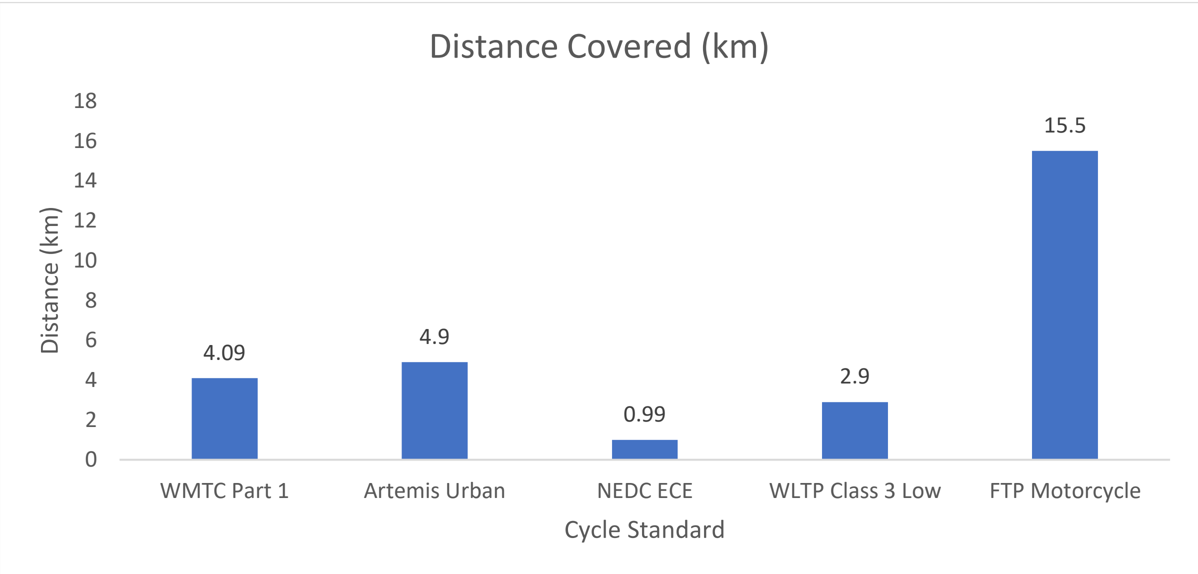


Figure 6.14 - Covered distance for every driving cycle in the input dataset

This distance has been computed by observing the speed-time set values in kph. Finally, the per-second distance covered has been calculated using the distance equation in its standard, non-differential form, as observed in equation 6.3. In reality, due to the telemetry data having a second-by-second resolution, employing the distance equation effectively means a multiplication by 1. Finally, in order to compute the total covered distance, every per-second distance has been added.

$$d = v * t$$

Equation 6.3 - Distance equation, non-differential form

Additionally, the previously presented energy results have been normalised by distance. This has been done in order to have a consistent energy usage benchmark under the form of a power/distance figure (in this case, Wh/km) has been used. The normalised energy consumption for all of the driving cycles can be observed in figure 6.15.

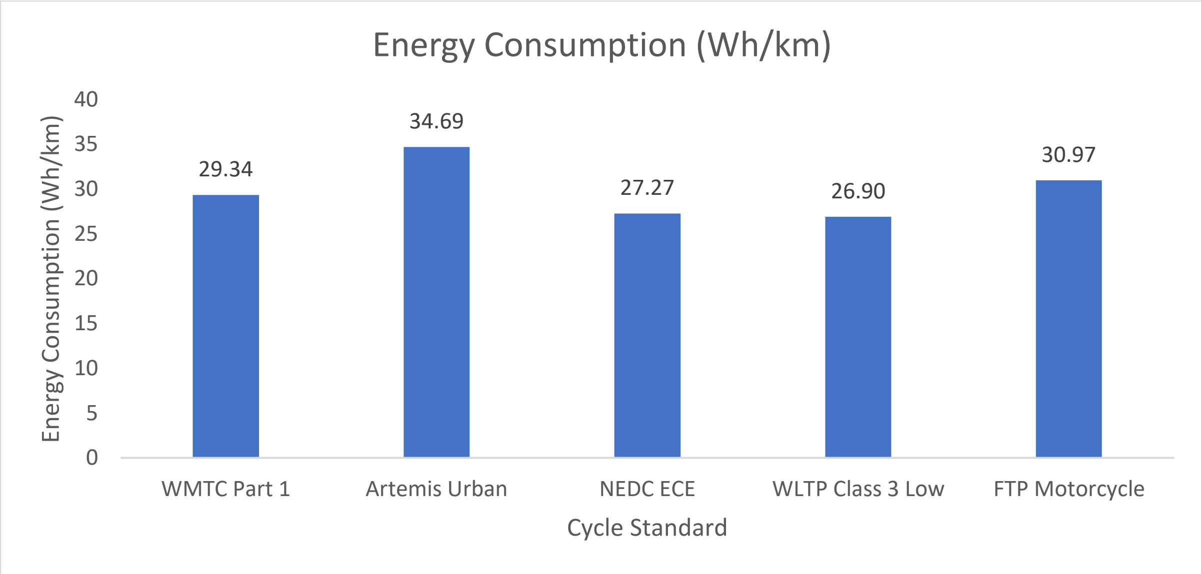


Figure 6.15 - Normalised energy consumption from simulation results

It can be observed that whilst the driving cycle results originate from different regions of the world and consequentially describe different driving styles, the variation in energy consumption figures is minimal. The similarity in these values may suggest that road-legal electric motorbikes have similar energy requirements regardless of environmental conditions, urban area and, to some extent, driving style. Moreover, the average energy consumption of the analysed driving cycles, which is set at 29.83 Wh/km integrates well with findings in similar literature [266]. This further validates the efficacy of the model when simulating lightweight powertrains.

Firstly, in order to put the resulting energy consumption figure into context, the energy storage system must be considered, which in this case is the vehicle battery. Previous experiments with publicly available findings have concluded that the average passenger car EV has an energy consumption figure set at 166Wh/km, with a battery size of 40kWh [267]. This suggests an average range of 235 km per a full charge, assuming a 2% energy buffer, in order to avoid battery operation close to maximum or minimum electrical storage capacity. The energy buffer is important as it has been observed that avoiding using the battery near minimum or maximum state of charge minimises battery degradation and in turn maximises battery life [268].

Having considered the high-level energy consumption performance of a regular passenger EV, in order for an electric motorbike to have similar range capability, a battery capable of storing approximately 8 kWh would be required. Depending on the chosen battery cell material specification, a battery holding 8 kWh would have a payload of approximately 27 kg [269]. A further 0.25kg may be added to the initial weight of the battery cells that represents the weight of the battery pack casing, totalling 27.25 kg for a complete battery pack. The casing weight has been computed assuming a cube-like packaging shape, with an aluminium casing thickness of 5mm [270].

This total battery pack weight value is comparable with the weight of a full fuel tank of an ICE-based motorbike and therefore should be able to be easily accommodated within the specified weight in the technical vehicle specification. Moreover, if range requirements were to be decreased, the required battery pack may be smaller and lighter, effectively freeing up space for more cargo capacity and resulting in the vehicle having a smaller energy consumption figure than the initial estimation.

Secondly, the benefits of an electric eBike may be observed when comparing emissions and costs due to energy refuelling. This analysis may be performed in a methodically similar way relative to presented estimations in the previous chapter 5, albeit the comparison metrics should be different. Given that this investigation does not rely on a real-life telemetry-based dataset, relying solely on emission cycle telemetry, the performance has been outlined in terms of kg CO_2/km and GBP/km.

Current ICE-powered motorbike models that are similar in total weight and rated power with the analysed electric motorbike specification set the advertised fuel consumption at 2.85 l/km [271]. This figure may then be further used to estimate the amount of produced carbon dioxide emissions by noting the amount of CO_2 produced when burning 1 litre of petrol [272]. Similarly, in order to estimate the amount of carbon dioxide produced by the electric motorbike prototype, the amount of CO_2 produced per kWh of generated electricity in the national electricity grid must be considered [210].

A comparison between the estimated values can be observed under figure 6.16.

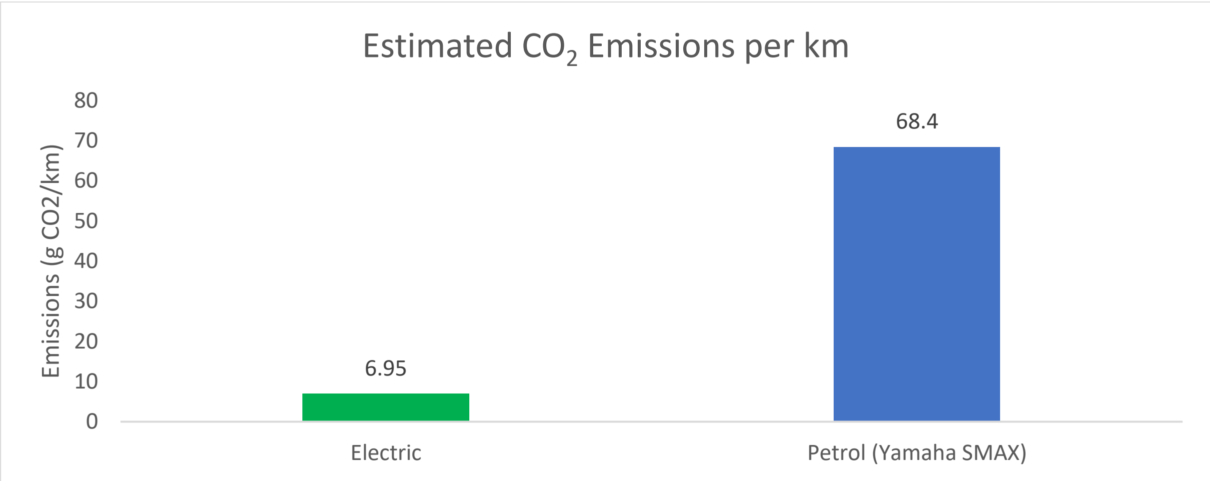


Figure 6.16 - Estimated carbon dioxide emissions

Similarly, a cost due to energy spending analysis may be carried out by considering the price of petrol and electricity. This comparison is outlined in figure 6.17.

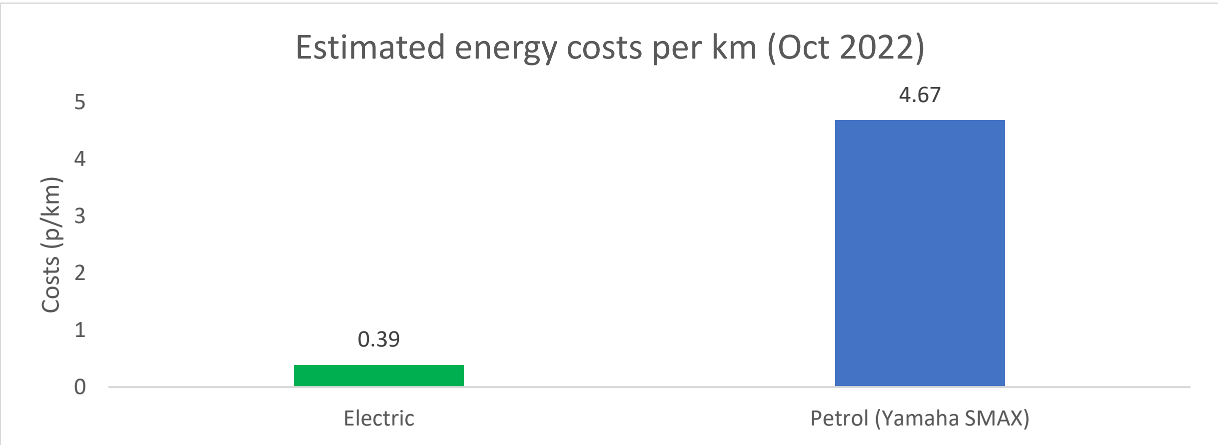


Figure 6.17 - Estimated energy costs (pence/km)

Preliminary estimated results indicate that whilst an ICE-powered comparative motorbike is relatively low in running costs and emits low emissions, the proposed electric alternative is able to reduce these numbers significantly. Additionally, similar to the heavyweight powertrains and passenger EVs, maintenance costs are likely to be smaller for the electric motorbike compared to the petrol-powered counterpart.

The results and findings presented in the previous thesis subsection (section 6.3) suggest that electric alternatives to currently available conventional, ICE-powered motorbikes are feasible from a design perspective in urban areas. Moreover, the presented comparison in CO_2 emissions and costs due to energy refuelling further highlights that electric motorbikes can have a positive influence towards the decarbonisation of the transport sector, and in a financially sustainable way.

Although it is likely that electric motorbikes will initially be more expensive than their traditional counterparts, government-funded decarbonisation subsidies and reduced refuelling and maintenance costs should alleviate the cost difference in time.

6.4. Chapter 6 Summary

This thesis chapter has outlined investigations looking into key aspects of simulating electric motorbike-based powertrains in different contexts. The aims of these investigations have ranged from validating the proposed software solution's flexibility, as well as understanding the estimated energy requirements of electric alternatives to current ICE-powered motorbikes. Additionally, this chapter has also outlined a novel methodology that applies OCR technology to acquiring telemetry from unconventional data sources. Whilst this methodology has been applied towards an investigation that looks into high-performance motorbikes, the procedure may be successfully applied to acquiring data for other types of vehicles as well, as the speed-time value pairs are powertrain-agnostic.

The findings presented in this chapter further demonstrates the software model's usability as well as providing key findings and figures that help with understanding whether current fossil fuel-powered motorbikes may be successfully replaced with electrified alternatives.

The next chapter outlines a further application of the proposed software, looking into understanding the challenges and energy consumption of electric trucks purposed for long distance trips.

7. Chapter 7 – Implementing electric powertrain technology in road freight transportation

7.1. Introduction

Having previously discussed the benefits and limitations concerning energy usage and harmful emissions of integrating electric powertrain technology in various vehicle categories, this chapter is concerned with assessing the impact of electric-powered powertrains to heavyweight, transport-purposed vehicles. The heavy-goods transport category constitutes over 62% of the total carbon emissions produced by freight worldwide [132]. Similarly, if road transport emissions alone are considered, heavyweight transport vehicles represent over 25% of emissions in the EU [273]. This figure appears consistent in other parts of the world, with reported shares of 20% in the UK [39] and 24% in the US [274]. Consequentially, it is expected that any reduction in energy usage brought by electrifying this section of the transport sector will have significant reduction on the total amount of emissions produced.

However, a significant difference in this vehicle category relative to the previously analysed vehicles is their day-to-day usage. Heavyweight transport vehicles, such as HGVs, are consistently being driven for long periods of time, predominantly at high motorway speeds [275]. Additionally, due to their high weight and low aerodynamic coefficient, the energy consumption of these vehicles is significantly higher than other vehicles [276]. In order to accommodate the high energy use, as well as the operational time, electrical storage systems for electric alternatives to conventional, ICE-powered trucks will also require a high capacity. This comes at the cost of increased energy storage volume and increased weight, which negatively affects the vehicle's useable payload.

Additionally, a high-capacity energy storage system will require significant amounts of time to be recharged, even with recent fast-charge vehicle charging technologies. Current eHGV designs feature batteries of significantly higher capacities relative private passenger small EVs of up to 1MWh. Considering a 350 kW DC charger, it would still take more than three hours to fill the electrical battery capacity completely from empty, before considering charging efficiency and battery charging dynamics. Although HGV drivers are required by law to observe regular breaks from driving, a significant charging time is unsuitable to the current business logistics model, which relies on speedy deliveries.

For these reasons, fleet managers may view the concept of an electrified HGV (eHGV) as unattractive. However, if a slightly different approach is applied to that taken in passenger cars, the electrification of the heavyweight transport sector could be financially sustainable, with minimal disruption to the supply chain, at the benefit of complete decarbonisation.

Furthermore, the electrification of road freight may be considered a key ingredient towards energy security. As opposed to their ICE counterparts, electric vehicles use electricity which can be sourced using several methods (fossil fuels, nuclear, wind, solar, hydro etc.), instead of relying solely on one type of energy production (i.e., burning petrol and/or diesel).

This chapter showcases a feasibility investigation into the potential benefits that may be brought about by electric alternatives to the current ICE vehicles in use. Additionally, a potential concept solution to address the problems related to the modest vehicle performance of current electric truck designs is presented, employing currently available battery technologies.

The research builds on previous literature in this field, as well as a blend of the most popular electric vehicle energy refill paradigms: vehicle charging and battery swapping. The originality of this research lies in its innovative analysis that takes advantage of both schools of thought concerning energy refill and combining these philosophies in a "pit stop" (like battery swapping and fast charging). This gives rise to an approach that aims to optimise vehicle range, downtime due to charging, and decreased useable payload.

7.2. Concept Objectives

The approach consists of employing modular, loadable, pallet-sized battery packs to temporarily act as a "power pack" for the electric trucks. The battery pallets are conceptualised such that they can act as independent energy storage systems, each having its own power connection interface adapted to current EV charging standards. However, minimal, software-related changes to the charging protocols may need to be considered, as currently vehicle charging capabilities are difficult during movement due to safety reasons.

Additionally, the concept takes advantage of the current energy delivery infrastructure, more predictable driving and operation styles (i.e. regular loading and unloading of cargo) of HGVs to ensure optimal weight loading relative to trip length [277] and minimise the effective payload decrease. Similarly, by taking advantage of the concept's modularity, the battery packs can also be repurposed as grid support energy storage systems when not in use and not fully depleted or being charged.

The presented concept aims to maximise transport efficiency while enabling electric trucks to be adapted to the current existing logistics models at minimal additional expense, energy grid stress, and productivity disruption. The system modularity, together with the real-life application model will ensure maximised exploitation of battery packs before end-of-life redundancy. Similarly, the modular nature of the concept will aid in creating eHGV designs purposed for pallet-sized battery swapping. The concept of pallet handling is well developed in the transportation and logistics industry, and most of the infrastructure required to apply this concept to real-world scenarios already exists, with minimal additional power connections needed (such as connecting the battery pack to the eHGV internal power system). This will shift the thinking behind considering the vehicle battery as the main "energy tank" towards relying more on the energy storage capabilities of the power packs. This allows the possibility to equip electric vehicles with smaller integrated batteries, which will result in better base energy consumption figures, that have a better weight-to-energy ratio than a conventional standalone BEV. This is due to the lighter vehicle weight, whilst maintaining similar powertrain capabilities.

The primary aim of the concept is to serve as an intermediate step towards a fully electrified freight transport sector. Additionally, as battery technology evolves and improved electric trucks appear on the market, it will enable current eHGV designs to match the range performance of their ICE counterparts, whilst remaining sustainable from a cost standpoint. Consequentially, as the power pack system will upgrade to benefit from new technologies, it will provide a cheaper way for system users to upgrade the range performance of their electric truck fleets without the need for fleet renewal, maximising the lifetime of their fleets and long-term sustainability.

The findings presented in this section are more conceptualised and intended to prompt further investigations towards assessing the feasibility of this concept in more specific contexts, since transport logistic models can have significant variations depending on the expected trip distance. Similarly, the battery pack shape and sizing could be tailored depending on the type of required transport, enabling feasible concept variations for a wide range of electric vehicles with predictable routing, such as LGVs. Another potential research avenue is represented by the versatility of the system design, for example allowing the charging time to be altered by changing the input charging power, optimising for performance or long-term battery health. Depending on the design requirements, the battery packs may be developed such that higher charging power can be employed.

Similarly, due to the somewhat relaxed shape of the load put on the pallets, the battery pack packaging may be adapted in order to minimise the impact on the usable load capacity.

7.3. Understanding Energy Consumption of Electrified Powertrain HGVs

In order to put the advantages offered by the presented concept into context, vehicle range performance of current electric HGVs must be considered. The capabilities of these vehicles have evolved significantly over the last few years due to the leaps in capacity of new battery technologies. Whilst there are many designs available on the market, the investigation will focus on the most popular eHGV models.

For heavy electric trucks, the most widely expected vehicle is the Tesla Semi [278], due to be launched for production in 2023. Although the manufacturer indicates a reasonable amount of information concerning vehicle range and energy consumption metrics, as well as maximum usable payload, there is not much publicly available data regarding the speeds at which these are achieved. In order to get a better understanding about the energy consumption performance of the vehicle at various speeds, an extrapolation involving passenger EV cars may be made. An electric lorry (eLGV)-based extrapolation has also been considered; however, this was deemed unsuitable due to lack of available speed-energy usage data in the publically accessible technical vehicle specifications.

Previous experimental data indicates that the optimal speeds at which maximum vehicle range is achieved for electric cars ranges around 20-25 mph [279]. This can be observed by determining at what range of speeds the vehicle energy consumption is minimal. By considering the stated energy consumption (and assuming this is the minimal energy consumption throughout the rated vehicle speed range) and the relative energy consumption delta at different speeds for a passenger EV car (figure 7.1), a similar energy consumption curve can be postulated for an eHGV. This is achieved by observing the stated energy consumption of the Tesla Semi eHGV and assuming this is measured at the same speed at which other Tesla vehicles achieve this. Following that, a consumption offset constant between the consumption of the eHGV and a reference Tesla EV can be established. The extrapolated energy consumption curve is then determined by applying this constant to every speed-data entry.

The extrapolation results can be observed seen in figure 7.2. The estimation performed through curve extrapolation has then been correlated with an estimation provided from a simulation based on the previously presented vehicle software model (see Chapter 3). The full eHGV vehicle specification used for this simulation can be found in the appendix 10.

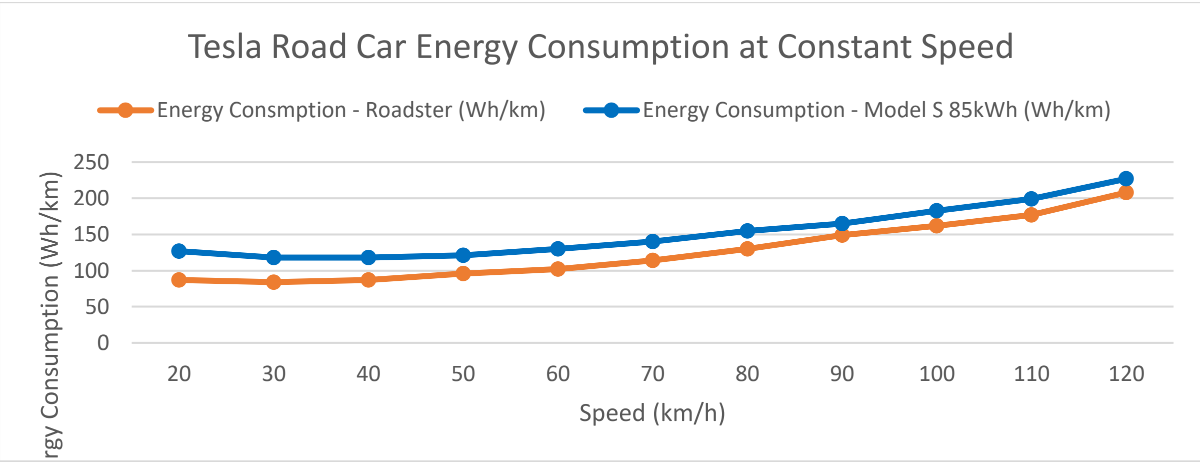


Figure 7.1 - Energy consumption curve for Tesla EV models. Source: Tesla Inc.

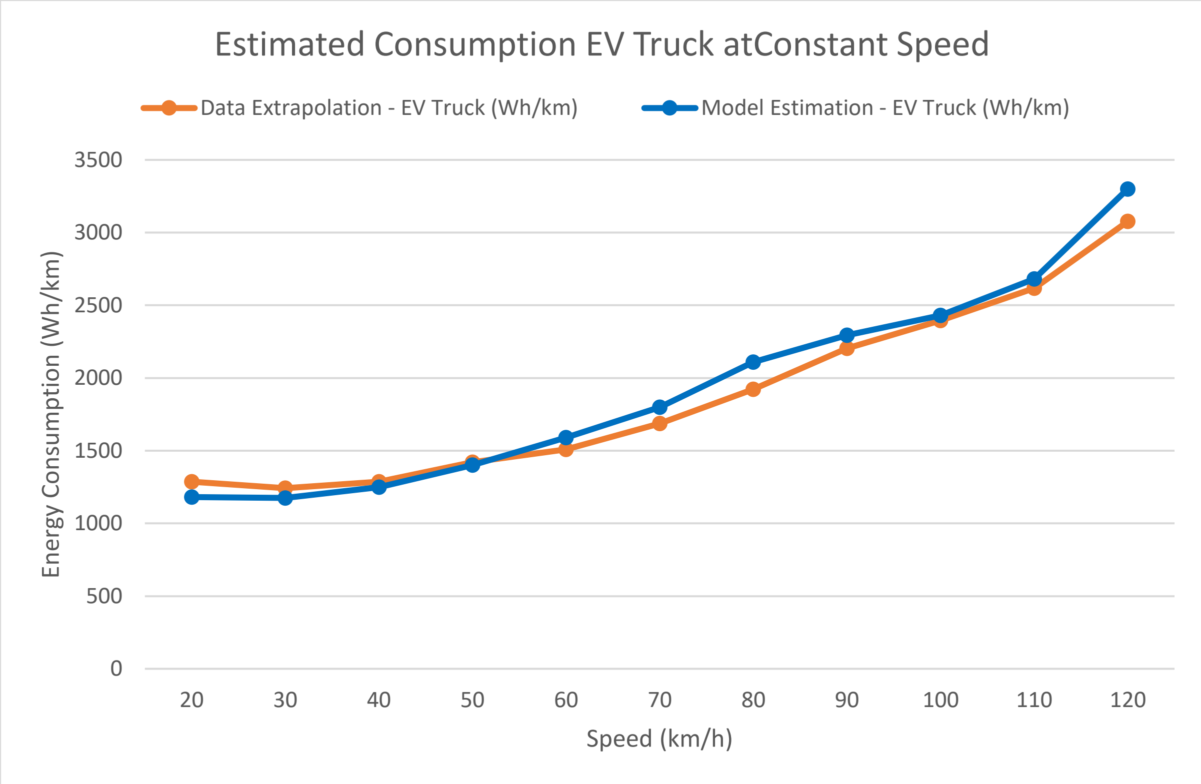


Figure 7.2 - Estimated energy consumption curve for eHGV

It must be noted that whilst the curve extrapolation method may be robust for most of the electric trucks, some inconsistencies may arise. Whilst there are plenty of delivery trucks operating in urban environments (i.e. last mile delivery), ensuring good transportation between depots in the same city or region; electric trucks are predominantly designed to be mostly driven on high-speed roads, such as motorways. This is because most electric passenger cars are purposed to be driven in urban environments, therefore the gearbox ratios are short, and designed for quick acceleration and limited top speed. This results in increased energy consumption figures at constant speeds beyond the urban threshold. In order to design a vehicle that is fully optimised for both city and motorway speeds, a two-speed (low gear for urban environment, high gear for motorway) gearbox should be considered. This can also allow vehicle acceleration performance to be somewhat increased by taking advantage of the low gearing. However, a multi-speed vehicle is likely to have some weight penalty, due to a heavier transmission system and gearbox.

However, in the dataset comprising the passenger cars considered for finding the optimal energy consumption speed, there are several EVs not advertised as “city cars”. These cars exhibit similar energy consumption figures when compared to the urban-focused designed passenger EVs. Furthermore, the estimated eHGV energy consumption figures produced by the curve extrapolation method are similar to the ones generated by simulation around a heavyweight powertrain EV model, described in previous research. [204]

Based on the estimated energy consumption figures, an argument concerning costs and carbon dioxide estimations of electric alternatives may be created. This can then be compared to conventional, diesel-powered trucks. The estimations for diesel-vehicles may be calculated employing an analysis that is similar to the previously presented investigations on other types of vehicles. By observing the declared fuel consumption of a comparative ICE-powered HGV [280], the carbon dioxide emissions generated by burning 1 litre of diesel [272], the energy consumption of a standard eHGV

[278] and the CO_2 per kWh generated in the energy grid [281], a kg CO_2/km comparison may be produced, as shown in figure 7.3.

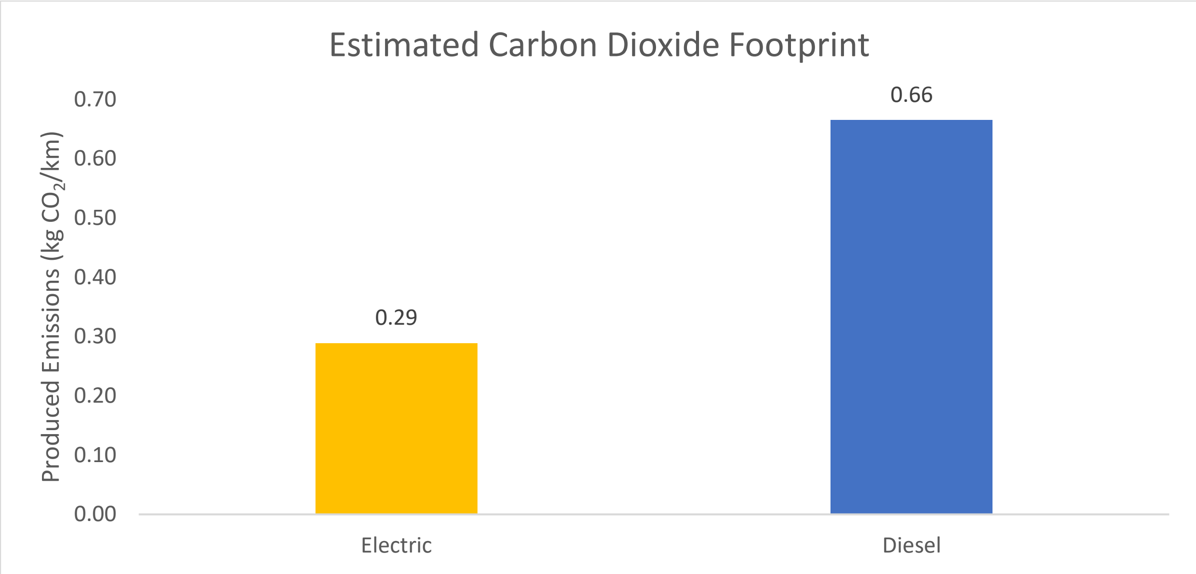


Figure 7.3 - Estimated eHGV normalised carbon footprint

Initial carbon footprint estimations suggest a significant portion of carbon dioxide emissions may be reduced by implementing electrified HGVs, a similar trend to the ones previously presented in this thesis. Estimations suggest a reduction of over 50% may be achievable. Whilst the emission reduction achieved over 1km may not be impressive in absolute terms, the theoretical lifetime (currently set at an average of 300,000 kms [282]) carbon footprint of an electric alternative HGV is almost 400 metric tonnes smaller than a diesel-based solution. This is equivalent to the emissions produced by nearly 100 passenger cars yearly [229].

Similarly, a normalised cost analysis directly concerned with energy spending may be calculated by integrating average pricing for diesel [283] (1.90 GBP/l) and electricity [281] (0.13 GBP/kWh) in the original calculation (Oct 2022). Figure 7.4. indicates that a significant reduction in energy spending may be expected when employing an electric HGV relative to a conventional, diesel-powered one. This may be further enhanced by the lower maintenance costs of electric vehicles.

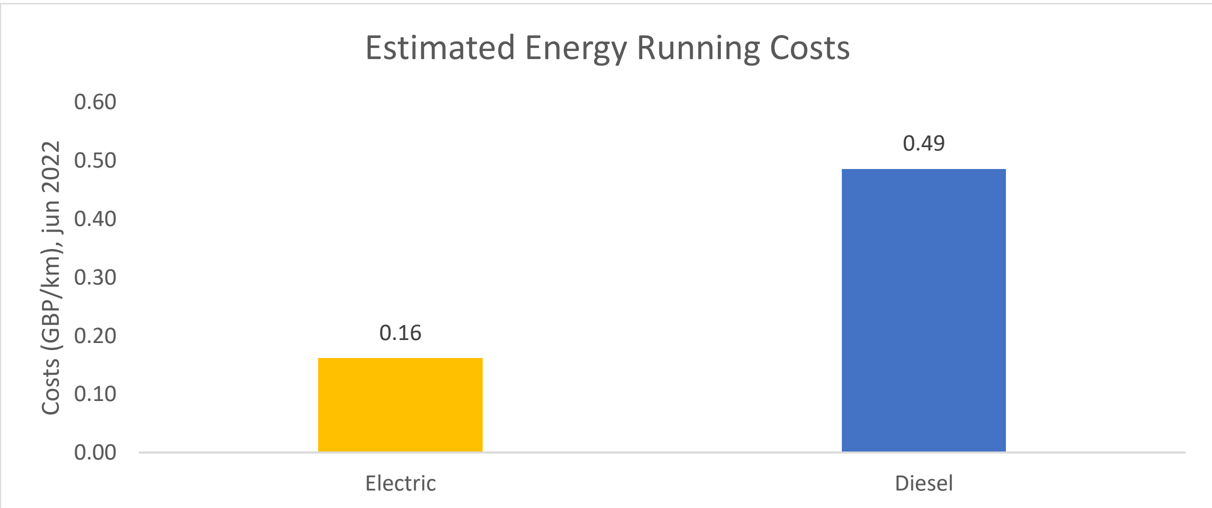


Figure 7.4 - Estimated eHGV costs due to energy refuelling

Finally, both the carbon footprint and costs of an electric HGV alternative may be further decreased by optimising vehicle mass. Statistics show that the battery weight represents a significant portion of a given EV's total vehicle mass [277]. Therefore, it is expected that the versatility offered by a concept pallet-battery system to adjust the battery sizing according to the expected distance for any given trip is likely to have a beneficial impact over energy consumption.

7.4. Basic energy consumption example

In order to extend the findings provided by the normalised carbon footprint and cost analysis, a further test has been examined. Considering the estimated range performance, a realistic, emulated example of telemetry has been assessed. The telemetry considered is representative of 15 minutes of pre-motorway driving, averaging an assumed 60 km/h, followed by 1 hour of motorway driving at 100 km/h, and finally a last 15-minute period of post-motorway driving at 60km/h. An improvement of up to 10% in energy usage can be observed if motorway speed is limited to 90 km/h, as seen in figure 7.5. Expected ranges assuming a full battery charge and presuming similar operations can be observed under table 7.1. Additionally, the expected full charge range figures are dependent on set average speeds and can be observed in figure 7.6.

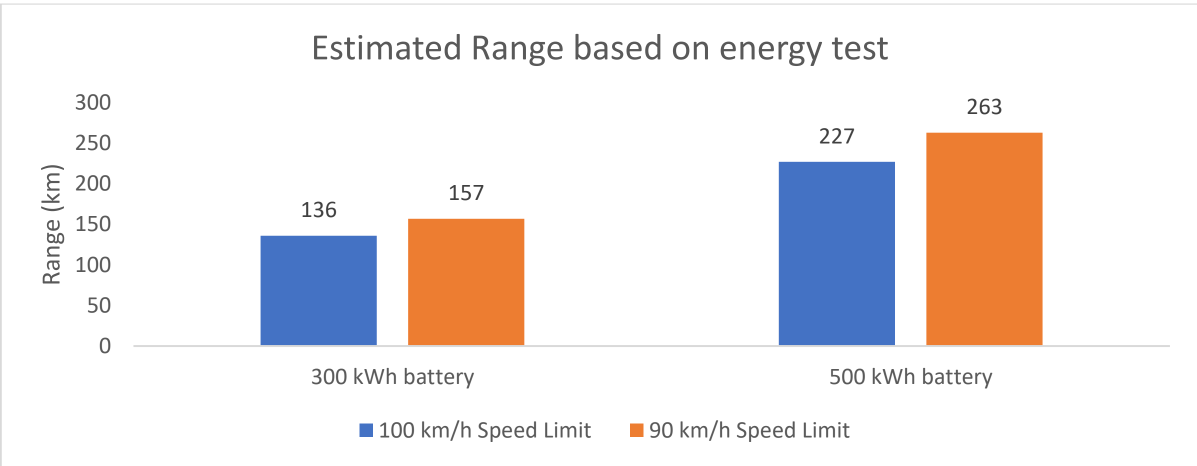


Figure 7.5 - Estimated eHGV energy usage for example telemetry

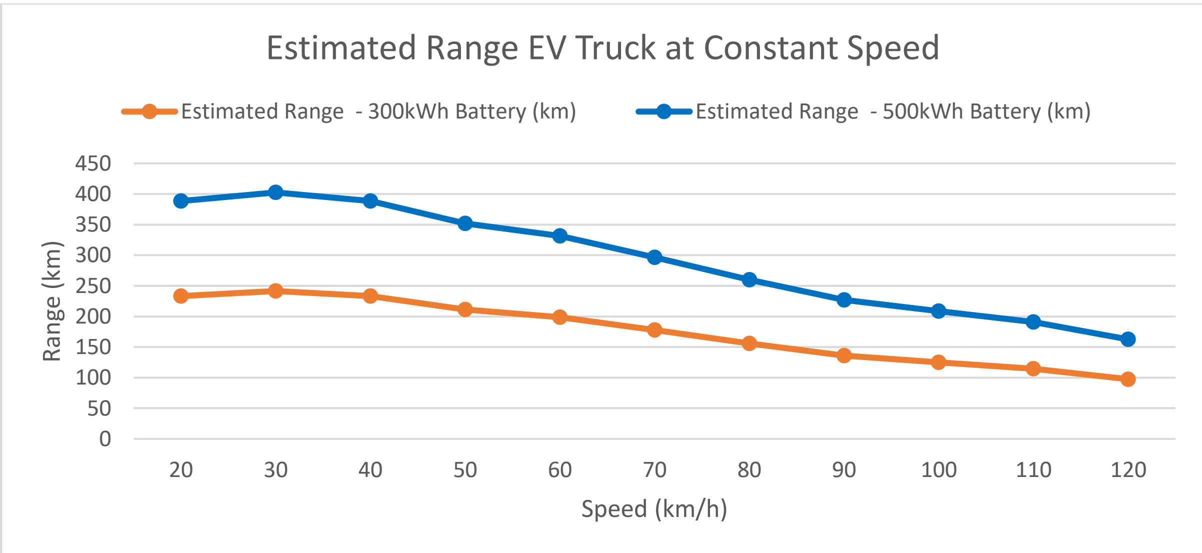


Figure 7.6 - eHGV range curve based on constant energy consumption at various speeds

Speed Limit (km/h)	Energy Usage (kWh)				Full Charge Est. Range (km)	
	Pre-motorway	Motorway	Post-motorway	Total	300 kWh battery	500 kWh battery
100 km/h Speed Limit	22.5	250	22.5	295	136	227
90 km/h Speed Limit	22.5	198	22.5	243	157	263

Table 7.1 - Expected eHGV vehicle range for presented telemetry scenario

By observing the results presented in the previous table, it must be noted that energy consumption is decreased at lower speeds, which has a positive effect on vehicle range. However, based on previously presented eHGV expected range values, it can be seen that current eHGV designs are unsuitable for the present freight haulage business model, which expects vehicle usage times to be significantly higher than the current eHGV capabilities [277]. While it is expected that eHGV range performance will significantly increase as new battery technologies are brought to market, there is still some degree of uncertainty concerning the actual vehicle range improvements.

Furthermore, fleet upgrade costs are expected to be higher, since EV technology is still significantly more expensive than conventional ICE-based alternatives [53]. While the extra cost may decrease in time due to lower maintenance costs for electric powertrains, the integrated battery approach will still bind the consumers to some degree of inflexibility.

7.5. Concept presentation

The proposed pallet sized battery pack concept aims to address some of the issues presented in the previous section, as well as offer an alternative to the single-battery vehicles. The concept aims to minimise the amount of fleet downtime due to energy replenishment as well as presenting itself as a sustainable alternative to bringing electric HGV/LGV vehicles towards competitiveness relative to conventional diesel technology. Moreover, the battery pallets themselves should be designed such that they may have the ability to utilise current EV charging infrastructure, whether the device is mounted on a vehicle or not. Finally, the system needs to be cost effective as a business operating model, through for example employing an optimised tier-based subscription system.

In order to achieve the stated aims and also ensure long-term reliability, the engineering design challenges have to be discussed. Firstly, limitations concerning sizing must be considered. EU-standard pallets are certified for having a maximum payload of 1250kg [284], therefore this figure has been considered as the maximum limit for the system weight in the analysis. The EU-certified pallets have been considered in order to ensure concept transferability between the EU and the UK. However, a parallel system that is purposed for national freight only could be considered, which would be limited by UK pallet regulations. Many popular battery materials have volumetric efficiency and weight efficiency constants (measured as kWh/kg and kWh/m^3 respectively) that help with determining the rest of the sizing parameters, as well as the electrical storage capacity of the device.

Several battery manufacturing materials can be considered as candidates. The ideal battery material would exhibit the following two properties; a high volumetric constant and a high weight efficiency constant, for this would create a high energy density battery. However, concessions can be made for lower volumetric and weight efficiency coefficients to achieve a lower cost. In order to fully maximise the usability of the system as well as offer more accessibility and choice to the end user, the system may employ a range of different battery pallet sizes, with different capacities and consequentially added vehicle range. Figures 7.7 and 7.8 show the volumetric (kWh/m³) and weight (kWh/kg) performance of some of currently available battery technologies [285].

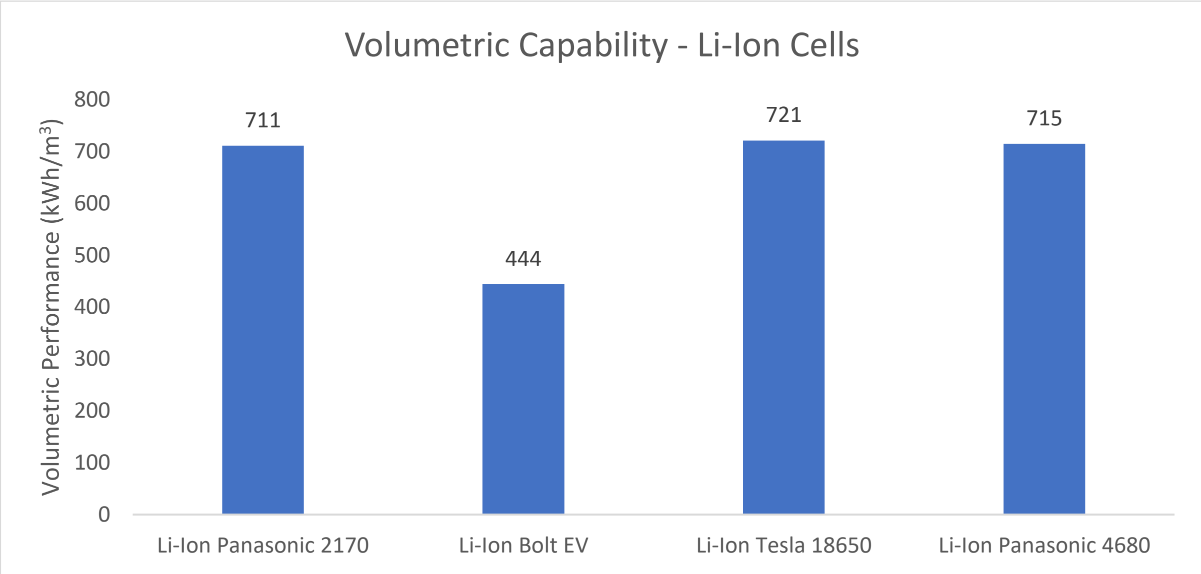


Figure 7.7 - Electrical storage capability with respect to displacement [285]

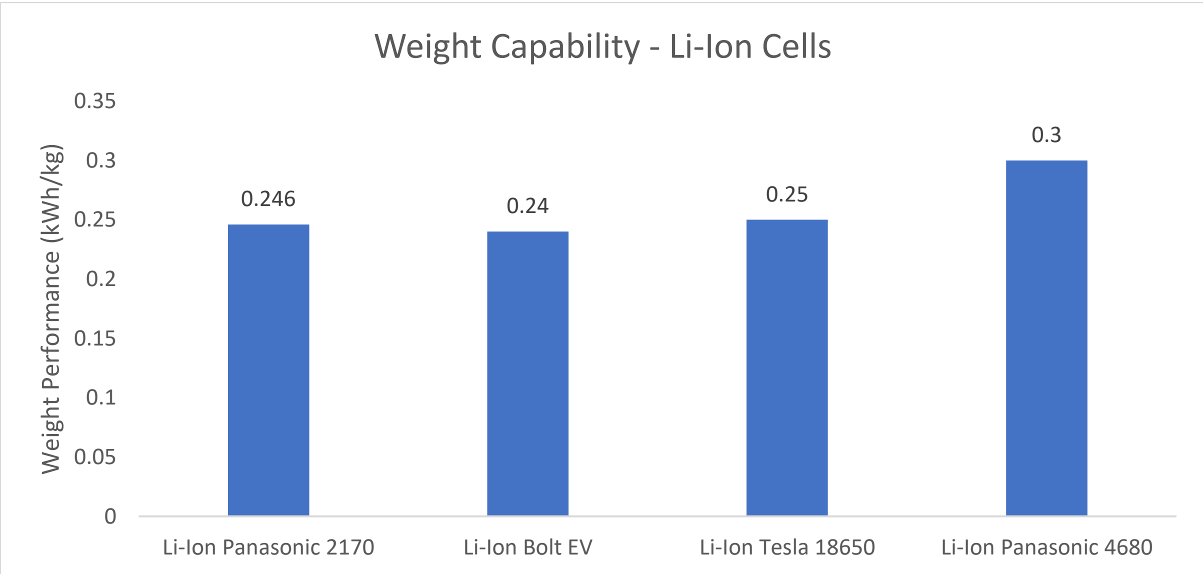


Figure 7.8 - Electrical storage capability with respect to weight [285]

It must be noted that in order to ensure system modularity, every battery pack has to be designed to work as a standalone device. Therefore, besides the material employed for energy storage, the previous sizing calculations also have to account for the electronics managing the charges of the multiple cells in the battery pallet. Similarly, the estimation also has to account for any space that may be taken for the device interfacing. Whilst the occupied space will have an impact over the electrical capacity of the device, the modular nature offered by this approach will have significant benefits in system usability. The auxiliary power electronics will enable the battery pallets to be interfaced with existing electric infrastructure, as well as the integrated batteries in the host electric vehicle. Battery management systems as well as power electronics have recently seen a significant reduction in size and weight due to new emerging technologies that are able to operate at higher frequencies [66]. For the purposes of the presented specification list, the electronics and electronic interfacing (charging terminal, information terminal) have been considered to account for 5% of the maximum payload, in line with recent trends in battery pack designs [126].

Similarly, device packaging must be considered. This is especially important in the case of Li-Ion battery cells, as they are prone to catching fire when the battery cell structure is exposed to air. Whilst these circumstances are uncommon, a device casing that is able to create an airtight, shock and puncture resistant container must be considered for safety purposes. Given that the volume of the case will not significantly affect the overall device sizing, weight is the parameter that should be targeted when considering casing material. Traditionally, the case for such devices has been manufactured using steel with an appropriate thickness to withstand knocks and other mechanical shocks. However, recent leaps in alloy composition technology have enabled custom-spec alloys to be suitable for these applications, being lighter and more resistant than the conventional solutions. [286]

Further optimisation to the battery pallet concepts may also be discussed. For example, altered device volume and mass distribution can be considered, such that the overall device would be shaped as a rectangular cuboid rather than a standard cube, with minimal height. This will ensure a low centre of gravity for the cargo load that will aid with overall vehicle stability. The overall volume of the device may be further minimised by integrating some of the electronics within the battery cells themselves – this will aid ensuring a high level of energy density [60]. Similarly, custom-shaped battery packs may be considered for special types of payloads.

Table 7.2 presents a potential specification list of battery packs fit for different haulage trips, with the strongest battery technology candidate found on the market. Battery weight includes a 5mm-thick aluminium battery cell casing, as well as a 10kg overhead for additional electronics and system interfacing.

Spec	Battery Tech	Total Weight (kg)	Est. Range (km)
Max, weight-limited only	Li-Ion, Panasonic 4680	1024	240
Super, $1m^3$ volume		855	200
Regular, $0.75m^3$ volume		637	150
Mini, $0.5m^3$ volume		443	100

Table 7.2 - Possible battery pallet spec range

7.6. Potential Benefits

The potential benefits brought by such a system implemented at large scale are situational and may only be discussed whilst considering a series of extrinsic factors, ranging from the type of range and haulage requirements normally fulfilled by the companies to the extensiveness of the system, charging times and downtime due to battery swapping. Table 7.2 above shows figures concerning the expected range for each of the battery specs presented in the previous section. However, as indicated by recent research [110], range has a high degree of variability in electric vehicles.

The investigation shows that whilst deliveries achievable with a single battery charge may be highly competitive relative to diesel vehicles in terms of duration, longer trips are bound to take longer because of the need to swap batteries and/or recharge them. However, freight companies may find the shipment delays acceptable due to lower overall energy costs compared to diesel, as indicated by recent statistics [130]. Moreover, whilst a battery swapping mechanism will bring additional costs due to personnel and system maintenance, it is likely that these will still be comparable to diesel vehicles.

To illustrate the concept, a UK-based route example from Sheffield to Newcastle upon Tyne of 214 km (266kWh required, assuming 1.24 kWh/km consumption) with potential different route options is presented below. The chosen route may be viewed in figure 7.9.

Figure 7.9 - Sheffield-Newcastle Route

- Option #1:
  - Start with 100% charge Mini Battery
  - Stop #1 – Swapping battery at station near Leeds (63 km away)
    - Battery remaining in Mini pack: approx. 50%
    - Quick stop, no charging needed. Battery swap performed as a pallet offload-onload operation.
    - Swap Mini Battery with 100% Super Battery
  - Arriving in Newcastle upon Tyne, trip duration estimate: 2h50m
- Option #2:
  - Start with 80% charge Super Battery
  - Stop #1 – Swapping battery at station near Darlington (156 km away)
    - Battery remaining in Super pack: approx. 2%
    - Quick stop, no charging needed. Battery swap performed as a pallet offload-onload operation.
    - Swap Super Battery with 75% new Mini Battery
  - Arriving in Newcastle upon Tyne, trip duration estimate: 2h50m

The fleet downtime may then be further decreased by employing GPS data algorithms that create smart routes that consider a multi-factor analysis. Such algorithms have already been researched and implemented [100] for charging-only stops by big automotive companies, therefore validated as a robust solution to the downtime issue. The generated routes often feature charging stops that do not imply waiting for the vehicle battery to fully charge, as this may not be the fastest way to reach the destination. This is because battery charging is not linear, with charging times becoming longer as the battery reaches its full charge capability [106]. The algorithms generating these routes are able to compute time comparisons between time spent charging and effective driving time. Finally, because the route creation solutions are flexible and can already calculate several trade-offs, integrating another batch of factors related to battery swapping scenarios should be relatively straightforward.

In order to maximise battery lifetime, calculations involving trips must also consider battery-cell factors. Studies indicate that batteries that have been extensively charged and discharged to extreme high and low levels of state of charge tend to lose their health quicker than battery units which have their charge managed under lower deltas of battery levels. Similarly, fast charging should be avoided wherever possible, as it has been shown that this charging technique can negatively affect battery health over time [268].

Finally, a number of factors that are extrinsic to the battery packs should also be considered. One example of this is represented by the availability of energy grid infrastructure in the designated places in which battery swapping stations are proposed. This must be considered as it will serve as a major factor in the placement of battery swap stations. Whilst in urban areas this will likely not cause any problems, rural areas need to be carefully considered. Some of these areas may not have suitable energy delivery capabilities, therefore the energy grid performance may need to be expanded such that it can accommodate high power demand battery swapping stations. Finally, station placement as well as battery storage should also be optimised relative to the traffic in the area.

7.7. Financial Implications

When analysing the costs incurred by the proposed system, there are several categories that must be analysed. The initial implementation costs are expected to be high, as these will include the station building costs, as well as the battery pack acquisition, but also other machinery required for the battery swap operation and maintenance. Installation costs may also include “adaptation” costs on a case-by-case basis, such as the funds required to extend energy grid capabilities.

Additionally, the system will be sustained by maintenance costs, which include personnel, battery pack replacement and recycling at critical end-of-life state, and other wear and tear processes that may happen. Finally, an incentive scheme that encourages freight companies to adopt the system may be considered. Whilst initial upfront investment costs are likely to be around 7-14 billion GBP in battery units alone (assuming the number of battery packs would be equal to the number of trucks on the road in the UK in 2022 [276], and the number would be equally split between specs), the zero-carbon emission benefits of the system will likely correlate well with the strategies and funding of many governing bodies around the world, for example the UK Government’s Department for Transport policies [127]. Similarly, it will have a significant impact, effectively ensuring a net-zero carbon emission cargo logistic system mode.

The projected pallet-sized battery pack system cost has been calculated to support 415,000 packs (i.e., the number of average daily HGVs [277]) operating in the UK, split evenly between the proposed spec sizing. An estimated unit cost analysis based on the Li-Ion Tesla 18650 battery cell can be viewed under table 7.3. The 18650 Tesla cell has been chosen as the previously mentioned Panasonic 4680 is still under review and not present on the market yet.

Battery Pack Spec	Battery Cell Technology (GBP)	Battery Cell Costs [285] (GBP)	Casing Costs - Aluminium [287] (GBP)	Connection Costs [288] (GBP)	Total Estimated Costs (GBP)
Super (200 km range)	Li-Ion Tesla 18650	34500	16	500	35016
Regular (150 km range)		25700	13		25713
Mini (100 km range)		17700	10		17710

Table 7.3 - Unit cost breakdown analysis

Comparison of the presented electric battery system with the current diesel technology must be carefully done. Whilst range performance of eHGV is unlikely to achieve the levels shown by diesel trucks, the difference may be less important when considering mandatory HGV driver downtime, which may be used for charging or swapping the onboard battery system. Additionally, kWh/km costs are likely to be significantly smaller for an electric HGV relative to a conventional ICE-based truck, as indicated by the cost breakdown below, see table 7.4. A further comparison with other alternative solutions (e.g., hydrogen or bio-methane HGVs) has not been carried out as the focus of the feasibility is to compare costs with traditional fuel vehicles. Furthermore, electric HGV maintenance costs are likely overestimated since most electric vehicle powertrains are significantly cheaper to maintain relative to their ICE-powered counterparts.

Cost description	**HGV Type**		
	Diesel [280]	**500kWh eHGV** [236]	**100kWh eHGV** [236]
Initial Cost (GBP)	85000	138000	90000
Running Costs			
Proposed pallet-sized battery packs system cost (GBP/km)	0	0.1	0.1
Fuel Costs + AdBlue/ Vehicle Charging (GBP/km) – Dec 2021	0.47	0.3	0.3
Vehicle Maintenance [277] (GBP/km)	0.05	0.05	0.05
Total Running Costs (GBP/km)	**0.52**	**0.45**	**0.45**

Table 7.4 - Estimated kWh/km cost breakdown, diesel vs electric HGV

Considering these maintenance costs presented above, the break-even point relative to diesel for an eHGV vehicle can be as low as 40,000 kms, indicating a potential strong alternative while also sustaining the costs of the entire battery pallet system. System costs may be further decreased by ensuring prolonged battery usage for older cells that do not hold a similar capacity to their design parameters anymore. These could be made available for users paying for a lower subscription tier, to account for smaller range at higher battery pallet weight.

Infrastructure costs should also be considered. Recent trends in land costs [289] indicate that renting space and building temporary battery swap and high-power charging facilities may attract significant increases in overall system costs. Moreover, such infrastructure that partially and, in some cases, fully meet the requirements of the battery swap stations already exist, represented by petrol stations and their adjacent auxiliary EV charging spaces, or even warehouses with pallet handling facilities. Such service spaces may be successfully converted to serving as battery hot-swapping stations in a progressive fashion, as the proposed concept gains industry-wide adoption. Additionally, many petrol stations have already been built in a given location based on feasibility studies based on traffic intensity, partially eliminating the need to carry out further analyses of logistic movement. Finally, in order to facilitate ease of access, a higher proportion of batteries capable to store large amounts of electrical energy should initially be assigned to stations close to major roadways and interchanges. This should guarantee maximum system attractiveness, as it has been shown that these roads have generally higher proportions of traffic.

Lastly, further system maintenance operations will have a financial impact. These include vehicle fleets purposed for optimising battery pack placement in a given area. Additionally, battery pack long range transportation may be handled by HGV operators that are currently contracted for petrol-related distribution. Transportation regulations will also need to be considered as battery cells are predominantly classified as dangerous goods, although petrol tankers are labelled in a similar fashion, which may alleviate any associated additional costs. Moreover, battery cell transportation handled by private haulage companies may be incentivised through various means depending on the chosen payment model. Such incentives may include one-off discounts to monthly or annual subscriptions, or consistent per-mile cost cuts if a distance-based concept use taxation is chosen. Additionally, a subscription-based service may also offer a tier-based system that discriminates between lower and upper tiers through allowing access to battery packs with higher state of health (SoH) percentages. This would ensure prolonged battery pack utilisation before phasing out battery packs with older cell technology. Similarly, a tier-based system may also consider access limitations to higher-capacity battery packs, but additionally provide access to auxiliary services, such as road-side assistance and on-the-spot battery swap replacement. In order to accurately determine the best business model, further research including a market review and cost analysis may be required.

7.8. Chapter 7 Summary

The material featured in this chapter has presented a concept system employing battery-sized loading pallets to extend the intrinsic capabilities of eHGVs or be employed as standalone energy modules. Whilst the initial estimations concerning technical performance and costs indicate that the system may be feasible as an alternative to the conventional freight transportation, significantly more work is needed in order to better understand its relevancy. Nonetheless, a battery pack system may significantly increase the attractiveness of electric powertrains in road freight heavyweight transportation, due to the ability to optimise vehicle mass depending on route length.

Future research may be directed to investigating system implementation more concretely, such as optimal battery swap station placement and optimising the number of battery units the system should use. Similarly, analysing the upfront and maintenance costs at a low-level will also help with better understanding the system capabilities in terms of financial performance. Finally, research could also be directed to whether the concept could be extended to other vehicle types that are employed with local deliveries, such as eLGV.

Having discussed energy usage of many of the important vehicle categories, the following chapter will focus on highlighting the main findings of the presented investigations, as well as suggesting several future research avenues.

8. Chapter 8 – Final Discussion & Conclusions

This thesis has presented several aspects that are key to a better understanding of the feasibility, sustainability and energy requirements posed by several categories of electric motor vehicles, including eBuses, eRCVs and eMotorbikes. The originality of the research outlined in the chapters is comprised several components. Firstly, a novel simulation method focused on estimating EV energy consumption has been developed. The proposed solution uses a model-based programming development approach, whilst also employing state-of-the-art programming software, and represents an original application of simulation engineering in the electrified automotive field. Additionally, the developed simulation model is then further combined with novel methodologies in order to investigate the energy usage of several types of electric powertrains, ranging from ePSVs to electric motorbikes. The results produced by these analyses represent an original contribution to the fields of automotive electrification and applied simulation engineering, further enhancing the novelty component present in this thesis. Finally, the findings and approaches demonstrated in the previous chapters form a significant addition to the current knowledge of EV performance, whilst also opening up new research opportunities in the field of electrified powertrains.

Although the scope of the presented work covers a broad range of components, ranging from the development of a novel vehicle software simulation solution to introducing an EV range extender battery-based concept, these can be presented in a simplified fashion.

The first chapter outlined an introduction covering the high-level justifications behind the presented work. The main reason advocating for mass adoption of EV technology in motor vehicles revolves around the ever-increasing, industry-produced CO_2 emissions. Through their higher energy efficiency and zero tailpipe emissions, it has been demonstrated that electric powertrains are able to significantly reduce the carbon dioxide footprint of the automotive and transportation sectors.

In chapter 2, a state-of-the-art literature review including historical evolution as well as the most recent developments in topics of interest to the research has been presented. Researched topics include the economic output of the automotive and transportation fields and predicted future CO_2 emissions as a result of implementing alternative green powertrain technologies, including EV. Additionally, technical aspects related to EV motor vehicles and psychological aspects preventing mass adoption of EV technology have been looked at, along future trends in powertrain electrification. Moreover, a review examining the most recent developments in simulation-based experimentation and telemetry-like data has been produced. The reviews outlined in this chapter have satisfied the objectives related to research aim 1, concerning the understanding of the relevant current scientific context.

The third and fourth chapters have presented a proposed software simulation solution aiming to provide accurate energy usage estimates for a wide range of electric vehicles, such as eBikes, eRCVs and eMotorbikes. Novel techniques have been used, such as model-based programming and state-of-the-art software components, such as SimScape, within the Matlab/Simulink environment. Similarly, a telemetry-producing Python script suite is also presented. The efficacy of the proposed solution is demonstrated through the presentation of accuracy results during the validation and testing phases of development. The work presented in these sections aim to fulfil research aim 2, targeting the development of a novel software simulation solution, tailored for energy consumption in electric vehicles.

Chapters 5 and 6 present how the developed software solution can be applied to real-life energy usage investigations. The findings and results presented in these chapters further detail the answer to questions concerning the feasibility of electric vehicles in contexts which have not been thoroughly investigated. The outlined conclusions targeting energy requirements may be of particular interest to local authorities and vehicle manufacturers, since understanding this concept is key to implementing sustainable electric vehicle fleets. Additionally, the investigation summaries also further clarified the challenges posed by the decarbonisation of the transport and automotive industry sectors. Furthermore, the model developed and utilised for the purposes of simulating vehicle energy consumption employed by the investigations represents a novel application of model-based programming through usage of commonly used software tools. Similarly, investigations looking at the energy consumption of eRCVs, eBuses and eMotorbikes, based on simulated estimates have been presented. These include comparing the produced carbon footprint and incurred costs of conventional ICE fleets to electric alternatives. Finally, the limitations of the proposed software simulation model have also been assessed through stress-testing simulations that aim to predict the energy usage of a high-performance, motorsport-spec electric motorbike performing high-speed laps around a racetrack. The research presented in these chapters demonstrate how research aim 3 and its objectives, related to energy usage estimation through software modelling, has been achieved.

In chapter 7, an example of how the energy usage investigations can be further employed to create more complex systems, such as a range extension method for eHGVs. This relies on usage of battery cells modelled as pallet loads in order to facilitate loading and unloading. Similarly, practical considerations regarding system implementation and costs have been presented. The findings presented in chapter 7 fulfil research aim 4 and the related objectives concerning how energy usage investigations can be further used as a basis towards building more complex battery-based, EV range extender systems.

Broadly, the findings presented in this thesis suggest that, if implemented correctly, albeit highly dependent on the energy source production, urban areas can successfully benefit from the deployment of electric alternatives to public service vehicles. A similar conclusion is also reached when considering lightweight vehicles. The reduction of localised CO_2 footprints proven by the carried-out analyses will not only help in minimising the total emitted carbon dioxide, but also improve local air quality, as demonstrated by previous studies [42]. This is also likely to have beneficial effects on the population's overall health, consequentially minimising public funds directed towards curing respiratory conditions [290]. From a cost-driven perspective, upfront vehicle costs for electric motor vehicles will be higher than ICE solutions across every vehicle category. This is mostly due to the costs incurred by the battery systems, as battery technology is still relatively expensive. However, due to significantly lower running and maintenance costs of EVs, it is expected that the overall lifetime vehicle costs will be lower for the electric vehicle alternatives. Furthermore, as battery technology evolves, battery material pricing will likely decrease, therefore lowering the upfront costs of electric vehicles.

Although the findings outlined in this thesis will add more consistency to answering questions concerning electric vehicle energy requirements, plenty of opportunities for future work exist. These may be focused on optimising the presented toolkit and expanding on the outlined investigations, but also implementing novel ideas on top of the presented results and benchmarking other vehicle technologies, adding more complexity in the analyses.

8.1. Vehicle Model & Route Builder – Future Improvement Opportunities

The presented solution model described in chapters 3 and 4 of this thesis consists of two elements. The first one is a model-based programming electric vehicle model developed in the Matlab environment, whilst the second element is represented by a suite of Python-coded scripts that build vehicle driving routes using Application Programming Interface (API) data and mathematical approximations. Whilst both parts of the solution have been developed using modern, state-of-the-art tooling, the capabilities of the employed toolkit have evolved significantly since the model development process.

There are several potential improvements that could be made to the vehicle model through implementing newer software design components. Firstly, the current PID-based control module that handles the vehicle model's system response to the telemetry input data may be swapped with a metaheuristic control module, such as a neural network-based one. Whilst the control error exhibited by the original PID control module has been considered acceptable, a non-deterministic algorithm approach may bring further accuracy improvements to the system response. However, it must be ensured that the algorithm is trained employing a significant amount of data beforehand, which may prove difficult to acquire. Nonetheless, use of a non-deterministic algorithm for controlling the vehicle model's response also implies the possibility of having simulation results with some variability between iterations. These may then be compared in order to determine how the vehicle technical specification may be further optimised.

Other potential improvement areas may lie in the vehicle aerodynamic and transmission modelling. Further complexity may be added to the gearbox and braking systems that should lead to a decrease in overall prediction error. Additionally, the tyre modelling within the presented software model can be improved by changing the modelling approach to a fixed, specification-based one, as opposed to utilising the Magic Tyre Formula coefficients. Finally, model usage can be simplified by implementing an automatic data import script that streamlines the simulation process.

Similarly, further improvements may be brought to the route builder script suite as well. Time execution can be further optimised by investigating the code and eliminating any redundant control flow elements, such as "for" loops. Additionally, both time and space constraints of the computation can be reduced by ensuring data is computed or acquired only once. Further accuracy benefits may be brought by implementing more refined mathematical approximations to the calculations, such as Simpson's rule. Finally, a potential research opportunity may lie in implementing machine learning-based route algorithms, as these may be able to provide better routing solutions than traditional numerical methods applied to point-to-point distances. A good starting point is represented by algorithms commonly used in solving travelling salesman problem (TSP)-like situations, such as Dijkstra's algorithm or A* [239].

8.2. Energy Usage Investigations – Limitations and Opportunities

The featured energy investigations presented in this thesis cover a wide range of vehicle categories and explore several driving contexts for some of them, such as urban and motorway driving. However, the current findings may be expanded by performing more refined, low-level investigations. While this thesis describes the expected energy usage of an eRCV when performing refuse collection, understanding energy consumption during normal driving is also key to having a better estimation of the energy requirements of this type of vehicle. Additionally, similar investigations could be performed for other types of vehicles with similar daily driving route patters, such as delivery vans. Due to the COVID-19 pandemic and the governmental measures taken, home deliveries with just-in-time characteristics have gained significant popularity. Consequentially, the delivery fleets of large corporations have expanded, therefore understanding the amount of energy utilised by electric alternatives to these vehicles would help to further answer energy requirement questions. Additionally, these fleets may also be utilised as grid support systems during peak demand hours for the energy grid, in a similar fashion to the system hypothesised employing eRCV fleets, effectively integrating a vehicle-to-grid (V2G) concept within the urban transportation. In order to facilitate this integration, studies concerning urban energy requirements and how these relate to the energy grid capacity should be undertaken.

Similarly, although the telemetry data employed for analysing energy consumption of road-legal eBikes (presented in chapter 6) relies on emission testing driving cycles throughout the world, real-life telemetry should further aid in clarifying inconsistencies. Harvesting telemetry data is relatively straightforward from a technological standpoint, as telemetry collection code modules can be easily integrated as software background service workers in mobile apps. These are already extensively used by eBike drivers who perform on-demand delivery services in the gig economy, as they are sometimes required to be connected to the delivery schedule handling app. Additionally, such a data collection feature is already likely in place in some GPS/Navigation mobile apps used worldwide, therefore large corporations may already have access to large amounts of telemetry data produced by eBikes that are currently in operation. This data may also prove to be useful for further refining potential analyses concerned with estimating energy usage of delivery vehicles. The investigations revolving around this may be targeted to fleet energy consumption usage and integrating these with localised power generation, such as depot-installed solar panels [291].

Besides performing investigations of different driving scenarios for various electric vehicle categories and comparing them against their conventional ICE counterparts, other alternative powertrain solutions may also be considered. The literature review presented in chapter 2 suggests that some of the current solutions currently under development, such as hydrogen combustion-powered vehicles may prove feasible alternatives in the long run as well, with the appropriate adjustments. As technology evolves, it is likely that hydrogen-based solutions may prove serious competitors to electric powertrains in specific application driving scenarios, once the technology has matured to the level of electric powertrains. Similarly, ICE powertrains may be considered as a viable option if net-zero methanol-based fuels and other synthetic fuel options advance beyond initial research and development investigations and go into production. These still have the advantage of having the ability to employ current refuelling infrastructure with minimal adaptations. However, a full comparison is yet to be determined by the scientific community and goes beyond the scope of this thesis.

8.3. EHGV Battery Swapping Concept – Limitations & Opportunities

Whilst the battery swap concept presented in this thesis under chapter 7 may show promise, further research is required in order to determine its full potential. The limitations of the presented research include a lack of concrete technical vehicle specification data. This has affected the accuracy of the energy usage predictions. Moreover, the current telemetry that has been analysed is limited to one driving cycle. Furthermore, the research only considers present battery technology without having a projection for new-gen battery technologies, which are expected to have higher volumetric and weight capacities.

Future research into this topic may be directed towards several aspects. Firstly, in order to refine the cost analysis and fully determine the total upfront costs of the installations, an investigation looking into determining the number of battery packs that should be in use simultaneously should be considered. This will likely depend on key logistic performance metrics, such as the total amount of cargo transported by road during a set time interval and the number of HGVs presently in use in the UK (or the geographical area in question) [277]. Similarly, in order to determine what a final battery pack specification should look like, statistics concerning the transportation trip lengths and a distance-based classification of these should be considered. Finally, in order to determine the optimal share between battery pack sizes at a given location, consideration towards the distance from that point to the cargo's final destination should be given. Although organising the data required for this type of investigation may prove a challenge in itself, modern data clean-up and classification software tools should simplify the process significantly. Moreover, plenty of the data indicators previously mentioned are likely to already be known through statistics gathered by transportation-focused organisations such as existing freight transport operators.

Secondly, the initial feasibility analysis may benefit from including more data in the energy consumption analysis. These should include telemetry data originating from HGV-specific emission testing driving cycles, as well as real-life transportation. This should help in fully understanding how eHGV energy consumption varies in different road or cargo load conditions. Furthermore, some vehicle technical specifications may then be further optimised for battery swapping concepts based on simulation findings. For example, the sizing of the vehicle integrated battery could be minimised, as it may be determined that excess electrical capacity is not required. This will in turn decrease the base vehicle energy consumption due to the base vehicle mass being smaller.

Additionally, research looking into the business models required for implementing the concept should be considered. There are several options for this – originating from the private and the public sector. The concept may be integrated as part of government schemes targeting transport sector decarbonisation. Similarly, a tier-based subscription service fee may be applied based on a time interval or a battery pack unit basis. This will also aid in attenuating some costs attributed to system maintenance.

The charging aspect of the concept should also be considered. Understanding whether current EV charging interfaces and standards are feasible for the purposes of charging the battery packs should be investigated. Alternatively, slow, grid-compatible charging using regular power outlets may be implemented depending on the usage of a given battery swapping station. This will have a beneficial long-term effect on battery health, extending the life of battery units.

Finally, the concept's logistic aspects will have to be investigated. These include a system that transports battery packs between locations, effectively re-balancing the geographical supply of battery packs. This may be implemented using a separate vehicle fleet or as an incentive-based system for freight companies willing to deliver packs to a given set of locations. However, a more refined feasibility analysis is required in order to determine the optimal solution.

8.4. Final Summary

The findings presented in this thesis indicate key observations related to the energy consumption of various electric vehicle categories. Moreover, it is demonstrated that electric vehicle fleet alternatives to commonly used ICE vehicles have the capability of being more economical and environmentally friendly, from a tailpipe emission perspective. Finally, the presented analyses open significant research opportunities that will further refine the picture of decarbonisation in the transport sector through powertrain electrification and clarify the role of EV technology in the transportation industry, along with other eco-friendly alternatives.

References

[1] M. A. Delucchi, “A Multi-Country Analysis of Lifecycle Emissions From Transportation Fuels and Motor Vehicles.” 01-May-2005.

[2] “Reducing CO2 emissions from heavy-duty vehicles | Climate Action.” [Online]. Available: https://ec.europa.eu/clima/policies/transport/vehicles/heavy_en. [Accessed: 28-Apr-2020].

[3] M. Noori and O. Tatari, “Development of an agent-based model for regional market penetration projections of electric vehicles in the United States,” *Energy*, vol. 96, pp. 215–230, 2016.

[4] E. Shafiei, H. Thorkelsson, E. I. Ásgeirsson, B. Davidsdottir, M. Raberto, and H. Stefansson, “An agent-based modeling approach to predict the evolution of market share of electric vehicles: A case study from Iceland,” *Technol. Forecast. Soc. Change*, vol. 79, no. 9, pp. 1638–1653, 2012.

[5] “Evidence | Facts – Climate Change: Vital Signs of the Planet.” [Online]. Available: https://climate.nasa.gov/evidence/. [Accessed: 10-Apr-2020].

[6] E. R. Khairullina *et al.*, “Global climate change: cyclical nature of natural and permanent nature of man-made processes,” *EurAsian J. Biosci. Eurasia J Biosci*, vol. 13, pp. 2311–2316, 2019.

[7] National Geographic, “Greenhouse Effect.” [Online]. Available: https://education.nationalgeographic.org/resource/greenhouse-effect/. [Accessed: 03-Mar-2023].

[8] “5 Notorious Greenhouse Gases | Britannica.” [Online]. Available: https://www.britannica.com/list/5-notorious-greenhouse-gases. [Accessed: 23-Feb-2023].

[9] D. M. Etheridge, L. P. Steele, R. L. Langenfelds, R. J. Francey, J. M. Barnola, and V. I. Morgan, “Global Monitoring Laboratory - Carbon Cycle Greenhouse Gases,” *J. Geophys. Res. Atmos.*, vol. 101, no. D2, pp. 4115–4128, 1996.

[10] N. Unger, D. T. Shindell, D. M. Koch, M. Amann, J. Cofala, and D. G. Streets, “Influences of man-made emissions and climate changes on tropospheric ozone, methane, and sulfate at 2030 from a broad range of possible futures,” *J. Geophys. Res. Atmos.*, vol. 111, no. D12, p. 12313, Jun. 2006.

[11] “The Paris Agreement | UNFCCC.” [Online]. Available: https://unfccc.int/process-and-meetings/the-paris-agreement/the-paris-agreement. [Accessed: 19-Jan-2023].

[12] “Transport – Topics - IEA.” [Online]. Available: https://www.iea.org/topics/transport. [Accessed: 18-May-2020].

[13] UK Department for Transport, “National Travel Survey Motorcycle use in England,” 2017.

[14] “Internal Combustion Engine Basics | Department of Energy.” [Online]. Available: https://www.energy.gov/eere/vehicles/articles/internal-combustion-engine-basics. [Accessed: 19-Jan-2023].

[15] S. Küfeoğlu and D. Khah Kok Hong, “Emissions performance of electric vehicles: A case study from the United Kingdom,” *Appl. Energy*, vol. 260, p. 114241, Feb. 2020.

[16] T. Denton, *Electric and Hybrid vehicles*. Routledge, 2016.

[17] Z. Shahan, *1 Million Pure EVs Worldwide: EV Revolution Begins!* Clean Technica, 2016.

[18] M. Roser and H. Ritchie, “Technological Progress,” *Our World Data*, May 2013.

[19] B. G. Buchanan, “A (Very) Brief History of Artificial Intelligence,” *AI Mag.*, pp. 53–60, 2005.

[20] G. Klink, M. Mathur, R. Kidambi, and K. Sen, “Contribution of The Automobile Industry to Technology and Value Creation,” *Auto Tech Rev. 2014 37*, vol. 3, no. 7, pp. 18–23, Jul. 2014.

[21] The World Bank, “GDP (current US$) | Data.” [Online]. Available: https://data.worldbank.org/indicator/NY.GDP.MKTP.CD. [Accessed: 05-Dec-2022].

[22] European Commission, “The 2021 EU Industrial R&D Investment Scoreboard,” 2021.

[23] W. W. Bottorf, “The First Car - A History of the Automobile.” [Online]. Available: https://web.archive.org/web/20110716152705/http://www.ausbcomp.com/~bbott/cars/carhist.htm. [Accessed: 05-Dec-2022].

[24] OICA, “Production Statistics.” [Online]. Available: https://www.oica.net/production-statistics/. [Accessed: 05-Dec-2022].

[25] World Economic Forum, “Automotive Statistics.” [Online]. Available: https://www.weforum.org/communities/automotive. [Accessed: 05-Dec-2022].

[26] UK Department for Business & Energy, “Final UK greenhouse gas emissions national statistics: 1990 to 2019 - GOV.UK,” *Final UK greenhouse gas emissions national statistics*, 2019. [Online]. Available: https://www.gov.uk/government/statistics/final-uk-greenhouse-gas-emissions-national-statistics-1990-to-2019. [Accessed: 03-Mar-2023].

[27] EUROSTAT, “Greenhouse gas emission statistics - air emissions accounts - Statistics Explained,” *Greenhouse gas emission statistics - air emissions accounts*. [Online]. Available:

https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Greenhouse_gas_emission_statistics_-_air_emissions_accounts. [Accessed: 03-Mar-2023].
[28] K. Aguirre *et al.*, "Lifecycle Analysis Comparison of a Battery Electric Vehicle and a Conventional Gasoline Vehicle," 2012.
[29] US EPA, "Learn About Green Vehicles | US EPA." [Online]. Available: https://www.epa.gov/greenvehicles/learn-about-green-vehicles. [Accessed: 30-May-2022].
[30] S. C. Davis and R. G. Boundy, "Transportation Energy Data Book: Edition 40."
[31] US EPA, "Sources of Greenhouse Gas Emissions." [Online]. Available: https://www.epa.gov/ghgemissions/sources-greenhouse-gas-emissions. [Accessed: 05-Dec-2022].
[32] "Global historical CO2 emissions 1750-2020 | Statista." [Online]. Available: https://www.statista.com/statistics/264699/worldwide-co2-emissions/. [Accessed: 05-Dec-2022].
[33] "Global transport CO2 emissions 1970-2020 | Statista." [Online]. Available: https://www.statista.com/statistics/1291615/carbon-dioxide-emissions-transport-sector-worldwide/. [Accessed: 05-Dec-2022].
[34] "The History of Electric Vehicles Began in 1830." [Online]. Available: https://www.thoughtco.com/history-of-electric-vehicles-1991603. [Accessed: 23-Feb-2023].
[35] Z. Yang, J. Tate, E. Morganti, I. Philips, and S. Shepherd, "How accelerating the electrification of the van sector in Great Britain can deliver faster CO2 and NOx reductions," *Sustain. Cities Soc.*, vol. 88, p. 104300, Jan. 2023.
[36] C. W. Su, X. Yuan, R. Tao, and M. Umar, "Can new energy vehicles help to achieve carbon neutrality targets?," *J. Environ. Manage.*, vol. 297, Nov. 2021.
[37] X. Yuan, L. Li, H. Gou, and T. Dong, "Energy and environmental impact of battery electric vehicle range in China," *Appl. Energy*, vol. 157, pp. 75–84, Nov. 2015.
[38] Clean Energy Wire, "Germany's greenhouse gas emissions and energy transition targets." [Online]. Available: https://www.cleanenergywire.org/factsheets/germanys-greenhouse-gas-emissions-and-climate-targets. [Accessed: 06-Dec-2022].
[39] UK Government, "Transport and environment statistics," *2022*. [Online]. Available: https://www.gov.uk/government/statistics/transport-and-environment-statistics-2022/transport-and-environment-statistics-2022. [Accessed: 18-Nov-2022].
[40] R. Kawamoto *et al.*, "Estimation of CO2 Emissions of Internal Combustion Engine Vehicle and Battery Electric Vehicle Using LCA," *Sustain. 2019, Vol. 11, Page 2690*, vol. 11, no. 9, p. 2690, May 2019.
[41] Q. Qiao, F. Zhao, Z. Liu, S. Jiang, and H. Hao, "Comparative Study on Life Cycle CO2 Emissions from the Production of Electric and Conventional Vehicles in China," *Energy Procedia*, vol. 105, pp. 3584–3595, May 2017.
[42] K. J. Dillman, Á. Árnadóttir, J. Heinonen, M. Czepkiewicz, and B. Davíðsdóttir, "Review and Meta-Analysis of EVs: Embodied Emissions and Environmental Breakeven," *Sustain. 2020, Vol. 12, Page 9390*, vol. 12, no. 22, p. 9390, Nov. 2020.
[43] I. Dolganova, A. Rödl, V. Bach, M. Kaltschmitt, and M. Finkbeiner, "A review of life cycle assessment studies of electric vehicles with a focus on resource use," *Resources*, vol. 9, no. 3, Mar. 2020.
[44] A. Beaudet, F. Larouche, K. Amouzegar, P. Bouchard, and K. Zaghib, "Key Challenges and Opportunities for Recycling Electric Vehicle Battery Materials," *Sustain. 2020, Vol. 12, Page 5837*, vol. 12, no. 14, p. 5837, Jul. 2020.
[45] J. Larminie and J. Lowry, *Electric Vehicle Techonology Explained*. 2012.
[46] C. Thiel, W. Nijs, S. Simoes, J. Schmidt, A. van Zyl, and E. Schmid, "The impact of the EU car CO2 regulation on the energy system and the role of electro-mobility to achieve transport decarbonisation," *Energy Policy*, vol. 96, pp. 153–166, Sep. 2016.
[47] J. C. González Palencia, T. Sakamaki, M. Araki, and S. Shiga, "Impact of powertrain electrification, vehicle size reduction and lightweight materials substitution on energy use, CO2 emissions and cost of a passenger light-duty vehicle fleet," *Energy*, vol. 93, pp. 1489–1504, 2015.
[48] J. C. González Palencia, T. Furubayashi, and T. Nakata, "Techno-economic assessment of lightweight and zero emission vehicles deployment in the passenger car fleet of developing countries," *Appl. Energy*, vol. 123, pp. 129–142, 2014.
[49] "Japan 2050 Low Carbon Navigator." [Online]. Available: http://www.2050-low-carbon-navi.jp/web/en/overview.html. [Accessed: 28-Apr-2020].
[50] C. Juan, "ScienceDirect Energy consumption and CO 2 emissions reduction potential of vehicle diffusion in a road freight vehicle fleet a ,* using the heat Assessing the feasibility of temperature

function a long-term district heat demand forecast," *Energy Procedia*, vol. 142, pp. 2936–2941, 2017.
[51] P. Z. Lévay, Y. Drossinos, and C. Thiel, "The effect of fiscal incentives on market penetration of electric vehicles: A pairwise comparison of total cost of ownership," *Energy Policy*, vol. 105, pp. 524–533, Jun. 2017.
[52] F. Duffner, M. Wentker, M. Greenwood, and J. Leker, "Battery cost modeling: A review and directions for future research," *Renew. Sustain. Energy Rev.*, vol. 127, p. 109872, Jul. 2020.
[53] P. Weldon, P. Morrissey, and M. O'Mahony, "Long-term cost of ownership comparative analysis between electric vehicles and internal combustion engine vehicles," *Sustain. Cities Soc.*, vol. 39, pp. 578–591, May 2018.
[54] "Plug-in car, van and truck grant to be targeted at more affordable models to allow more people to make the switch - GOV.UK." [Online]. Available: https://www.gov.uk/government/news/plug-in-car-van-and-truck-grant-to-be-targeted-at-more-affordable-models-to-allow-more-people-to-make-the-switch. [Accessed: 23-Feb-2023].
[55] IEA, "Global EV Outlook 2016: beyond one million electric cars," 2016.
[56] I. López, E. Ibarra, A. Matallana, J. Andreu, and I. Kortabarria, "Next generation electric drives for HEV/EV propulsion systems: Technology, trends and challenges," *Renew. Sustain. Energy Rev.*, vol. 114, p. 109336, Oct. 2019.
[57] S. R. Shakya and R. M. Shrestha, "Transport sector electrification in a hydropower resource rich developing country: Energy security, environmental and climate change co-benefits," *Energy Sustain. Dev.*, vol. 15, no. 2, pp. 147–159, Jun. 2011.
[58] "Conflict in Ukraine | Global Conflict Tracker." [Online]. Available: https://www.cfr.org/global-conflict-tracker/conflict/conflict-ukraine. [Accessed: 12-Dec-2022].
[59] B. McWilliams, G. Sgaravatti, S. Tagliapietra, and G. Zachmann, "A grand bargain to steer through the European Union's energy crisis," *Policy Contrib.*, no. 14, 2022.
[60] S. Manzetti and F. Mariasiu, "Electric vehicle battery technologies: From present state to future systems," *Renew. Sustain. Energy Rev.*, vol. 51, pp. 1004–1012, Jul. 2015.
[61] T. R. Hawkins, B. Singh, G. Majeau-Bettez, and A. H. Strømman, "Comparative Environmental Life Cycle Assessment of Conventional and Electric Vehicles," *J. Ind. Ecol.*, vol. 17, no. 1, pp. 53–64, 2013.
[62] K. Young, C. Wang, L. Y. Wang, and K. Strunz, "Electric vehicle battery technologies," *Electr. Veh. Integr. into Mod. Power Networks*, pp. 15–56, Jan. 2013.
[63] M. Park, H. Sun, H. Lee, J. Lee, and J. Cho, "Lithium-Air Batteries: Survey on the Current Status and Perspectives Towards Automotive Applications from a Battery Industry Standpoint," *Adv. Energy Mater.*, vol. 2, no. 7, pp. 780–800, Jul. 2012.
[64] H.-F. Wang, X.-X. Wang, F. Li, and J.-J. Xu, "Fundamental Understanding and Construction of Solid-State Li−Air Batteries," *Small Sci.*, vol. 2, no. 5, p. 2200005, May 2022.
[65] J. V. P. S. Chennu, R. Maheshwari, and H. Li, "New Resonant Gate Driver Circuit for High-Frequency Application of Silicon Carbide MOSFETs," *IEEE Trans. Ind. Electron.*, vol. 64, no. 10, pp. 8277–8287, Oct. 2017.
[66] J. Zhang, H. Wu, J. Zhao, Y. Zhang, and Y. Zhu, "A Resonant Gate Driver for Silicon Carbide MOSFETs," *IEEE Access*, vol. 6, pp. 78394–78401, 2018.
[67] A. Letellier, M. R. Dubois, J. P. Trovao, and H. Maher, "Gallium Nitride Semiconductors in Power Electronics for Electric Vehicles: Advantages and Challenges," *2015 IEEE Veh. Power Propuls. Conf. VPPC 2015 - Proc.*, Dec. 2015.
[68] F. Rahmani, P. Niknejad, T. Agarwal, and M. Barzegaran, "Gallium Nitride Inverter Design with Compatible Snubber Circuits for Implementing Wireless Charging of Electric Vehicle Batteries," *Mach. 2020, Vol. 8, Page 56*, vol. 8, no. 3, p. 56, Sep. 2020.
[69] R. Collin, Y. Miao, A. Yokochi, P. Enjeti, and A. Von Jouanne, "Advanced Electric Vehicle Fast-Charging Technologies," *Energies 2019, Vol. 12, Page 1839*, vol. 12, no. 10, p. 1839, May 2019.
[70] N. Trivedi, N. S. Gujar, S. Sarkar, and S. P. S. Pundir, "Different fast charging methods and topologies for EV charging," *2018 IEEMA Eng. Infin. Conf. eTechNxT 2018*, pp. 1–5, Jun. 2018.
[71] A. Schroeder and T. Traber, "The economics of fast charging infrastructure for electric vehicles," *Energy Policy*, vol. 43, pp. 136–144, Apr. 2012.
[72] N. Wassiliadis *et al.*, "Review of fast charging strategies for lithium-ion battery systems and their applicability for battery electric vehicles," *J. Energy Storage*, vol. 44, p. 103306, Dec. 2021.
[73] B. Bose, A. Garg, B. K. Panigrahi, and J. Kim, "Study on Li-ion battery fast charging strategies: Review, challenges and proposed charging framework," *J. Energy Storage*, vol. 55, p. 105507, Nov. 2022.
[74] Z. B. Omariba, L. Zhang, and D. Sun, "Review on Health Management System for Lithium-Ion Batteries

of Electric Vehicles," *Electron. 2018, Vol. 7, Page 72*, vol. 7, no. 5, p. 72, May 2018.
[75] M. S. H. Lipu *et al.*, "A review of state of health and remaining useful life estimation methods for lithium-ion battery in electric vehicles: Challenges and recommendations," *J. Clean. Prod.*, vol. 205, pp. 115–133, Dec. 2018.
[76] M. J. Kim, S. H. Chae, and Y. K. Moon, "Adaptive Battery State-of-Charge Estimation Method for Electric Vehicle Battery Management System," *Proc. - Int. SoC Des. Conf. ISOCC 2020*, pp. 288–289, Oct. 2020.
[77] A. P. Talie, W. A. Pribyl, and G. Hofer, "Electric Vehicle Battery Management System Using Power Line Communication Technique," *PRIME 2018 - 14th Conf. Ph.D. Res. Microelectron. Electron.*, pp. 225–228, Aug. 2018.
[78] M. Wikström, L. Eriksson, and L. Hansson, "Introducing plug-in electric vehicles in public authorities," *Res. Transp. Bus. Manag.*, vol. 18, pp. 29–37, 2016.
[79] D. Margaritis, A. Anagnostopoulou, A. Tromaras, and M. Boile, "Electric commercial vehicles: Practical perspectives and future research directions," *Res. Transp. Bus. Manag.*, vol. 18, pp. 4–10, 2016.
[80] A. M. Bazzi, "Electric machines and energy storage technologies in EVs and HEVs for over a century," *Proc. 2013 IEEE Int. Electr. Mach. Drives Conf. IEMDC 2013*, pp. 212–219, 2013.
[81] Y. Guan, Z. Q. Zhu, I. A. A. Afinowi, J. C. Mipo, and P. Farah, "Difference in maximum torque-speed characteristics of induction machine between motor and generator operation modes for electric vehicle application," *Proc. - 2014 Int. Conf. Electr. Mach. ICEM 2014*, pp. 130–136, Nov. 2014.
[82] S. Morimoto, S. Ooi, Y. Inoue, and M. Sanada, "Experimental evaluation of a rare-earth-free PMASynRM with ferrite magnets for automotive applications," *IEEE Trans. Ind. Electron.*, vol. 61, no. 10, pp. 5749–5756, 2014.
[83] W. Ding, S. Yang, Y. Hu, S. Li, T. Wang, and Z. Yin, "Design Consideration and Evaluation of a 12/8 High-Torque Modular-Stator Hybrid Excitation Switched Reluctance Machine for EV Applications," *IEEE Trans. Ind. Electron.*, vol. 64, no. 12, pp. 9221–9232, Dec. 2017.
[84] T. Finken, M. Felden, and K. Hameyer, "Comparison and design of different electrical machine types regarding their applicability in hybrid electrical vehicles," *Proc. 2008 Int. Conf. Electr. Mach. ICEM'08*, 2008.
[85] Y. B. Khoo, C. H. Wang, P. Paevere, and A. Higgins, "Statistical modeling of Electric Vehicle electricity consumption in the Victorian EV Trial, Australia," *Transp. Res. Part D Transp. Environ.*, vol. 32, pp. 263–277, Oct. 2014.
[86] K. Qian, C. Zhou, M. Allan, and Y. Yuan, "Modeling of load demand due to EV battery charging in distribution systems," *IEEE Trans. Power Syst.*, vol. 26, no. 2, pp. 802–810, May 2011.
[87] "Reducing emissions from road transport: Road to Zero Strategy - GOV.UK." [Online]. Available: https://www.gov.uk/government/publications/reducing-emissions-from-road-transport-road-to-zero-strategy. [Accessed: 03-Oct-2022].
[88] H. S. Das, M. M. Rahman, S. Li, and C. W. Tan, "Electric vehicles standards, charging infrastructure, and impact on grid integration: A technological review," *Renew. Sustain. Energy Rev.*, vol. 120, p. 109618, Mar. 2020.
[89] T. Niels, M. Gerstenberger, K. Bogenberger, C. Hessel, A. Gigl, and K. Wagner, "Model-based optimization of public charging infrastructure planning in rural areas," *Transp. Res. Procedia*, vol. 41, pp. 342–353, Jan. 2019.
[90] S. Lasisi, U. Inyang-Udoh, O. T. Olakoyejo, E. O. B. Ogedengbe, O. G. Awosanya, and S. M. Abolarin, "Operational classification of torrefied biomass in a gasifier as an alternative source of electricity for ev charging station," *AIAA Propuls. Energy 2020 Forum*, pp. 1–25, 2020.
[91] T. Chen *et al.*, "A Review on Electric Vehicle Charging Infrastructure Development in the UK," *J. Mod. Power Syst. Clean Energy*, vol. 8, no. 2, pp. 193–205, Mar. 2020.
[92] J. Dixon, P. B. Andersen, K. Bell, and C. Træholt, "On the ease of being green: An investigation of the inconvenience of electric vehicle charging," *Appl. Energy*, vol. 258, p. 114090, Jan. 2020.
[93] P. Jin, "Micro-grid System in Auxiliary Power System of Substation," *Adv. Intell. Syst. Comput.*, vol. 1058, pp. 1065–1071, 2020.
[94] H. Qin, X. Su, T. Ren, and Z. Luo, "A review on the electric vehicle routing problems: Variants and algorithms," *Front. Eng. Manag. 2021 83*, vol. 8, no. 3, pp. 370–389, May 2021.
[95] R. Abousleiman and O. Rawashdeh, "Energy-efficient routing for electric vehicles using metaheuristic optimization frameworks," *Proc. Mediterr. Electrotech. Conf. - MELECON*, no. April, pp. 298–304, 2014.
[96] R. Abousleiman and O. Rawashdeh, "Electric vehicle modelling and energy-efficient routing using particle swarm optimization," *IET Intell. Transp. Syst.*, vol. 10, no. 2, pp. 65–72, 2016.
[97] R. Abousleiman and O. Rawashdeh, "An application of ant colony optimization to energy efficient

routing for electric vehicles," *SAE Tech. Pap.*, vol. 2, 2013.
[98] R. Abousleiman and O. Rawashdeh, "Tabu search based solution to the electric vehicle energy efficient routing problem," *2014 IEEE Transp. Electrif. Conf. Expo Components, Syst. Power Electron. - From Technol. to Bus. Public Policy, ITEC 2014*, pp. 1–6, 2014.
[99] R. Abousleiman and O. Rawashdeh, "A bellman-ford approach to energy efficient routing of electric vehicles," *2015 IEEE Transp. Electrif. Conf. Expo, ITEC 2015*, pp. 1–4, 2015.
[100] "Google Maps can now pick the most efficient route for EVs | Ars Technica." [Online]. Available: https://arstechnica.com/gadgets/2022/09/google-maps-can-now-pick-the-most-efficient-route-for-evs/. [Accessed: 15-Dec-2022].
[101] T. M. Aljohani, A. Ebrahim, and O. Mohammed, "Real-Time metadata-driven routing optimization for electric vehicle energy consumption minimization using deep reinforcement learning and Markov chain model," *Electr. Power Syst. Res.*, vol. 192, p. 106962, Mar. 2021.
[102] "Mapping Toolbox - MATLAB." [Online]. Available: https://uk.mathworks.com/products/mapping.html. [Accessed: 10-Apr-2020].
[103] O. Erdinç, K. Yetilmezsoy, A. K. Erenoğlu, and O. Erdinç, "Route optimization of an electric garbage truck fleet for sustainable environmental and energy management," *J. Clean. Prod.*, vol. 234, pp. 1275–1286, 2019.
[104] D. D. Eisenstein, A. V Iyer, D. D. Eisenstein, and A. V Iyer, "Garbage Collection in Chicago: A Dynamic Scheduling Model," vol. 43, no. 7, pp. 922–933, 2017.
[105] A. Triviño-Cabrera, J. A. Aguado, and S. de la Torre, "Joint routing and scheduling for electric vehicles in smart grids with V2G," *Energy*, vol. 175, pp. 113–122, May 2019.
[106] J. Barco, A. Guerra, L. Muñoz, and N. Quijano, "Optimal Routing and Scheduling of Charge for Electric Vehicles: A Case Study," *Math. Probl. Eng.*, vol. 2017, 2017.
[107] T. Franke and J. F. Krems, "Interacting with limited mobility resources: Psychological range levels in electric vehicle use," *Transp. Res. Part A Policy Pract.*, vol. 48, pp. 109–122, Feb. 2013.
[108] Z. Rezvani, J. Jansson, and J. Bodin, "Advances in consumer electric vehicle adoption research: A review and research agenda," *Transp. Res. Part D Transp. Environ.*, vol. 34, pp. 122–136, Jan. 2015.
[109] L. Noel, G. Zarazua de Rubens, B. K. Sovacool, and J. Kester, "Fear and loathing of electric vehicles: The reactionary rhetoric of range anxiety," *Energy Res. Soc. Sci.*, vol. 48, pp. 96–107, Feb. 2019.
[110] N. S. Pearre, W. Kempton, R. L. Guensler, and V. V. Elango, "Electric vehicles: How much range is required for a day's driving?," *Transp. Res. Part C Emerg. Technol.*, vol. 19, no. 6, pp. 1171–1184, Dec. 2011.
[111] S. Saxena, C. Le Floch, J. Macdonald, and S. Moura, "Quantifying EV battery end-of-life through analysis of travel needs with vehicle powertrain models," *J. Power Sources*, vol. 282, pp. 265–276, May 2015.
[112] L. Zhang, B. Shaffer, T. Brown, and G. Scott Samuelsen, "The optimization of DC fast charging deployment in California," *Appl. Energy*, vol. 157, pp. 111–122, Nov. 2015.
[113] J. Neubauer and E. Wood, "The impact of range anxiety and home, workplace, and public charging infrastructure on simulated battery electric vehicle lifetime utility," *J. Power Sources*, vol. 257, pp. 12–20, Jul. 2014.
[114] N. Rauh, T. Franke, and J. F. Krems, "Understanding the Impact of Electric Vehicle Driving Experience on Range Anxiety," *https://doi.org/10.1177/0018720814546372*, vol. 57, no. 1, pp. 177–187, Aug. 2014.
[115] T. Franke, P. Cocron, F. Bühler, I. Neumann, and J. F. Krems, "ADAPTING TO THE RANGE OF AN ELECTRIC VEHICLE-THE RELATION OF EXPERIENCE TO SUBJECTIVELY AVAILABLE MOBILITY RESOURCES," pp. 95–103, 2012.
[116] Department of Energy, "Alternative Fuel Vehicles | Department of Energy." [Online]. Available: https://www.energy.gov/alternative-fuel-vehicles#/find/nearest?country=US. [Accessed: 22-Sep-2023].
[117] B. L. Salvi, K. A. Subramanian, and N. L. Panwar, "Alternative fuels for transportation vehicles: A technical review," *Renew. Sustain. Energy Rev.*, vol. 25, pp. 404–419, Sep. 2013.
[118] S. Yeh, "An empirical analysis on the adoption of alternative fuel vehicles: The case of natural gas vehicles," *Energy Policy*, vol. 35, no. 11, pp. 5865–5875, Nov. 2007.
[119] M. Achtnicht, G. Bühler, and C. Hermeling, "The impact of fuel availability on demand for alternative-fuel vehicles," *Transp. Res. Part D Transp. Environ.*, vol. 17, no. 3, pp. 262–269, May 2012.
[120] J. Berghmans and M. Vanierschot, "Safety Aspects of CNG Cars," *Procedia Eng.*, vol. 84, pp. 33–46, Jan. 2014.
[121] IEA, "Evolution of average range of electric vehicles by powertrain, 2010-2021 – Charts – Data &

Statistics - IEA.” [Online]. Available: https://www.iea.org/data-and-statistics/charts/evolution-of-average-range-of-electric-vehicles-by-powertrain-2010-2021. [Accessed: 19-Dec-2022].
[122] C. Rizet, C. Cruz, and M. Vromant, “The Constraints of Vehicle Range and Congestion for the Use of Electric Vehicles for Urban Freight in France,” *Transp. Res. Procedia*, vol. 12, pp. 500–507, 2016.
[123] M. Qasim and C. Csiszár, “Major Barriers in Adoption of Electric Trucks in Logistics System,” *Promet - Traffic&Transportation*, vol. 33, no. 6, pp. 833–846, Dec. 2021.
[124] S. Hosseinpour, H. Chen, and H. Tang, “Barriers to the wide adoption of electric vehicles: A literature review based discussion,” *Portl. Int. Conf. Manag. Eng. Technol.*, vol. 2015-September, pp. 2329–2336, Sep. 2015.
[125] D. Nicolaides, D. Cebon, and J. Miles, “Prospects for Electrification of Road Freight,” *IEEE Syst. J.*, vol. 12, no. 2, pp. 1838–1849, Jun. 2018.
[126] I. Husain *et al.*, “Electric Drive Technology Trends, Challenges, and Opportunities for Future Electric Vehicles,” *Proc. IEEE*, vol. 109, no. 6, pp. 1039–1059, Jun. 2021.
[127] D. for Transport, “The Road to Zero Next steps towards cleaner road transport and delivering our Industrial Strategy,” 2018.
[128] H. Wang *et al.*, “Real-world carbon emissions evaluation for prefabricated component transportation by battery electric vehicles,” *Energy Reports*, vol. 8, pp. 8186–8199, Nov. 2022.
[129] E. Rosenberg, K. Espegren, J. Danebergs, L. Fridstrøm, I. Beate Hovi, and A. Madslien, “Modelling the interaction between the energy system and road freight in Norway,” *Transp. Res. Part D Transp. Environ.*, vol. 114, Jan. 2023.
[130] M. Tanco, L. Cat, and S. Garat, “A break-even analysis for battery electric trucks in Latin America,” *J. Clean. Prod.*, vol. 228, pp. 1354–1367, Aug. 2019.
[131] V. Cantillo, J. Amaya, I. Serrano, V. Cantillo-García, and J. Galván, “Influencing factors of trucking companies willingness to shift to alternative fuel vehicles,” *Transp. Res. Part E Logist. Transp. Rev.*, vol. 163, Jul. 2022.
[132] ITF, “ITF Transport Outlook 2019,” OECD, May 2019.
[133] C. Mueller, “A Qualitative Assessment of the Deployment of Zero-Emission Heavy-Duty Trucks in Logistics—Deriving Recommendations for Action from a Socio-Technical Approach on the Regional Level,” *Futur. Transp. 2023, Vol. 3, Pages 57-74*, vol. 3, no. 1, pp. 57–74, Jan. 2023.
[134] P. Bastida-Molina, E. Hurtado-Pérez, E. Peñalvo-López, and M. Cristina Moros-Gómez, “Assessing transport emissions reduction while increasing electric vehicles and renewable generation levels,” *Transp. Res. Part D Transp. Environ.*, vol. 88, p. 102560, Nov. 2020.
[135] M. Muratori *et al.*, “The rise of electric vehicles—2020 status and future expectations,” *Prog. Energy*, vol. 3, no. 2, p. 022002, Mar. 2021.
[136] M. K. Tran *et al.*, “A Review of Range Extenders in Battery Electric Vehicles: Current Progress and Future Perspectives,” *World Electr. Veh. J. 2021, Vol. 12, Page 54*, vol. 12, no. 2, p. 54, Apr. 2021.
[137] W. Ejaz and A. Anpalagan, “Internet of Things Enabled Electric Vehicles in Smart Cities,” pp. 39–46, 2019.
[138] Y. Wu and L. Zhang, “Can the development of electric vehicles reduce the emission of air pollutants and greenhouse gases in developing countries?,” *Transp. Res. Part D Transp. Environ.*, vol. 51, pp. 129–145, Mar. 2017.
[139] K. Itani, A. De Bernardinis, Z. Khatir, A. Jammal, and M. Oueidat, “Regenerative braking modeling, control, and simulation of a hybrid energy storage system for an electric vehicle in extreme conditions,” *IEEE Trans. Transp. Electrif.*, vol. 2, no. 4, pp. 465–479, 2016.
[140] ABB, “EV Charging | Electric Vehicle Chargers | ABB.” [Online]. Available: https://new.abb.com/ev-charging. [Accessed: 17-Jan-2021].
[141] T. Yabe, K. Akatsu, N. Okui, T. Niikuni, and T. Kawai, “Efficiency improvement of regenerative energy for an EV,” in *26th Electric Vehicle Symposium 2012*, 2012, vol. 1, pp. 634–640.
[142] “What is KERS? How It is used in Formula One? | Mechead.com.” [Online]. Available: http://www.mechead.com/kers-used-formula-1/. [Accessed: 17-Jan-2021].
[143] G. Orido, P. G. Ngunjiri, and D. M. Njue, “Exhaust Gases Energy Recovered from Internal Combustion Engine for Useful Applications,” *IOSR J. Mech. Civ. Eng.*, vol. 14, no. 03, pp. 01–07, Jun. 2017.
[144] P. Punov, T. Evtimov, R. Chiriac, A. Clenci, Q. Danel, and G. Descombes, “Progress in high performance, low emissions, and exergy recovery in internal combustion engines,” *Int. J. Energy Res.*, vol. 41, no. 9, pp. 1229–1241, Jul. 2017.
[145] “Reducing emissions from road transport: Road to Zero Strategy - GOV.UK.” [Online]. Available: https://www.gov.uk/government/publications/reducing-emissions-from-road-transport-road-to-zero-

strategy. [Accessed: 21-Jan-2021].
[146] K. Zhao, G. Dolan, and C. Chatterton, "A Brief Review on Methanol-Fuelled Vehicles (MFV) in China and Implementation Policy," *Energy, Environ. Sustain.*, pp. 139–159, 2021.
[147] M. A. Adnan, M. A. Khan, P. M. Ajayan, M. M. Rahman, J. Hu, and M. G. Kibria, "Transition pathways towards net-zero emissions methanol production," *Green Chem.*, vol. 23, no. 24, pp. 9844–9854, Dec. 2021.
[148] C. Li, M. Negnevitsky, and X. Wang, "Review of methanol vehicle policies in China: current status and future implications," *Energy Procedia*, vol. 160, pp. 324–331, Feb. 2019.
[149] "Drive Change with Renewable Methanol — CRI - Carbon Recycling International." [Online]. Available: https://www.carbonrecycling.is/products. [Accessed: 09-Jan-2023].
[150] "Porsche starts production of e-fuel that could provide gas alternative." [Online]. Available: https://www.cnbc.com/2022/12/20/porsche-starts-production-of-e-fuel-that-could-provide-gas-alternative.html. [Accessed: 09-Jan-2023].
[151] Y. Manoharan *et al.*, "Hydrogen Fuel Cell Vehicles; Current Status and Future Prospect."
[152] U. Khan, T. Yamamoto, and H. Sato, "Consumer preferences for hydrogen fuel cell vehicles in Japan," *Transp. Res. Part D Transp. Environ.*, vol. 87, p. 102542, Oct. 2020.
[153] M. Gurz, E. Baltacioglu, Y. Hames, and K. Kaya, "The meeting of hydrogen and automotive: A review," *Int. J. Hydrogen Energy*, vol. 42, no. 36, pp. 23334–23346, Sep. 2017.
[154] "Fuel Cell Cars: A Commercial Failure | IDTechEx Research Article." [Online]. Available: https://www.idtechex.com/en/research-article/fuel-cell-cars-a-commercial-failure/22155. [Accessed: 17-Jan-2021].
[155] G. D. Berry, A. D. Pasternak, G. D. Rambach, J. R. Smith, and R. N. Schock, "Hydrogen as a future transportation fuel," *Energy*, vol. 21, no. 4, pp. 289–303, Apr. 1996.
[156] A. Boretti, "Hydrogen internal combustion engines to 2030," *Int. J. Hydrogen Energy*, vol. 45, no. 43, pp. 23692–23703, Sep. 2020.
[157] "Toyota commissions Yamaha Motor to develop hydrogen-fueled engine." [Online]. Available: https://www.cnbc.com/2022/02/22/toyota-commissions-yamaha-motor-to-develop-hydrogen-fueled-engine.html. [Accessed: 09-Jan-2023].
[158] B. Helgeson and J. Peter, "The role of electricity in decarbonizing European road transport – Development and assessment of an integrated multi-sectoral model," *Appl. Energy*, vol. 262, p. 114365, Mar. 2020.
[159] J. Banks, "Discrete-event system simulation," p. 594, 2001.
[160] J. A. Sokolowski and C. M. Banks, "Principles of modeling and simulation : a multidisciplinary approach," p. 259, 2009.
[161] J. McLeod, "Simulation; the dynamic modeling of ideas and systems with computers.," p. 351, 1968.
[162] L. E. Widman, K. A. Loparo, and N. R. (Norman R. . Nielsen, "Artificial intelligence, simulation, and modeling," p. 556, 1989.
[163] P. Bauer, A. Thorpe, and G. Brunet, "The quiet revolution of numerical weather prediction," *Nat. 2015 5257567*, vol. 525, no. 7567, pp. 47–55, Sep. 2015.
[164] K. Dembrower *et al.*, "Effect of artificial intelligence-based triaging of breast cancer screening mammograms on cancer detection and radiologist workload: a retrospective simulation study," *Lancet Digit. Heal.*, vol. 2, no. 9, pp. e468–e474, Sep. 2020.
[165] B. C. Williams, M. D. Ingham, S. H. Chung, and P. H. Elliott, "Model-based programming of intelligent embedded systems and robotic space explorers," *Proc. IEEE*, vol. 91, no. 1, pp. 212–236, 2003.
[166] M. S. Johnson, N. Srinivasan, R. Sowdhamini, and T. L. Blundell, "Knowledge-Based Protein Modeling," *http://dx.doi.org/10.3109/10409239409086797*, vol. 29, no. 1, pp. 1–68, 2008.
[167] S. Elekdag, R. Lalonde, D. Laxton, D. Muir, and P. Pesenti, "Oil price movements and the global economy: A model-based assessment," *IMF Staff Pap.*, vol. 55, no. 2, pp. 297–311, Jun. 2008.
[168] M. Islam *et al.*, "Application of Detached-Eddy Simulation for Automotive Aerodynamics Development."
[169] L. Balamurugan and J. Jancirani, "An investigation on semi-active suspension damper and control strategies for vehicle ride comfort and road holding," *Proc. Inst. Mech. Eng. Part I J. Syst. Control Eng.*, vol. 226, no. 8, pp. 1119–1129, Sep. 2012.
[170] K. V. Mohan, O. Arici, S. L. Yang, and J. H. Johnson, "A Computer Simulation of the Turbocharged Diesel Engine as an Enhancement of the Vehicle Engine Cooling System Simulation," *SAE Tech. Pap.*, May 1997.
[171] A. M. de Souza, C. A. R. L. Brennand, R. S. Yokoyama, E. A. Donato, E. R. M. Madeira, and L. A. Villas,

"Traffic management systems: A classification, review, challenges, and future perspectives," *Int. J. Distrib. Sens. Networks*, vol. 13, no. 4, Apr. 2017.
[172] A. Doniec, R. Mandiau, S. Piechowiak, and S. Espié, "A behavioral multi-agent model for road traffic simulation," *Eng. Appl. Artif. Intell.*, vol. 21, no. 8, pp. 1443–1454, Dec. 2008.
[173] M. Chowdhury *et al.*, "Applications of Artificial Intelligence Paradigms to Decision Support in Real-Time Traffic Management," *https://doi.org/10.1177/0361198106196800111*, vol. 1968, no. 1, pp. 92–98, Jan. 2006.
[174] B. Luin, S. Petelin, and F. Al-Mansour, "Microsimulation of electric vehicle energy consumption," *Energy*, vol. 174, pp. 24–32, May 2019.
[175] Y. Xie *et al.*, "Microsimulation of electric vehicle energy consumption and driving range," *Appl. Energy*, vol. 267, p. 115081, Jun. 2020.
[176] M. Hammadi, J. Y. Choley, O. Penas, and A. Riviere, "Multidisciplinary approach for modelling and optimization of Road Electric Vehicles in conceptual design level," *Electr. Syst. Aircraft, Railw. Sh. Propulsion, ESARS*, pp. 1–6, 2012.
[177] D. Martino, A. Di Martino, M. Miraftabzadeh, and M. Longo, "Strategies for the Modelisation of Electric Vehicle Energy Consumption: A Review," *Energies 2022, Vol. 15, Page 8115*, vol. 15, no. 21, p. 8115, Oct. 2022.
[178] "What is Telemetry? How Telemetry Works, Benefits, and Tutorial." [Online]. Available: https://stackify.com/telemetry-tutorial/. [Accessed: 11-Jan-2023].
[179] F. Carden, R. P. Jedlicka, and R. Henry, "Telemetry systems engineering," p. 596, 2002.
[180] U. A. Bakshi, A. V. Bakshi, and K. A. Bakshi, "Electrical measurements," 2007.
[181] G. C. de Oliveira Neto, I. Costa, W. C. de Sousa, M. P. C. Amorim, and M. Godinho Filho, "Adoption of a telemetry system by a logistics service provider for road transport of express cargo: a case study in Brazil," *https://doi.org/10.1080/13675567.2018.1564253*, vol. 22, no. 6, pp. 592–613, Nov. 2019.
[182] Y. Wei, F. Mahnaz, O. Bulan, Y. Mengistu, S. Mahesh, and M. A. Losh, "Creating Semantic HD Maps From Aerial Imagery and Aggregated Vehicle Telemetry for Autonomous Vehicles," *IEEE Trans. Intell. Transp. Syst.*, vol. 23, no. 9, pp. 15382–15395, Sep. 2022.
[183] J. Terán, L. Navarro, C. G. Quintero M., and M. Pardo, "Intelligent Driving Assistant Based on Road Accident Risk Map Analysis and Vehicle Telemetry," *Sensors 2020, Vol. 20, Page 1763*, vol. 20, no. 6, p. 1763, Mar. 2020.
[184] "How Cloud Data-Crunching Power Accelerates the F1 Racing Experience | Data Center Frontier." [Online]. Available: https://www.datacenterfrontier.com/cloud/article/11427867/how-cloud-data-crunching-power-accelerates-the-f1-racing-experience. [Accessed: 11-Jan-2023].
[185] C. Manzie, S. Kim, and R. Sharma, "Optimal use of telemetry by parallel hybrid vehicles in urban driving," *Transp. Res. Part C*, vol. 25, pp. 134–151, 2012.
[186] L. Taccari *et al.*, "Classification of Crash and Near-Crash Events from Dashcam Videos and Telematics," *IEEE Conf. Intell. Transp. Syst. Proceedings, ITSC*, vol. 2018-November, pp. 2460–2465, Dec. 2018.
[187] "Why Do So Many Russian Drivers Have Dashboard Cams? | Mental Floss." [Online]. Available: https://www.mentalfloss.com/article/48952/why-do-so-many-russian-drivers-have-dashboard-cams. [Accessed: 11-Jan-2023].
[188] J. W. Joubert and S. Meintjes, "Repeatability & reproducibility: Implications of using GPS data for freight activity chains," *Transp. Res. Part B Methodol.*, vol. 76, pp. 81–92, Jun. 2015.
[189] P. Cubon, J. Sedo, R. Radvan, J. Stancek, P. Spanik, and J. Uricek, "Calculation of demand of electric power of small electric vehicle using Matlab GUI," *10th Int. Conf. ELEKTRO 2014 - Proc.*, pp. 149–153, 2014.
[190] P. Cubon, R. Radvan, and V. Vavrus, "Optimization source structure of electric vehicle using calculation of energy consumption in Matlab GUI," *Adv. Electr. Electron. Eng.*, vol. 13, no. 2, pp. 156–161, 2015.
[191] G. Xu, W. Li, K. Xu, and Z. Song, "An intelligent regenerative braking strategy for electric vehicles," *Energies*, vol. 4, no. 9, pp. 1461–1477, 2011.
[192] "Eclipse SUMO - Simulation of Urban MObility." [Online]. Available: https://www.eclipse.org/sumo/. [Accessed: 13-Apr-2022].
[193] R. Maia, M. Silva, R. Araújo, and U. Nunes, "Electrical vehicle modeling: A fuzzy logic model for regenerative braking," *Expert Syst. Appl.*, vol. 42, no. 22, pp. 8504–8519, 2015.
[194] P. Cocron, F. Bühler, T. Franke, I. Neumann, B. Dielmann, and J. F. Krems, "Energy recapture through deceleration - regenerative braking in electric vehicles from a user perspective," *Ergonomics*, vol. 56, no. 8, pp. 1203–1215, 2013.
[195] I. Baboselac, T. Benšić, and Ž. Hederić, "MatLab simulation model for dynamic mode of the Lithium-Ion

batteries to power the EV," *Teh. Glas.*, vol. 11, no. 1–2, pp. 7–13, 2017.
[196] K. Benabdelaziz and M. Maaroufi, "Battery dynamic energy model for use in electric vehicle simulation," *Proc. 2016 Int. Renew. Sustain. Energy Conf. IRSEC 2016*, vol. 42, no. 30, pp. 927–932, 2017.
[197] "Battery State of Charge Determination." [Online]. Available: https://www.mpoweruk.com/soc.htm. [Accessed: 28-Apr-2020].
[198] M. Araki, *PID Control*. .
[199] "Tire-road dynamics given by magic formula coefficients - Simulink - MathWorks United Kingdom." [Online]. Available: https://uk.mathworks.com/help/physmod/sdl/ref/tireroadinteractionmagicformula.html. [Accessed: 28-Apr-2020].
[200] "Solver - MATLAB & Simulink - MathWorks United Kingdom." [Online]. Available: https://uk.mathworks.com/help/simulink/gui/solver.html. [Accessed: 17-Apr-2020].
[201] R. L. Burden and J. D. Faires, *Numerical Analysis Brooks Cole*, 7th ed. Canada: Brooks/Cole, Cengage Learning, 2000.
[202] I. Fathy, D. Fadl, and M. Aref, "Rich Semantic Representation Based Approach for Text Generation."
[203] K. E. Atkinson, *An introduction to numerical analysis*, 2nd ed. New York: John Wiley & Sons, 1989.
[204] R. Zhao, T. Stincescu, E. E. F. Ballantyne, and D. A. Stone, "Sustainable City: Energy Usage Prediction Method for Electrified Refuse Collection Vehicles," *Smart Cities*, vol. 3, no. 3, pp. 1100–1116, Sep. 2020.
[205] G. S. Almasi and A. Gottlieb, *Highly parallel computing*, 2nd editio. Benjamin/Cummings, 1994.
[206] G. M. Amdahl, "Validity of the Single Processor Approach to Achieving Large Scale Computing Capabilities, Reprinted from the AFIPS Conference Proceedings, Vol. 30 (Atlantic City, N.J., Apr. 18–20), AFIPS Press, Reston, Va., 1967, pp. 483–485, when Dr. Amdahl was at International Business Machines Corporation, Sunnyvale, California," *IEEE Solid-State Circuits Newsl.*, vol. 12, no. 3, pp. 19–20, Feb. 2009.
[207] "Parallel Computing Toolbox - MATLAB." [Online]. Available: https://uk.mathworks.com/products/parallel-computing.html. [Accessed: 19-Nov-2020].
[208] "Simulate dynamic system multiple times in parallel or serial - MATLAB parsim - MathWorks United Kingdom." [Online]. Available: https://uk.mathworks.com/help/simulink/slref/parsim.html. [Accessed: 19-Nov-2020].
[209] "Heat values of various fuels - World Nuclear Association." [Online]. Available: https://world-nuclear.org/information-library/facts-and-figures/heat-values-of-various-fuels.aspx. [Accessed: 03-Oct-2022].
[210] "Digest of UK Energy Statistics (DUKES): energy - GOV.UK." [Online]. Available: https://www.gov.uk/government/statistics/energy-chapter-1-digest-of-united-kingdom-energy-statistics-dukes. [Accessed: 03-Oct-2022].
[211] D. Y. Lee, V. M. Thomas, and M. A. Brown, "Electric urban delivery trucks: Energy use, greenhouse gas emissions, and cost-effectiveness," *Environ. Sci. Technol.*, vol. 47, no. 14, pp. 8022–8030, Jul. 2013.
[212] L. Fridstrøm and V. Østli, "Direct and cross price elasticities of demand for gasoline, diesel, hybrid and battery electric cars: the case of Norway," *Eur. Transp. Res. Rev.*, vol. 13, no. 1, pp. 1–24, Dec. 2021.
[213] "Urban passenger model - Vehicle activities and emissions." [Online]. Available: https://stats.oecd.org/Index.aspx?DataSetCode=ITF_OUTLOOK_URB_PAX_EMIS. [Accessed: 03-Oct-2022].
[214] O. Vilppo and J. Markkula, "Feasibility of electric buses in public transport," *World Electr. Veh. J.*, vol. 7, no. 3, pp. 357–365, 2015.
[215] "European vehicle emissions standards – Euro 7 for cars, vans, lorries and buses." [Online]. Available: https://ec.europa.eu/info/law/better-regulation/have-your-say/initiatives/12313-European-vehicle-emissions-standards-Euro-7-for-cars-vans-lorries-and-buses_en. [Accessed: 03-Oct-2022].
[216] Transport for London, "New Routemaster buses on Route 453 - Transport for London." [Online]. Available: https://tfl.gov.uk/info-for/media/press-releases/2014/october/new-routemaster-buses-on-route-453. [Accessed: 17-Oct-2022].
[217] R. B. Duffey, "Sustainable futures using nuclear energy," *Prog. Nucl. Energy*, vol. 47, no. 1–4, pp. 535–543, Jan. 2005.
[218] A. Saadon Al-Ogaili *et al.*, "Estimation of the energy consumption of battery driven electric buses by integrating digital elevation and longitudinal dynamic models: Malaysia as a case study," *Appl. Energy*, vol. 280, p. 115873, Dec. 2020.

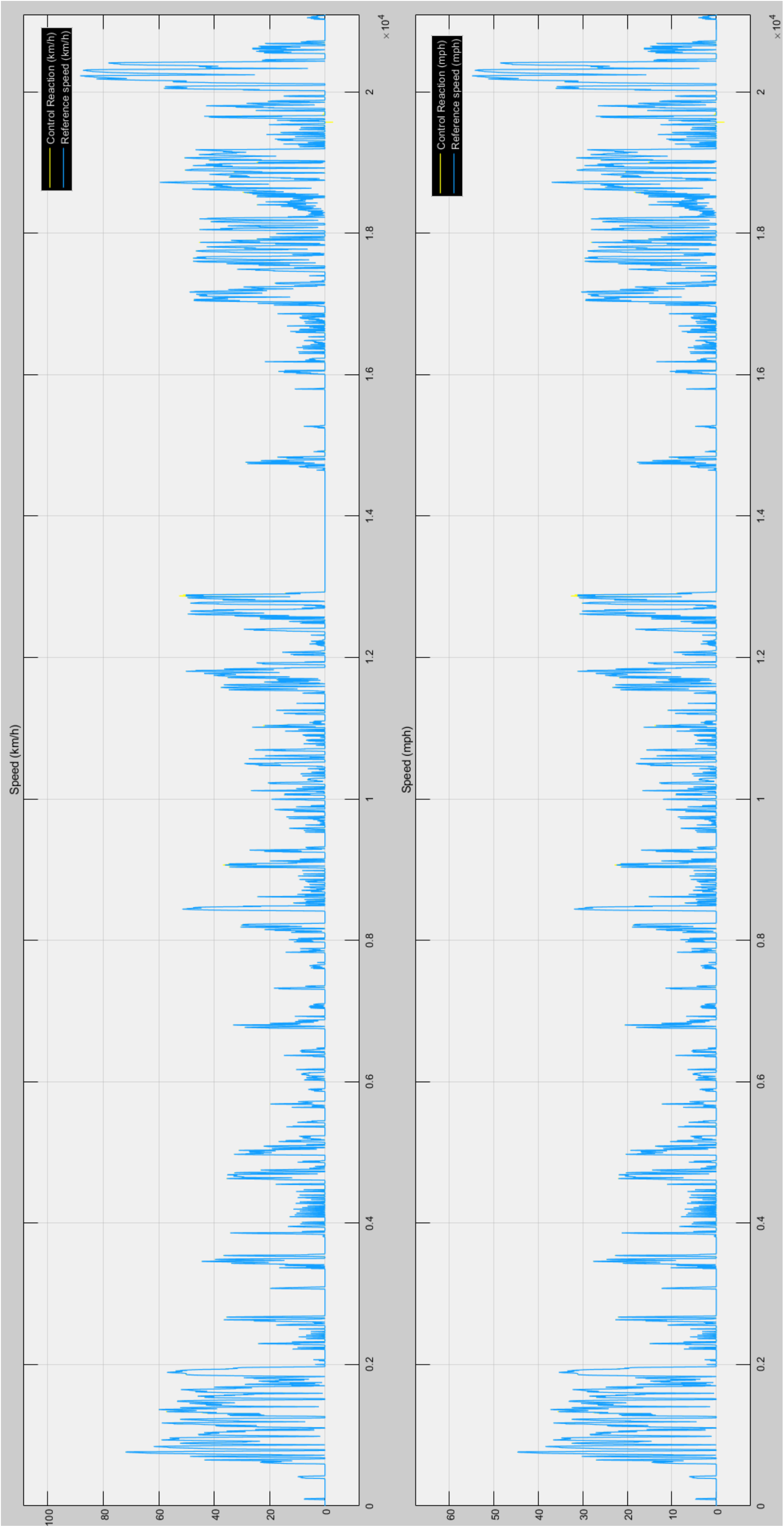
[219] R. Suarez-Bertoa *et al.*, "Effect of Low Ambient Temperature on Emissions and Electric Range of Plug-In Hybrid Electric Vehicles," *ACS Omega*, vol. 4, no. 2, pp. 3159–3168, Feb. 2019.
[220] A. Łebkowski, "Studies of energy consumption by a city bus powered by a hybrid energy storage system in variable road conditions," *Energies*, vol. 12, no. 5, 2019.
[221] Y. Hu and J. Hellendoorn, "Uncertainty modeling for urban traffic model predictive control based on urban patterns," *IEEE Conf. Intell. Transp. Syst. Proceedings, ITSC*, pp. 845–850, 2013.
[222] M. Mruzek, I. Gajdáč, Ľ. Kučera, and D. Barta, "Analysis of Parameters Influencing Electric Vehicle Range," *Procedia Eng.*, vol. 134, pp. 165–174, Jan. 2016.
[223] "GLOBAL POSITIONING SYSTEM STANDARD POSITIONING SERVICE PERFORMANCE STANDARD 4 th Edition," 2008.
[224] "Garmin eTrex® 10 | Outdoor GPS." [Online]. Available: https://www.garmin.com/en-GB/p/87768. [Accessed: 22-Feb-2023].
[225] "Dashboard | Strava." [Online]. Available: https://www.strava.com/dashboard. [Accessed: 22-Feb-2023].
[226] "Download BaseCamp | Garmin ." [Online]. Available: https://www.garmin.com/en-US/software/basecamp/. [Accessed: 22-Feb-2023].
[227] G. Van Brummelen, "Heavenly mathematics: The forgotten art of spherical trigonometry," *Heaven. Math. Forgot. Art Spherical Trigonometry*, Dec. 2012.
[228] "GitHub - dtcooper/python-fitparse: Python library to parse ANT/Garmin .FIT files." [Online]. Available: https://github.com/dtcooper/python-fitparse. [Accessed: 22-Feb-2023].
[229] "Greenhouse Gas Emissions from a Typical Passenger Vehicle | US EPA." [Online]. Available: https://www.epa.gov/greenvehicles/greenhouse-gas-emissions-typical-passenger-vehicle. [Accessed: 03-Oct-2022].
[230] M. Ehsani, A. Ahmadi, and D. Fadai, "Modeling of vehicle fuel consumption and carbon dioxide emission in road transport," *Renew. Sustain. Energy Rev.*, vol. 53, pp. 1638–1648, Jan. 2016.
[231] Y. Zhao, M. Noori, and O. Tatari, "Vehicle to Grid regulation services of electric delivery trucks: Economic and environmental benefit analysis," *Appl. Energy*, vol. 170, pp. 161–175, May 2016.
[232] R. Chandrappa and D. B. Das, "Waste Quantities and Characteristics," *Environ. Sci. Eng.*, pp. 47–63, 2012.
[233] D. Hoornweg, P. Bhada-Tata, and C. Kennedy, "Environment: Waste production must peak this century," *Nat. 2013 5027473*, vol. 502, no. 7473, pp. 615–617, Oct. 2013.
[234] "Ford E-Transit: The Electric Van For Your Business | Ford UK." [Online]. Available: https://www.ford.co.uk/vans-and-pickups/e-transit. [Accessed: 06-Oct-2022].
[235] M. Smuts, B. Scholtz, and J. Wesson, "A critical review of factors influencing the remaining driving range of electric vehicles," *2017 1st Int. Conf. Next Gener. Comput. Appl. NextComp 2017*, pp. 196–201, Aug. 2017.
[236] DAF N.V., "DAF LF ELECTRIC - DAF Trucks N.V.," 2022. [Online]. Available: https://www.daf.com/en/about-daf/sustainability/alternative-fuels-and-drivelines/battery-electric-vehicles/daf-lf-electric. [Accessed: 30-May-2022].
[237] A. Schrijver, *Volume B. Matroids, Trees, Stable Sets*. Springer, 2003.
[238] "Google Maps launches eco-friendly routing in the US | TechCrunch." [Online]. Available: https://techcrunch.com/2021/10/06/google-maps-launches-eco-friendly-routing-in-the-u-s/?guccounter=1. [Accessed: 03-Oct-2022].
[239] I. Kucukoglu, R. Dewil, and D. Cattrysse, "The electric vehicle routing problem and its variations," *Comput. Ind. Eng.*, vol. 161, Nov. 2021.
[240] M. Eisel, *Analyzing the Range Barrier to Electric Vehicle Adoption The Case of Range Anxiety*. .
[241] G. S. Vidya and V. S. Hari, "Prediction of Bus Passenger Traffic using Gaussian Process Regression," *J. Signal Process. Syst.*, pp. 1–12, Jun. 2022.
[242] D. Perrotta *et al.*, "Route Planning for Electric Buses: A Case Study in Oporto," *Procedia - Soc. Behav. Sci.*, vol. 111, pp. 1004–1014, Feb. 2014.
[243] T. Bektaş and G. Laporte, "The Pollution-Routing Problem," *Transp. Res. Part B Methodol.*, vol. 45, no. 8, pp. 1232–1250, Sep. 2011.
[244] "Urban Mobility: 10 Cities Leading the Way in Asia Pacific." [Online]. Available: https://www.clc.gov.sg/research-publications/publications/books/view/urban-mobility-10-cities-leading-the-way-in-asia-pacific. [Accessed: 11-Oct-2022].
[245] D. N. Huu and V. N. Ngoc, "Analysis Study of Current Transportation Status in Vietnam's Urban Traffic and the Transition to Electric Two-Wheelers Mobility," *Sustain. 2021, Vol. 13, Page 5577*, vol. 13, no.

10, p. 5577, May 2021.
[246] W. P. Tyas, M. Damayanti, J. K. Hutama, and D. D. Saragih, "The Role of Food Delivery Services by Online Motorcycle Taxi on the Development of Culinary Home-Based Enterprises," *IOP Conf. Ser. Earth Environ. Sci.*, vol. 396, no. 1, p. 012010, Nov. 2019.
[247] T. Stincescu, R. Zhao, E. E. F. Ballantyne, D. A. Stone, and M. P. Foster, "Matlab-based High-Performance Electric Motorbike Energy Model, Utilising Video Data," *2021 16th Int. Conf. Ecol. Veh. Renew. Energies, EVER 2021*, May 2021.
[248] R. Zhao, T. Stincescu, E. E. F. Ballantyne, D. A. Stone, and M. P. Foster, "Dashcam Video-Driven, Route Distinctive Energy Consumption Pre-Evaluation for Electrifying Public Services Fleets," *2021 16th Int. Conf. Ecol. Veh. Renew. Energies, EVER 2021*, May 2021.
[249] K. Jung, K. I. Kim, and A. K. Jain, "Text information extraction in images and video: A survey," *Pattern Recognit.*, vol. 37, no. 5, pp. 977–997, May 2004.
[250] J. Liang, D. Doermann, and H. Li, "Camera-based analysis of text and documents: a survey," *Int. J. Doc. Anal. Recognit. 2005 72*, vol. 7, no. 2, pp. 84–104, Jul. 2005.
[251] Q. Ye and D. Doermann, "Text Detection and Recognition in Imagery: A Survey," 2014.
[252] X. C. Yin, Z. Y. Zuo, S. Tian, and C. L. Liu, "Text Detection, Tracking and Recognition in Video: A Comprehensive Survey," *IEEE Trans. Image Process.*, vol. 25, no. 6, pp. 2752–2773, Jun. 2016.
[253] R. Smith, "An Overview of the Tesseract OCR Engine."
[254] Y. H. Hu and J. N. Hwang, "Introduction to neural networks for signal processing," *Handb. Neural Netw. Signal Process.*, pp. 1-1-1–30, Jan. 2001.
[255] M. D. Garris, C. L. Wilson, and J. L. Blue, "Neural network-based systems for handprint OCR applications," *IEEE Trans. Image Process.*, vol. 7, no. 8, pp. 1097–1112, 1998.
[256] J. Wang and X. Hu, "Gated Recurrent Convolution Neural Network for OCR," *Adv. Neural Inf. Process. Syst.*, vol. 30, 2017.
[257] "Courses - iomtt.com: The World's #1 TT Website." [Online]. Available: https://www.iomtt.com/tt-database/courses. [Accessed: 11-Oct-2022].
[258] "Mugen Shinden Hachi: specifications and technical sheet - epaddock.it." [Online]. Available: https://www.epaddock.it/en/mugen-shinden-hachi-data-sheet/. [Accessed: 11-Oct-2022].
[259] N. Dal Bianco, R. Lot, and K. Matthys, "Lap time simulation and design optimisation of a brushed DC electric motorcycle for the Isle of Man TT Zero Challenge," *Veh. Syst. Dyn.*, vol. 56, no. 1, pp. 27–54, Jan. 2018.
[260] M. Massaro and D. J. N. Limebeer, "Minimum-lap-time optimisation and simulation," *Veh. Syst. Dyn.*, vol. 59, no. 7, pp. 1069–1113, 2021.
[261] T. J. Barlow, S. Latham, I. S. Mccrae, and P. G. Boulter, "A reference book of driving cycles for use in the measurement of road vehicle emissions."
[262] Transport Policy, "EU: Light-duty: Artemis | Transport Policy." [Online]. Available: https://www.transportpolicy.net/standard/eu-light-duty-artemis/. [Accessed: 25-Oct-2022].
[263] Transport Policy, "EU: Light-duty: New European Driving Cycle | Transport Policy." [Online]. Available: https://www.transportpolicy.net/standard/eu-light-duty-new-european-driving-cycle/. [Accessed: 25-Oct-2022].
[264] WLTPFacts.eu, "WLTPfacts.eu - Worldwide Harmonised Light Vehicle Test Procedure." [Online]. Available: https://www.wltpfacts.eu/. [Accessed: 25-Oct-2022].
[265] US EPA, "Dynamometer Drive Schedules." [Online]. Available: https://www.epa.gov/vehicle-and-fuel-emissions-testing/dynamometer-drive-schedules. [Accessed: 25-Oct-2022].
[266] N. Kammuang-lue, S. Pattana, and K. Wiratkasem, "Draft of the MEPS and HEPS for two-wheel electric motorcycles in Thailand," *Energy Reports*, vol. 6, pp. 851–855, Dec. 2020.
[267] E-ON International, "Electric vehicles | Battery | Capacity and Lifespan." [Online]. Available: https://www.eonenergy.com/electric-vehicle-charging/costs-and-benefits/battery-capacity-and-lifespan.html. [Accessed: 25-Oct-2022].
[268] X. Zhang, Y. Han, and W. Zhang, "A Review of Factors Affecting the Lifespan of Lithium-ion Battery and its Health Estimation Methods," *Trans. Electr. Electron. Mater.*, vol. 22, no. 5, pp. 567–574, Oct. 2021.
[269] Insideevs.com, "Tesla's 4680-Type Battery Cell Teardown: Specs Revealed." [Online]. Available: https://insideevs.com/news/598656/tesla-4680-battery-cell-specs/. [Accessed: 25-Oct-2022].
[270] Thyssenkrupp, "The Density of Aluminium and its Alloys - thyssenkrupp Materials (UK)." [Online]. Available: https://www.thyssenkrupp-materials.co.uk/density-of-aluminium.html. [Accessed: 25-Oct-2022].
[271] Yamaha Inc., "2022 Yamaha SMAX Specs, Top Speed, Mileage, & Price." [Online]. Available:

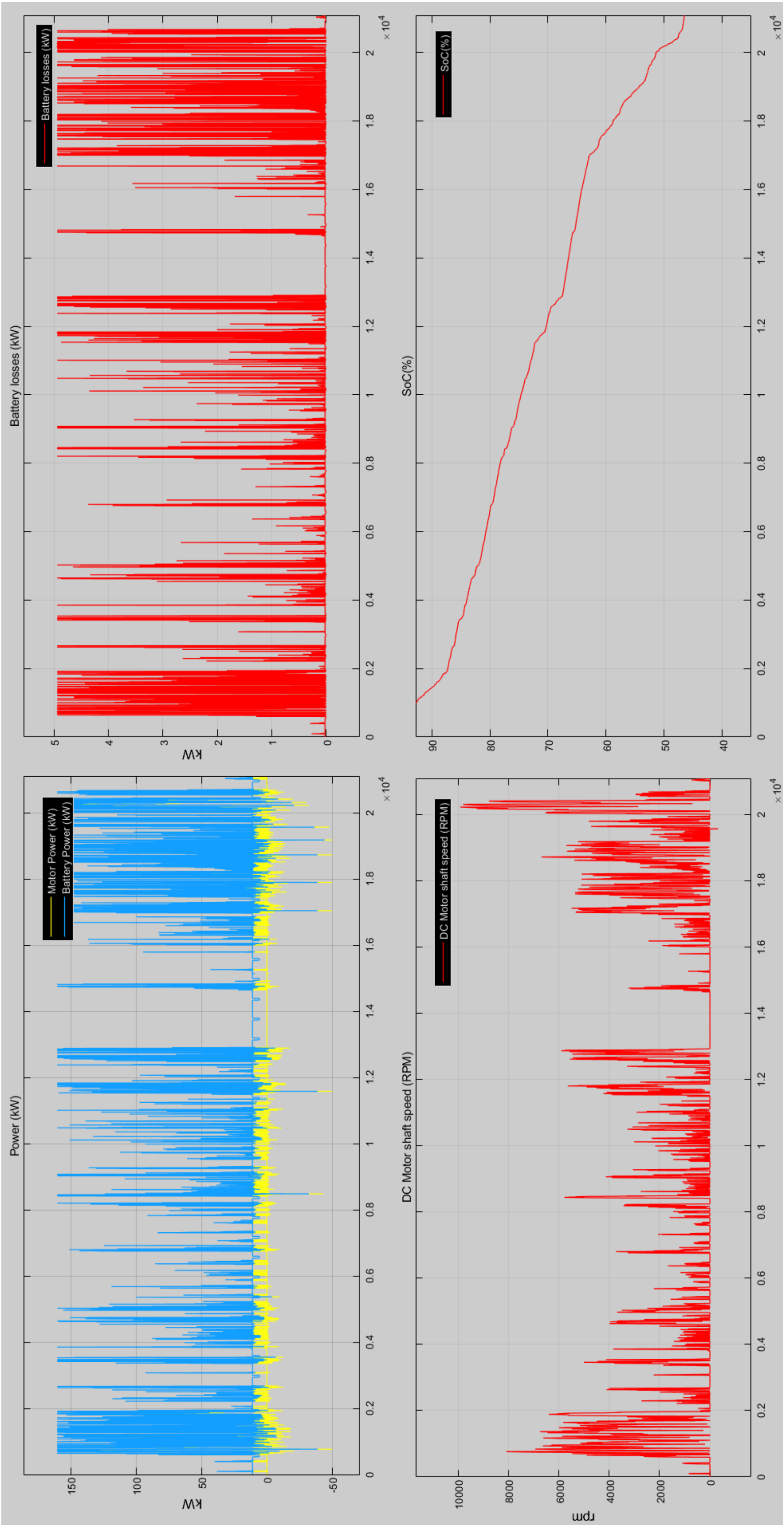
https://www.scootyblog.com/yamaha-smax/. [Accessed: 25-Oct-2022].
[272] Ecoscore, "Ecoscore - CO2 emissions." [Online]. Available: https://ecoscore.be/en/info/ecoscore/co2. [Accessed: 25-Oct-2022].
[273] European Enviornment Agency, "Heavy duty vehicles," *2022*. [Online]. Available: https://www.eea.europa.eu/themes/transport/heavy-duty-vehicles. [Accessed: 18-Nov-2022].
[274] US Federal Vehicle Standards, "Center for Climate and Energy SolutionsCenter for Climate and Energy Solutions." [Online]. Available: https://www.c2es.org/content/regulating-transportation-sector-carbon-emissions/. [Accessed: 18-Nov-2022].
[275] Freight Management and Operations, "Table 3-8. Average Truck Speeds on Selected Interstate Highways: 2009 - Freight Facts and Figures 2010 - FHWA Freight Management and Operations." [Online]. Available: https://ops.fhwa.dot.gov/freight/freight_analysis/nat_freight_stats/docs/10factsfigures/table3_8.htm . [Accessed: 18-Nov-2022].
[276] Department for Transport, "Truck Specification for Best Operational Efficiency Guide."
[277] S. Angus, "Statistical Release-Domestic Road Freight Statistics-Page 2," 2004.
[278] Tesla Inc., "Semi | Tesla." [Online]. Available: https://www.tesla.com/semi. [Accessed: 30-May-2022].
[279] Wall Street Journal, "For Maximum EV Efficiency, Stick to 25 Miles an Hour, Ignore Angry Drivers - WSJ." [Online]. Available: https://www.wsj.com/articles/ev-electric-car-battery-charge-hypermiler-11642517385. [Accessed: 18-Nov-2022].
[280] MACK Inc., "Mack's Anthem Gets Improved Fuel-Efficiency Package | Transport Topics." [Online]. Available: https://www.ttnews.com/articles/mack-introduces-redesigned-anthem-truck. [Accessed: 18-Nov-2022].
[281] Bulb, "Carbon tracker | Bulb." [Online]. Available: https://bulb.co.uk/carbon-tracker/. [Accessed: 18-Nov-2022].
[282] EUROSTAT, "Road freight transport by journey characteristics - Statistics Explained." [Online]. Available: https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Road_freight_transport_by_journey_characteristics. [Accessed: 17-Feb-2023].
[283] "UK: monthly diesel price 2022 | Statista." [Online]. Available: https://www.statista.com/statistics/299552/average-price-of-diesel-in-the-united-kingdom/. [Accessed: 17-Feb-2023].
[284] Mainfreight, "Pallet and Packaging types." [Online]. Available: https://www.mainfreight.com/europe/en-nz/info-point/pallet-and-packaging-types. [Accessed: 30-May-2022].
[285] "Check Electric Cars Listed By Weight Per Battery Capacity (kWh)." [Online]. Available: https://insideevs.com/news/528346/ev-weight-per-battery-capacity/. [Accessed: 27-Jan-2023].
[286] L. H. Saw, Y. Ye, and A. A. O. Tay, "Feasibility study of Boron Nitride coating on Lithium-ion battery casing," 2014.
[287] "Aluminum - 2023 Data - 1989-2022 Historical - 2024 Forecast - Price - Quote - Chart." [Online]. Available: https://tradingeconomics.com/commodity/aluminum. [Accessed: 20-Feb-2023].
[288] "Technology and Market Intelligence: Hybrid Vehicle Power Inverters Cost Analysis Collection Cut-Off," 2011.
[289] "Savills UK | Rural land values." [Online]. Available: https://www.savills.co.uk/landing-pages/rural-land-values/rural-land-values.aspx. [Accessed: 03-Dec-2022].
[290] J.-F. Delvaen, "Modelling Potential Health Impact by Reducing Vehicle Emission through Introducing Electric Vehicle Fleet for Short Trip Metropolitan Deliveries," *J. Transp. Heal.*, vol. 14, p. 100747, Sep. 2019.
[291] M. Nunez Munoz, E. E. F. Ballantyne, and D. A. Stone, "Development and evaluation of empirical models for the estimation of hourly horizontal diffuse solar irradiance in the United Kingdom," *Energy*, vol. 241, p. 122820, Feb. 2022.

Appendices

Appendix 1a – Further example of processed speed data



Appendix 1b – Further example of processed power data



Appendix 2 – Link to GitHub repository containing the telemetry emulation route builder script.

https://github.com/EVLogisticsResearch/RoadSimCode/blob/3cff4121d3f1350edbd6cb3d6efb791c5b30857e/RoadSim.py

Appendix 3 – eRCV technical vehicle specification

Vehicle	Front/Back drive		Rear wheel drive
	Empty weight	kg	15500
	Maximum vehicle weight with payload	kg	26000
	Front area	mm^2	6163200
	Wheel radius (315/80 R22.5)	m	0.5218
	Rolling resistance coefficient	%	1.2
	Vehicle aerodynamic drag coefficient		0.633
Drivetrain	Drivetrain efficiency	%	90 %
	Number of gears (if applicable)		1
	Drivetrain drive ratio		6.83 (axle ratio)
	Drive ratio on gear (if applicable)		3.405
Motor	Motor power	kW	150
	Maximum torque	N·m	1055
	Motor rated speed	rpm	7500
	Motor maximum speed	rpm	10000
	Motor system efficiency	%	94%
Regeneration	Regeneration power	kW	50
	Regeneration system efficiency	%	94%
Battery	Working voltage	V	526V nominal
	Battery capacity	kWh	300
	Type of battery		Lithium-ion
	Minimum discharge voltage	V	403
	Maximum charging voltage	V	605
	Battery temperature controller target (if any)	°C	-10 - 45
	Weight of battery system	kg	1870
	Battery system efficiency	%	90
Other	Compress system power	kW	4
	Compress system efficiency	%	85.8

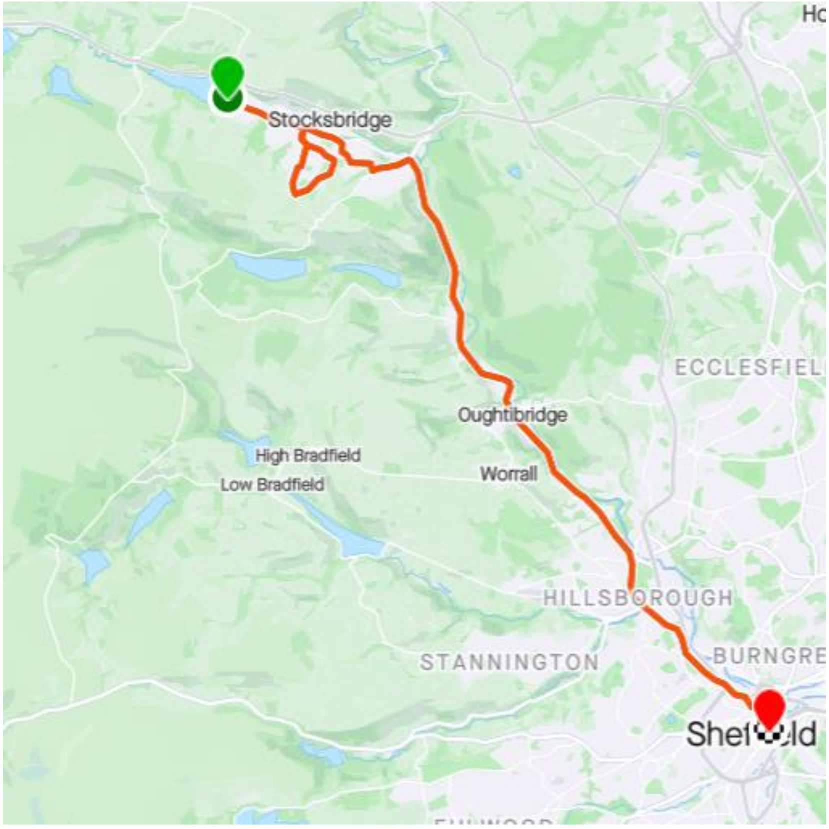
Appendix 4 – eBus, single deck technical vehicle specification

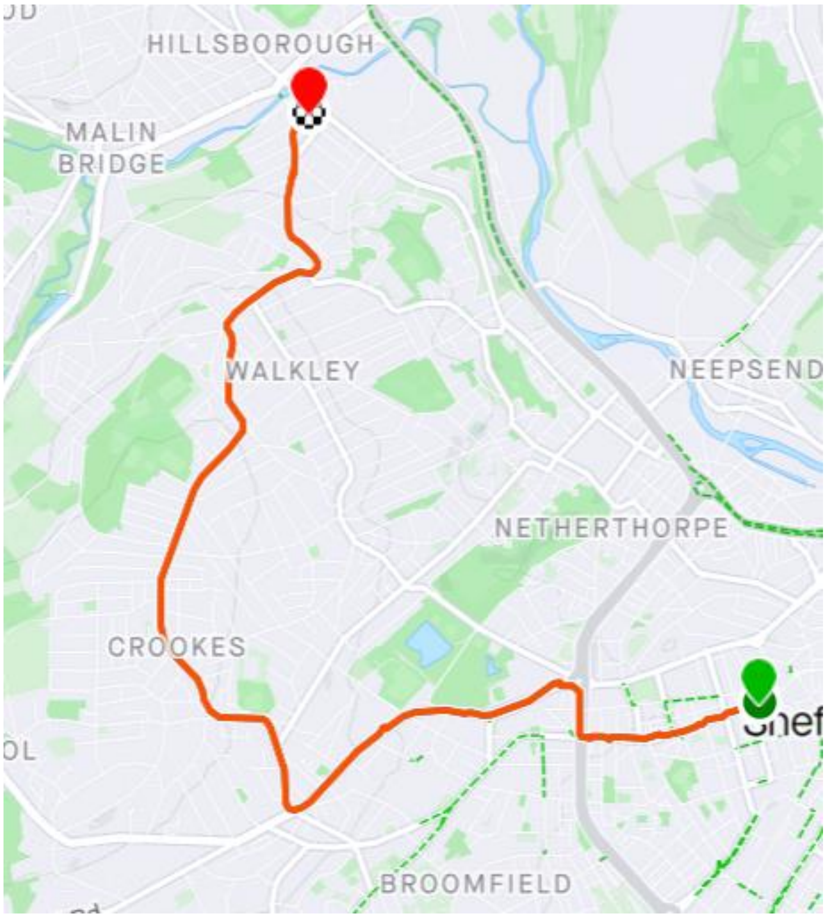
Vehicle	Front/Back drive		Rear wheel drive
	Empty weight	kg	12850
	Maximum vehicle weight with payload	kg	19000
	Front area	mm^2	8466000
	Wheel radius	m	0.5218
	Rolling resistance coefficient	%	1.2
	Vehicle aerodynamic drag coefficient		0.633
Drivetrain	Drivetrain efficiency	%	90 %
	Number of gears		1
	Drivetrain drive ratio		6.83
	Drive ratio on gear		3.405
Motor	Motor power	kW	250
	Maximum torque	N·m	1730
	Motor rated speed	rpm	7500
	Motor maximum speed	rpm	10000
	Motor system efficiency	%	94%
Regeneration	Regeneration power	kW	50
	Regeneration system efficiency	%	94%
Battery	Working voltage	V	500V nominal
	Battery capacity	kWh	400
	Type of battery		Lithium-ion
	Minimum discharge voltage	V	403
	Maximum charging voltage	V	605
	Battery temperature controller target (if any)	℃	-10 - 45
	Weight of battery system	kg	1870
	Battery system efficiency	%	90

Appendix 5 – eBus, double deck technical vehicle specification

Vehicle	Front/Back drive		Rear wheel drive
	Empty weight	kg	19000
	Maximum vehicle weight with payload	kg	26000
	Front area	mm^2	10965000
	Wheel radius (275/70 R22.5)	m	0.5
	Rolling resistance coefficient	%	1.15
	Vehicle aerodynamic drag coefficient		0.6
Drivetrain	Drivetrain efficiency	%	90 %
	Number of gears		1
	Drivetrain drive ratio		6.83
	Drive ratio on gear		3.405
Motor	Motor power	kW	250
	Maximum torque	N·m	2200
	Motor rated speed	rpm	7500
	Motor maximum speed	rpm	10000
	Motor system efficiency	%	94%
Regeneration	Regeneration power	kW	50
	Regeneration system efficiency	%	94%
Battery	Working voltage	V	500V nominal
	Battery capacity	kWh	382
	Type of battery		Lithium-ion
	Minimum discharge voltage	V	403
	Maximum charging voltage	V	605
	Battery temperature controller target (if any)	℃	-10 - 45
	Weight of battery system	kg	1870
	Battery system efficiency	%	90

Appendix 6 – Further mapped examples of bus routes





Appendix 7 – Code for extracting Strava-proprietary enhanced telemetry data

```
from fitparse import FitFile
import os
import csv

# the overall max speed in meter p/s
max_speed = 0.0
speed_data = []
altitude_data = []
timestamp_data = []
x = {}

# loop through all fit files in directory
for filename in os.listdir(os.path.abspath(os.getcwd())):

    if filename.endswith(".fit"):

        # open fitfile
        fitfile = FitFile(filename)

        # Get all data messages that are of type record
        for record in fitfile.get_messages('record'):

            # Go through all the data entries in this record
            for record_data in record:
                #print(record_data)
                x = record_data.name
                if record_data.name == "enhanced_speed":

                    # save new max speed if higher than previous
value
                    if record_data.value > max_speed:
                        max_speed = record_data.value
                    speed_data.append(record_data.value * 3.6)

                if record_data.name == "enhanced_altitude":
                    altitude_data.append(record_data.value)

                if record_data.name == "timestamp":
                    timestamp_data.append(record_data.value)

        #write data to output csv
        with open('output.csv', 'w', newline='') as csvfile:
            writer = csv.writer(csvfile)

            # write each value in the array to a separate row
            for x in range(len(speed_data)):
```

```
                writer.writerow([speed_data[x], altitude_data[x],
timestamp_data[x]])

    # continue if not a fit file
    else:
        continue


print (str(max_speed * 3.6))
```

Appendix 8 – High-performance eBike technical vehicle specification

Vehicle	Front/Back drive		AWD
	Empty weight	kg	248
	Maximum vehicle weight with payload	kg	328
	Front area	mm^2	942430
	Wheel radius (275/70 R22.5)	m	0.32
	Rolling resistance coefficient	%	0.022
	Vehicle aerodynamic drag coefficient		0.55
Drivetrain	Drivetrain efficiency	%	90 %
	Number of gears		1
	Drivetrain drive ratio		N/A
	Drive ratio on gear		2.5-3.8
Motor	Motor power	kW	120
	Maximum torque	N·m	210
	Motor rated speed	rpm	7500
	Motor maximum speed	rpm	10000
	Motor system efficiency	%	100%
Regeneration	Regeneration power	kW	50
	Regeneration system efficiency	%	94%
Battery	Working voltage	V	370
	Battery capacity	kWh	N/A
	Type of battery		Lithium-ion
	Battery system efficiency	%	90

Appendix 9 - Road-legal spec eBike technical vehicle specification

Vehicle	Front/Back drive		FWD
	Empty weight	kg	125
	Maximum vehicle weight with payload	kg	205
	Front area	mm^2	663000
	Wheel radius (190/55 R17)	m	0.32
	Rolling resistance coefficient	%	0.022
	Vehicle aerodynamic drag coefficient		0.63
Drivetrain	Drivetrain efficiency	%	95 %
	Number of gears		1
	Drivetrain drive ratio		N/A
	Drive ratio on gear		2-7
Motor	Motor power	kW	10
	Maximum torque	N·m	65
	Motor rated speed	rpm	5000
	Motor maximum speed	rpm	7500
	Motor system efficiency	%	98%
Regeneration	Regeneration power	kW	2
	Regeneration system efficiency	%	100%*
Battery	Working voltage	V	150
	Battery capacity	kWh	N/A
	Type of battery		Lithium-ion
	Battery system efficiency	%	90

Appendix 10 – eHGV technical vehicle specification

Vehicle	Front/Back drive		FWD
	Maximum vehicle weight with payload	Kg	37000
	Front area	mm^2	7000000
	Wheel radius (315/80 R22.5)	m	0.5218
	Rolling resistance coefficient	%	1.2
	Vehicle aerodynamic drag coefficient		0.35
Drivetrain	Drivetrain efficiency	%	95 %
	Number of gears		1
	Drivetrain drive ratio		6
	Drive ratio on gear		2-7
Motor	Motor power	kW	250
	Maximum torque	N·m	2200
	Motor rated speed	rpm	7500
	Motor maximum speed	rpm	10000
	Motor system efficiency	%	94%
Regeneration	Regeneration power	kW	25
	Regeneration system efficiency	%	100%*
Battery	Working voltage	V	526
	Battery capacity	kWh	500 (?)
	Vehicle Energy Consumption	kWh/km	1.26
	Type of battery		Lithium-ion
	Battery system efficiency	%	90