Facilitating the Uptake of Electric Vehicles in Rural Communities

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ABSTRACT

With increasing concerns arising over the impact of Climate Change, multiple countries, including the UK have set ambitious targets to reduce Greenhouse Gas (GHG) emissions, in particular CO_2 emissions. Electric Vehicles (EVs) have been recognised as a positive contributor towards these goals, including various other environmental, social, and governmental policies. For these reasons, we are amid a large-scale socio-techno transition; from conventional internal combustion engine (ICE) vehicles to EVs. Substantial work has been conducted for this transition in relation to an urban setting, however, little has been done for rural communities. This thesis addresses the EV transition for rural areas by exploring their feasibility, capabilities, and the impact for both these communities and grid operators.

This thesis presents a novel Travel Demand Model to simulate private passenger vehicle usage for rural communities. Based on statistics for a real-world location, the temporal-spatial travel patterns for a population of rural vehicles is achieved. Building upon the Travel Demand Model, a novel EV Charging Model has been developed to understand the energy consumptions should these travel patterns be completed by EVs. Through repeating the results of the Travel Demand Model, energy consumptions for the fleet of EVs was calculated for a month long simulation period, longer than many of the past EV charging models in literature. The EV Charging Model also scheduled regular charging events, focusing on home charging only. Multiple recharging scenarios were investigated, varying parameters such as household electricity tariffs and charging behaviour.

With the energy and power demands for a rural EV population understood, these results were combined with real-world grid data from National Grid (formerly known as Western Power Distribution). A thorough investigation into the impact on grid supply demand due to EV uptake in rural areas is presented, including analysis of potential grid overload events, planned and unplanned power cuts and the utilisation of Demand Side Management techniques to mitigate the issues which arise.

Finally, this thesis presents the findings from an online survey which was developed and distributed to rural communities within the Peak District, UK. This work was done firstly to engage with the rural community, an often overlooked stakeholder in large-scale socio-techno transitions, as well as provide validation to the aforementioned models presented in this thesis.

The research presented in this thesis seeks to fill multiple gaps found in literature pertaining to the EV transition in rural areas, as well as providing a better understanding for the nuances faced by these communities. Furthermore, this thesis identifies potential avenues for further work to build upon the findings of this thesis, to only improve and ensure that rural communities are not left behind in this EV transition.

DECLARATION

I, the author, confirm that this 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.

Thomas Richard McKinney

September 2023

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Journal Articles

McKinney, T. R., Ballantyne, E. E. F, Stone, D. A. (2023). Rural EV Charging: The Effects of Charging Behaviour and Electricity. Energy Reports. Vol 9, pp. 2323-2334. Available at: https://doi.org/10.1016/j.egyr.2023.01.056

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McKinney, T. R., Ballantyne, E. E. F, Stone, D. A. (2022). Using Lifestyle Scenarios to Investigate Electric Vehicle Impacts in UK Rural Areas. The 54th Annual UTSG Conference. Edinburgh, Scotland, 4-6 July.

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LIST OF ABBREVIATIONS

ABM	Activity Based Model
AC	Alternating Current
AFV	Alternative Fuel Vehicle
AVAS	Acoustic Vehicle Alert System
BEV	Battery Electric Vehicle
CAFE	Corporate Average Fuel Economy
CAZ	Clean Air Zone
COA	Census Output Area
CPP	Critical Peak Pricing
DC	Direct Current
DLC	Direct Load Control
DR	Demand Response
DSM	Demand Side Management
DUOATS	Direct Use of Observed Activity Travel Schedules
EPA	Environmental Protection Agency
ESEC	Electricity Supply Emergency Code
EV	Electric Vehicle
EVHS	Electric Vehicle Homecharge Scheme
FCEV	Fuel Cell Electric Vehicle
GHG	Greenhouse Gas
GPS	Global Positioning System
HBO	Home-Base Other
HBW	Home-Base Work
HEV	Hybrid Electric Vehicle
HOV	High Occupancy Vehicle
ICE	Internal Combustion Engine
ICT	Information and Communication Technology
LEZ	Low Emission Zone
LULUCF	Land Use, Land Use Change and Forestry
MCM	Markov Chain Model
MPG	Miles per Gallon
NHB	Non-Home Base
NHTS	National Household Travel Survey
NTS	National Travel Survey
OA	Output Area
ONS	Office for National Statistics
OZEV	Office of Zero Emission Vehicle
PFC	Power Factor Correction
PHEV	Plug-in Hybrid Electric Vehicle
PICG	Plug-in Car Grant
PLC	Powerline Carrier
POV	Point of View
PV	Photovoltaic
ROI	Return on Investment
RTP	Real Time Pricing
SMILE	Simulation Model of the Irish Local Economy

SOC	State of Charge
SORN	Statutory Off-Road Notification
STSM	Summary Travel Statistics Model
TCO	Total Cost of Ownership
TDI	Turbocharge Direct Injection
TDM	Travel Demand Model
TOU	Time of Use
ULEV	Ultra Low Emission Vehicle
ULEZ	Ultra Low Emission Zone
V2G	Vehicle to Grid
VAT	Value Added Tax
VDC	Vehicle Day Cluster
VOAMM	Vehicle Ownership and Annual Mileage Models
WPD	Western Power Distribution
WREV	Warwickshire Rural Electric Vehicle
ZEV	Zero Emission Vehicle

LIST OF PARAMETERS

Travel Demand Model	
Number of Vehicles	The total number of vehicles belonging to an area of interest
Number of Households	The total number of households belonging to an area of interest
Household Occupancies	The number of people within each household of an area of interest
Household Composition	The number of vehicles and people belonging to each household of an area of interest
Lifestyle Scenario	A proposed prediction, based upon the household composition, for the individuals within each household of an area of interest. This prediction influence the potential driving habits and trips that these individuals must take in order to fulfil the lifestyle scenario prediction
Trip Purpose	The reason for driving a journey. Can be one of five: Commuting, Education, Shopping, Other, and Day Trip
Trip Duration	The time taken for the driving journey to an activity based upon the trip purpose
Trip Distance	The distance of the journey driven to an activity/trip purpose
Trip Start Time	The time at which the journey begins
Day(s) of Week for Trip	Which day(s) of the week the journey takes place
Number of Trips (by Trip Purpose)	The number of times across one week this trip takes place
Duration of Activity (Trip Purpose)	The total time for the trip purpose, i.e. commuting to work and the duration of work is 8hrs. This is to determine how long a car is away for trips

EV Charging Model	
Consumption Rate	The energy consumed by an EV to complete a specific mileage of travel
Fleet Composition	The models and makes of vehicle which make up the ‘Number of Vehicles’ belonging to an area of interest
Charge Points	The specification of the EV charging points, in particular, power rating. Directly related to speed of charging
Total Battery Capacity	The total battery capacity of the EVs comprising of the fleet for the number of vehicles in an area of interest
Accessible Battery Capacity	The total capacity of the EV battery(s) available to a consumer
Consumer Battery Capacity	The available battery capacity available to agents of the EV Charging model. Thresholds (lower and upper) for the EV charging model to initiate or stop charging of an EV
Electricity Tariffs	The electricity tariff serving each household of an area of interest.
Charging Behaviour	The over-arching behaviour of charging EVs employed, dictating largely when EVs begin charging
Number of Charge Points	The Number of charge points per vehicle and per household.

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CHAPTER 1: INTRODUCTION

The Earths average global temperature has been increasing at an unprecedented rate over the past 50 years (NRDC, 2016). This global temperature increase can be largely attributed to human activities, through the release of Greenhouse Gas (GHG) emissions from burning fossil fuels (Syed and Khan, 2008). This warming results in the phenomenon of Climate Change, including rising sea levels, changes in weather patterns, increased risk of droughts and floods, and threats to biodiversity (Syed and Khan 2008).

In 2015, 196 state parties (including the UK) signed the Paris Agreement (UNFCCC, 2015), a legally binding international treaty aimed at tackling global warming and the corresponding Climate Change affects. The Paris Agreements long-term goal is to keep the average global temperature below 2°C above pre-industrial levels (1850-1900) (UNFCCC, 2015).

The UK's latest response to Climate Change, as of 2019, set a net-zero target by 2050 (BEIS, 2019). This target aims for a 100% decrease in GHG emissions by 2050, compared to 1990 levels. The Climate Change Act of 2008 commits the UK Government by law to achieve this goal (CCC, 2023). To achieve this goal, all sectors of our society will need to reduce their carbon footprints. One of the most crucial sectors, and the wider focus of this thesis, is the Transport Sector.

As of 2021 the Transport sector was the largest polluting sector, contributing 26% (109.5 MtCO_2e) of UKs total GHG emissions (BEIS, 2023). Figure 1.1 shows each sector and their contribution to the UK's GHG emissions.

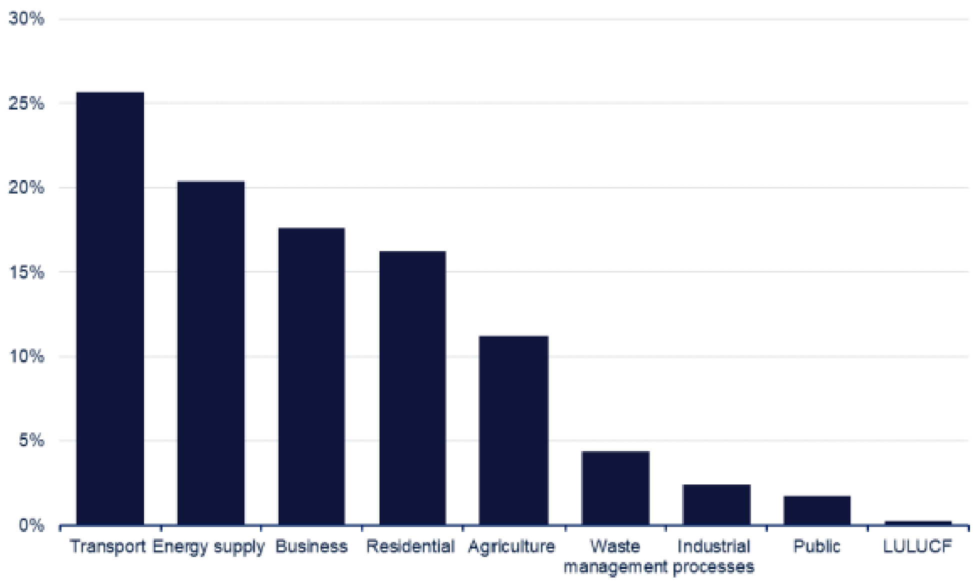


Figure 1.1: Net territorial UK greenhouse gas emissions by NC sector, 2021 (%). Extracted from BEIS (2023), (LULUCF - Land Use, Land Use Change and Forestry)

For the years up to 2020, GHG emissions from the transport sector had varied very little over the past three decades. In 2019, emissions were only 4% lower than they were in 1990 (BEIS, 2023). However, since 2020, transport has been significantly impacted by the COVID-19 pandemic. Vehicle usage reduced massively as people were instructed to stay at home as much as possible. This led to an estimated reduction of 15% in emissions for the transport sector in 2021 (BEIS, 2023). The corresponding reduction seen in kilometres of driving in the UK over this time period can be seen in figure 1.2.

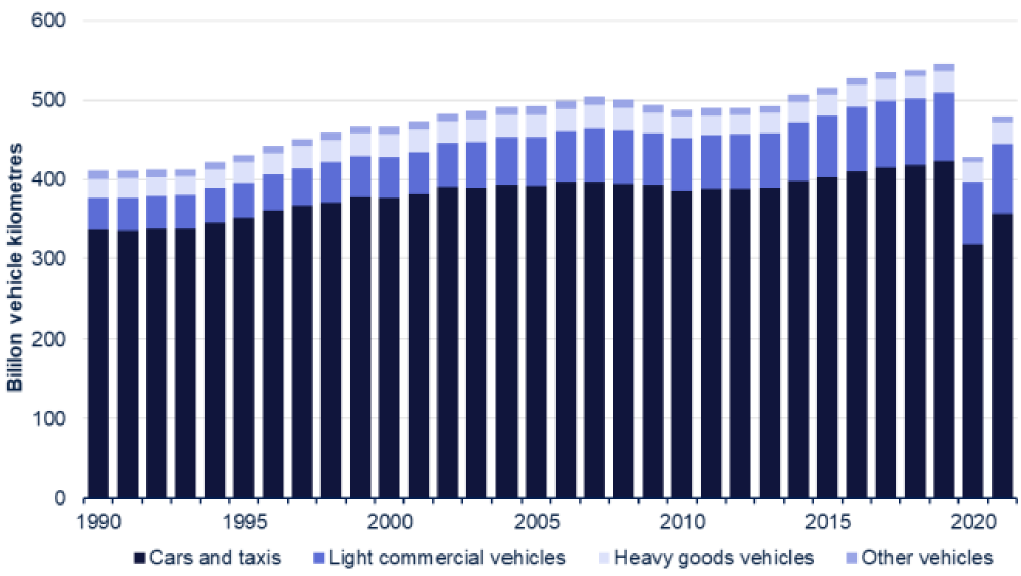


Figure 1.2: Motor vehicle traffic, Great Britain 1990-2021 (Billion vehicle kilometres). Extracted from BEIS (2023).

The last of the COVID-19 restrictions were lifted in the UK during 2022 and the sources of emissions most affected by the pandemic saw increases as a result, particularly transport (DESNZ, 2023). Between 2021 and 2022, carbon emissions rose by 23.2%, largely as a result of this greater use of road transport (DESNZ, 2023), which can also be seen in figure 1.2. With life returning to normal, even more so in 2023, and the corresponding travel habits doing so too, the decision was made to omit COVID-19 and its impacts for the work presented in this thesis. As records are still fluctuating following the effects of the pandemic, pre-COVID statistics and behaviours were chosen as the basis for this thesis.

Returning to UK emissions, road transport is the most significant source of emissions within the transport sector, in particular passenger vehicles (BEIS, 2023). Figure 1.3 shows the corresponding breakdown of GHG emissions for each transport mode, for both 1990 and 2020.

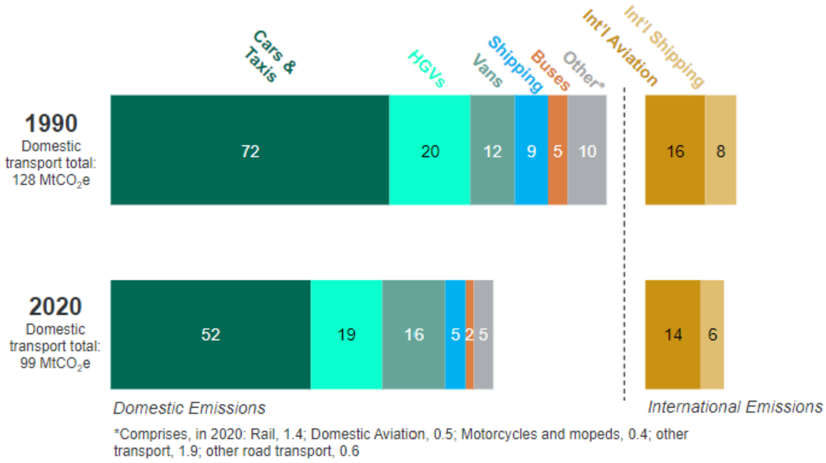


Figure 1.3: Greenhouse gas emissions by transport mode, 1990 and 2020. Extracted from (DfT, 2022c)

All transport modes have reduced their emissions in 2020 compared to 1990 levels. However, 'cars and taxis' remain the largest contributing transport mode, making up 52% of total GHG emissions for this sector. Over the last several years the UK Government has slowly increased pressures to reduce the number of petrol and diesel vehicles on UK roads, and by extension the GHG emissions associated. In 2017, the Air Quality Plan for Nitrogen Dioxide (NO_2) was announced which detailed the ending of sales of new conventional petrol and diesel cars and vans by 2040 (DEFRA & DfT, 2017). This was reiterated by the 'Road to Zero' Strategy in 2018, which was also first to focus on Electric Vehicles (EVs) as the solution, in part, for the reduction of the UKs transport sector's GHG emissions (DfT, 2018a). The ending of sales for new petrol and diesel vehicles was then brought forward to 2030 in the UK Governments 'Ten Point Plan' for a Green Industrial Revolution in 2020 (Energy Saving Trust, 2021). Most recently, in 2021, the Transport Decarbonisation Plan was released (DfT, 2023c) with targets of achieving a zero emission fleet of cars, vans, motorcycles, and scooters across the UK. Electric vehicles are expected to play a major role in achieving this goal.

EVs have been recognised as a positive contributor to a wide range of transport policy goals (Hirst, 2020; Hill et al., 2019; Mathieson et al., 2016), including the improvement of air quality, GHG emission reduction and the reduction of noise pollution. The Transport Decarbonisation Plan pledges funding to three core aspects required for a successful EV transition; £1 billion to build the necessary EV supply chain for the UK, £1.3 billion to accelerate the development of the UKs charging infrastructure and £582 million for plug in vehicle grants (DfT, 2021). With these investments in mind, the UK Government has illustrated that a transition to EVs has been deemed the most viable approach. In turn, pressuring the vehicle industry to develop EVs, reducing its carbon footprint and aiding the reduction of GHG emissions for the UKs transport sector. However, when considering a UK wide transition from current internal combustion engine (ICE) vehicles to electric, one area in particularly is at risk of being neglected – rural areas.

1.1 Research Aims & Objectives

This thesis seeks to understand the implications, requirements and logistics of electric vehicles replacing conventional ICE vehicles in rural areas. To achieve this, a model based approach is proposed to simulate current vehicle usage in these areas, the corresponding energy requirements should these vehicles all be swapped to electric, and energy and power demands from recharging events to ensure sufficient battery state of charge levels. The models include key factors particular to the rural case, which have not been incorporated into previous models before, models which have focused largely on the urban environment. Following the understanding of rural EV charging patterns, exploration into the rural electrical grid, its capabilities, and possible solutions for mitigating any cause for concerns surrounding this EV transition are investigated. To achieve this, real-life grid demand is analysed and combined with the results from the proposed models developed in this thesis. To ensure a smoother transition for the rural community to electric vehicles, an online survey is used to gather further data, as well as validate the findings from the aforementioned models and highlight any further areas in need of consideration. Consequently, the research aims and objectives of this thesis are as follows:

(1) **Research Aim 1** – To understand recent developments in the field of electric vehicles particular to the transition from ICE vehicles in rural areas. In addition, to identify research gaps that need to be filled and highlight any pre-existing processes which could be utilised.
   a) **Objective 1a** – To conduct a literature review on electric vehicles and rural areas, including methods for assessing their impact and understanding the requirements for switching to an electrified transport system.
   b) **Objective 1b** – To highlight and address the lack of academic discourse on the EV transition for rural areas.

(2) **Research Aim 2** – To examine the energy and power requirements of EVs in rural areas to identify barriers to the uptake of EVs in these environments.
   a) **Objective 2a** – To develop a Travel Demand Model with high tempo-spatial capabilities and behaviours specific to the rural demographic built in.
   b) **Objective 2b** – To develop an EV Charging Model, capable of adaptation to any rural community and ability to manipulate parameters to simulate a range of scenarios.

(3) **Research Aim 3** – To investigate the added grid supply demand due to the EV uptake in rural areas.
   a) **Objective 3a** – To combined power requirements from the EV charging model to the pre-existing demand on rural grid infrastructure.
   b) **Objective 3b** – To review the ability of maintaining EV charging patterns under circumstances of reduce grid supply and capacity.

c) **Objective 3c –** To investigate mitigation techniques for reducing the EV power demand on local grid infrastructure.

(4) **Research Aim 4** – To incorporate the rural community for understanding the implications of the EV transition in these areas.

a) **Objective 4a** – To develop and distribute a survey for data collection to the rural community.

b) **Objective 4b –** Utilise the results from the survey to validate the aforementioned Travel Demand Model and EV charging model.

1.2 Overview of Thesis

Having provided background context, as well as the aims and objectives this thesis sets out to achieve, a brief overview of the following chapters will now be provided.

Chapter 2 presents a literature review on six key topics surrounding those which will be the focus of the work within this thesis. A review of literature not only provides more context to this thesis as a whole, but also fulfils '*Objective 1a'* to achieve '*Research Aim 1'*. The six key topics are as follows:

- Electric vehicles, reviewing aspects on the transition itself, as well as surrounding policy and technologies to provide a holistic view for the thesis
- Aspects of the rural environment which identify key nuances which need to be accounted for, creating a large part of the novelty of this thesis' work
- Travel Demand Modelling
- Electric Vehicle Charging
- The Electrical Grid, including the grid infrastructure itself, worst case scenarios, and potential mitigation technology
- Previous surveys which have been conducted related to the EV transition

Key findings from literature within each topic have been identified to aid and influence the decisions for modelling techniques presented in later chapters, as well as provide comparisons with other results.

In Chapter 3, a novel Travel Demand Model, built specifically to account for the nuances associated with rural travel. This model is able to deliver temporal-spatial predictions for the vehicle population belonging to a small rural village in the Peak District, Bradbourne. With a high fidelity of 30 minutes, details on any vehicle simulated, including location, distance travelled that day, and journey purpose are predicted. With the fulfilment of '*Objective 2a*', an understanding of how the current vehicles in a rural area are used has been achieved. Effort then sought to understand how electric vehicles might cope with said use.

Chapter 4 seeks to build upon the travel demand model presented in Chapter 3 with an EV Charging Model. This model supposes all the vehicles belonging to the village of Bradbourne have been switched to electric and calculates the associated energy consumption, the battery State of Charge over time of each vehicle, and recharging events. Multiple recharging scenarios have been simulated to anticipate the impact of various behaviours and choices, previously not seen in past literature. With each vehicles energy and power demand determined, the impact on the grid for a rural electric vehicle population can be analysed. Together with Chapter 3, the material presented in these two chapters works towards the fulfilment of '*Research Aim 2*'.

Chapter 5 presents the local grid infrastructure to Bradbourne and the surrounding areas, for which real-world power demand data has been acquired. This has been combined with the results from the EV Charging Model to assess the impact of electric vehicles for this community and others in the area. Additional work is also presented to investigate the potential for grid failure due to the influx of electric vehicles and also a timeline to predict when this level of market penetration for electric vehicles will occur for these rural communities. The results presented in this chapter have multiple implications for multiple stakeholders to the EV transition, including grid operators, policy makers, and consumers, and represent a significant step forward in achieving '*Research Aim 3*'.

Chapter 6 follows with further exploration into the impact of electric vehicles on rural grid infrastructure. This chapter addresses two key topics, firstly to understand how electric vehicles will cope should power outages of various kinds occur, and secondly the implementation of demand side management techniques to alleviate the added pressures on the grid following the EV transition.

Chapter 7 presents the survey data collected to validate and compare against the simulation and modelling results. This involved the development and distribution of an online survey to rural communities local to the research area of interest, Bradbourne. A full analyses and presentation of the results is provided, as well as their comparison with past literature and the results from the models developed in this thesis in an effort for validation. The work presented in this chapter seeks to achieve '*Research Aim 4*'.

Finally, Chapter 8 concludes the thesis and includes a discussion on the limitations across the work presented in this thesis, as well as suggestions for future work and improvements. All models and data presented in this thesis are either publicly available or can be found following this ***link***. Having introduced this thesis and outlined its contents, a literature review will be presented in the next chapter.

CHAPTER 2: LITERATURE REVIEW

Having described the issues behind the drive towards EV uptake in the UK, and in particular, the need to ensure that rural communities are not left behind in this transition, this chapter presents the state of the art with respect to studies carried out in this area. With the core focus of this thesis on facilitating the uptake of, not only a new technology (EVs), but one that is so intrinsic to day-to-day life, the work presented in this thesis covers a wide range of topics. A literature review has been conducted to define the problem more specifically, identify the research gaps which remain, and to solidify the novelty of this thesis within these fields of study.

This chapter will begin with outlining the approach to the literature review, including the methodology, search strategy and scope etc. A more in-depth description of EVs than was presented in the previous introduction chapter, including a review on EV adoption policy, emission zones and the main drivers and barriers for adoption across society is presented in Section 2.2. Section 2.3 presents the aspect which sets the uniqueness of the work conducted within this thesis, rural areas. Following an understanding of the nuance factors setting the rural environment apart in this EV transition, a summary of approaches to Travel Demand Modelling is provided in Section 2.4. This will be followed by a review of current literature surrounding EV charging and the impact on the electrical grid in Section 2.5 and Section 2.6, respectively. The chapter will then introduce a qualitative aspect for this thesis in Section 2.7, with a focus on previous surveys and questionnaires related to the EV transition. This will continue on with reviewing the theoretical approaches behind this thesis in Section 2.8. Section 2.9 will summarise and conclude the chapter.

To note, some of the material presented in this Chapter has been published or is currently under review at the time of writing, in conference and journal papers. References to these papers are as follows: McKinney et al., (2023a, b, c, d, e, f), and McKinney et al., (2022).

2.1 Literature Review Approach

This literature adopts a hybrid approach, combing narrative and systematic methodologies to explore the complex domain of the EV transition particular to rural areas (Turnball et al., 2023; Rusli et al., 2023). This dual approach was necessitated by the multifaceted research questions guiding this thesis, which seeks to not only map out the existing evidence base but also to understand the broader thematic and conceptual developments within the field of EV uptake, especially within rural UK contexts.

Initially facing the vastness of available literature without clear directions, the review began with a narrative approach, guided by a broad understanding and the search for emergent themes, keywords, and ideas. This exploratory phase was crucial in uncovering specific terms and concepts previously unknown, such as “Travel Demand Modelling”, which then became focal points for a more targeted inquiry.

Transitioning to a systematic approach allowed for a structured and comprehensive analysis of literature centred on these identified themes, ensuring a thorough exploration of the topic at hand. This method enabled the identification and synthesis of empirical evidence on the EV transition, focusing on the intricacies of rural electrification, the impact of policy and infrastructure development, and the socio-economic considerations unique to rural communities.

By merging these approaches, this review provides a comprehensive understanding of the current state of EV adoption, highlighting both the empirical findings and the evolving narrative landscape. This hybrid methodology not only bridges the gap between narrative and systematic traditions but also offers a nuanced understanding of a complex and dynamic field, setting the stage for the thesis’s contributions to knowledge.

2.1.1 Literature Review Process

DATABASE AND SEARCH STRATEGY

The literature review process primarily utilized Google Scholar as a pivotal resource for identifying scholarly articles and research papers pertinent to the field of this thesis. Recognizing the importance of saturating the field of literature, a comprehensive approach by not only searching for papers directly through Google Scholar but also reviewing the references cited within these papers was adopted. This method of tracing references served as a crucial strategy for uncovering additional, relevant literature that might not have been directly captured through initial searches. Moreover, the scholarly journey was further enriched by incorporating papers recommended by colleagues and supervisors, ensuring a diverse and robust collection of research materials. This multifaceted approach facilitated a thorough exploration of the available literature, enabling the construction of a solid foundation for the review itself.

SCREENING PROCESS

Literature found through the means of the above database and search strategy were first screened based upon their title. If deemed relevant, the abstract would then be read and assessed. If this was deemed acceptable, the full paper would be taken forward and reviewed in depth for this literature review. Unlike a systematic review approach though, the numbers indicating the initial number of studies found, studies excluded based on titles and abstracts etc were not recorded.

QUALITY ASSESSMENT

The integrity and reliability of the literature incorporated into this review, particularly those identified through systematic search strategies focusing on specific fields or keywords, were evaluated using the University's Star Plus database. This platform served as a benchmark for quality, providing access to a vast repository of peer-reviewed and academically accredited sources. In instances where a paper identified via Google Scholar could not be located within the Star Plus database, it was excluded from consideration. This criterion ensured that only literature from reputable and recognised academic and scientific channels was included in this review.

SYNTHESIS

A combination of the insights gleaned from the narrative and systematic approaches were used to construct a coherent understanding of the existing body of knowledge. This process involved a critical analysis of the methodologies, findings, and theoretical contributions of the selected studies. By integrating these diverse perspectives, the overarching themes, as well as gaps in the current research landscape could be identified.

Through the comprehensive and nuanced analysis a direction for the subsequent empirical research was established. The synthesis thus served as a crucial step in bridging the initial exploratory phase of our literature review with the focused, systematic investigation of specific research fields.

2.1.2 Selection Criteria

SCOPE OF LITERATURE

The scope of literature for this review was deliberately expansive, covering a diverse range of topics related to EV uptake, with a particular focus on the inclusion of rural communities in the transition towards sustainable transportation. This included, but was not limited to, studies from transportation engineering, urban planning, environmental science, and computational modelling. Recognising the novelty of this field and the initial lack of a clear research direction, no temporal boundaries were imposed. This approach facilitated a comprehensive understanding of the field's development and the identification of seminal works and pivotal developments, such as those in travel demand modelling (this particular example will be discussed in Section 2.4).

SOURCE TYPES

In the construction of this literature review, a diverse array of source types was selected to ensure a multifaceted exploration of EV uptake and rural areas. Peer-reviewed journal articles constituted the primary foundation of the research corpus. Recognising the importance of current industry insights and policy developments, official government reports were also integral, providing authoritative information on regulations, incentives, and future directions in EV policy. Conference papers and technical reports from leading industry bodies and research institutions were also included to capture ongoing innovations and practical challenges in EV infrastructure and technology. Grey Literature was found and has been used extensively throughout this thesis, especially in relation to data. The main process for identifying grey literature was done so through the primary pieces of literature – i.e. extracting data and their sources from journal papers, conferences papers etc found from the Narrative-Systematic Hybrid literature review. Upon reflection, a direct search for grey literature should have been undertaken, which would have found additional potential sources of data and useful material, i.e. The Society of Motor Manufacturers and Traders (SMMT) (SMMT, 2023). This mix of source types was essential to producing a comprehensive picture of the current state of EV adoption, allowing for a nuanced understanding of the field that is both academically rigorous and grounded in practical realities.

SEARCH KEYWORDS

Table 2.1 below details the keywords used for searches, listed in as accurate representation as possible for finding further keywords and areas of interest as the search morphed from a narrative approach to a more systematic one in nature.

Keywords
Electric Vehicle Transition
Rural Electric Vehicles
Travel Demand Modelling
Activity Based Travel Demand Model
Electric Vehicle Policy
Rural Transport
Emission Zones
EV Charging
Electric Vehicles Electrical Grid
Electric Vehicles Natural Disasters
Demand Side Management
Electric Vehicle Surveys
Pragmatism
Stakeholder Theory
Case Study

Table 2.1: Literature Search Keywords

INCLUSION/EXCLUSION CRITERIA

In developing the inclusion/exclusion criteria for this literature review, studies centred on urban contexts were not strictly excluded. Despite the primary focus on rural electrification, it was recognised that urban areas, as more traditionally researched contexts for EV uptake, could offer valuable insights. This perspective acknowledges the potential applicability or urban methodologies, practices, and findings to rural settings. The examination of urban-focused literature was deemed essential for providing a well-rounded background and fostering a broader understanding of the challenges and opportunities in sustainable transportation. The full methodology for the literature review presented in this thesis is illustrated in Figure 2.1 below.

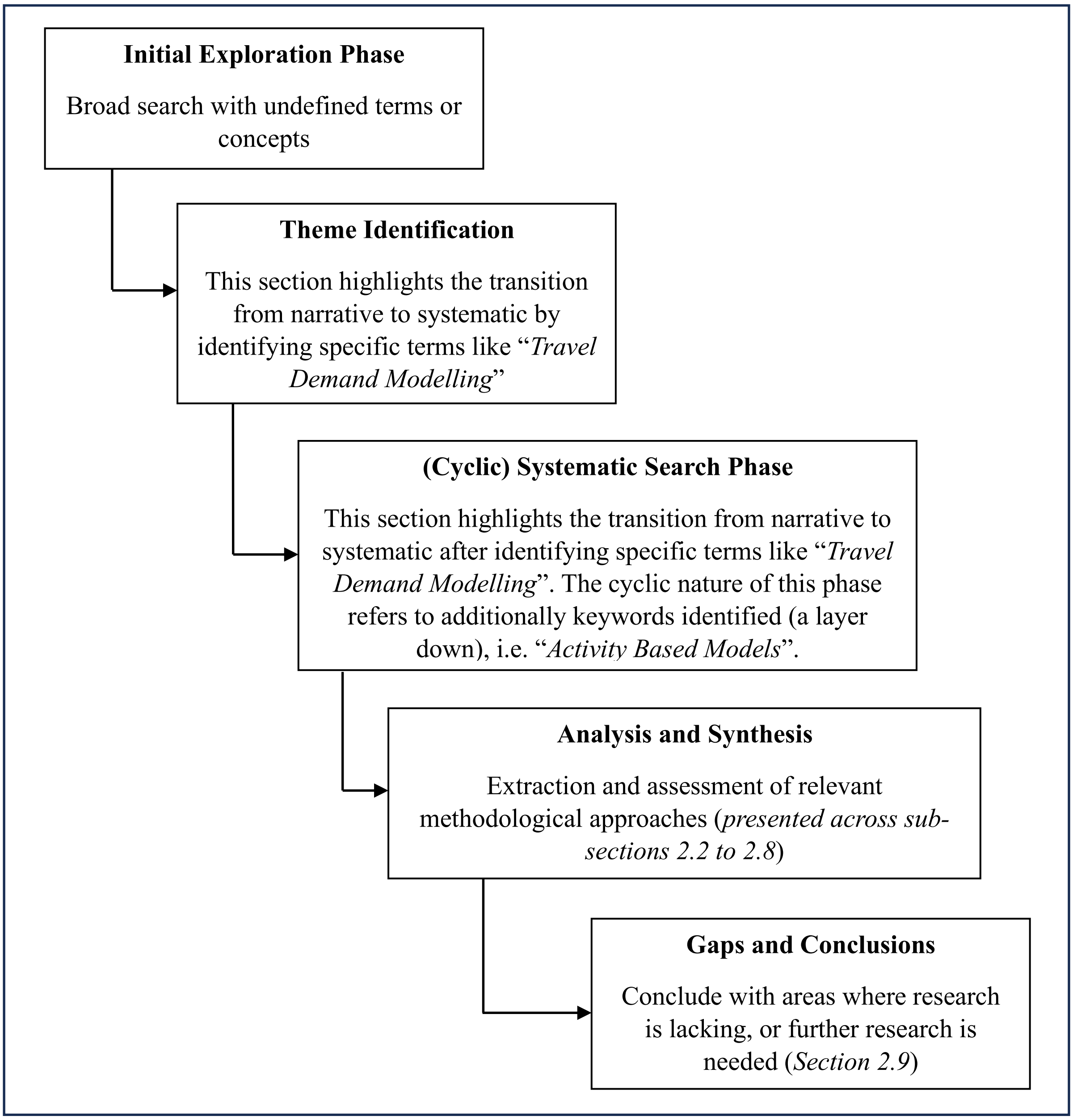


Figure 2.1: Literature Review Methodology: Narrative-Systematic Hybrid Approach

A total of 196 pieces of literature have been referenced in this thesis. As a precursor to the to the results of the literature review and those used throughout the thesis, Figures 2.2 and 2.3 present a breakdown for the found literature. These figures include the age of the pieces, as well as the type of source, respectively.

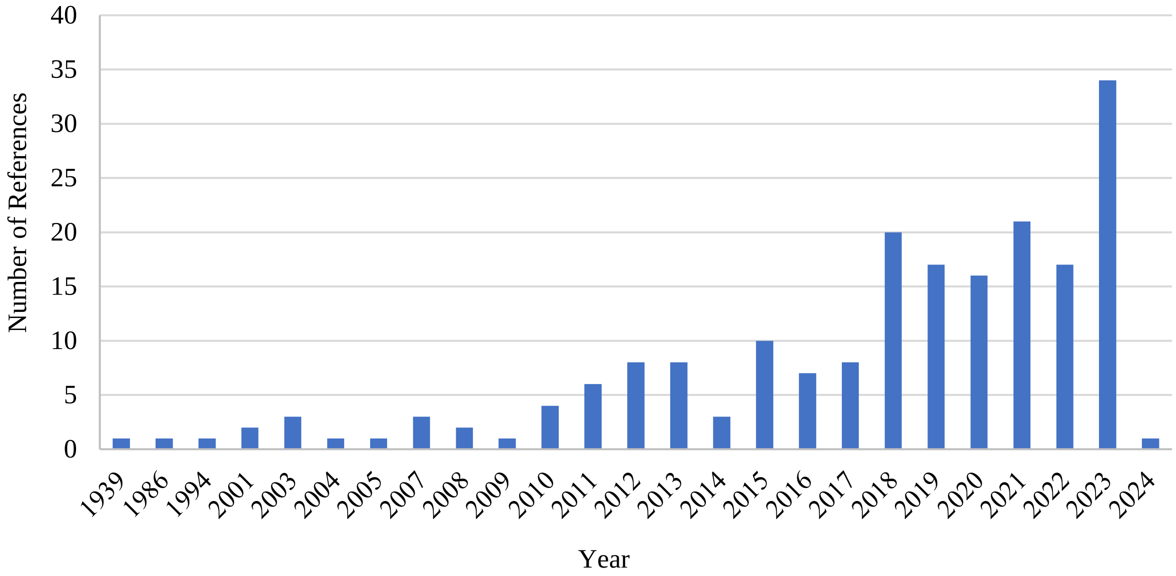


Figure 2.2: Age Breakdown for literature in this thesis

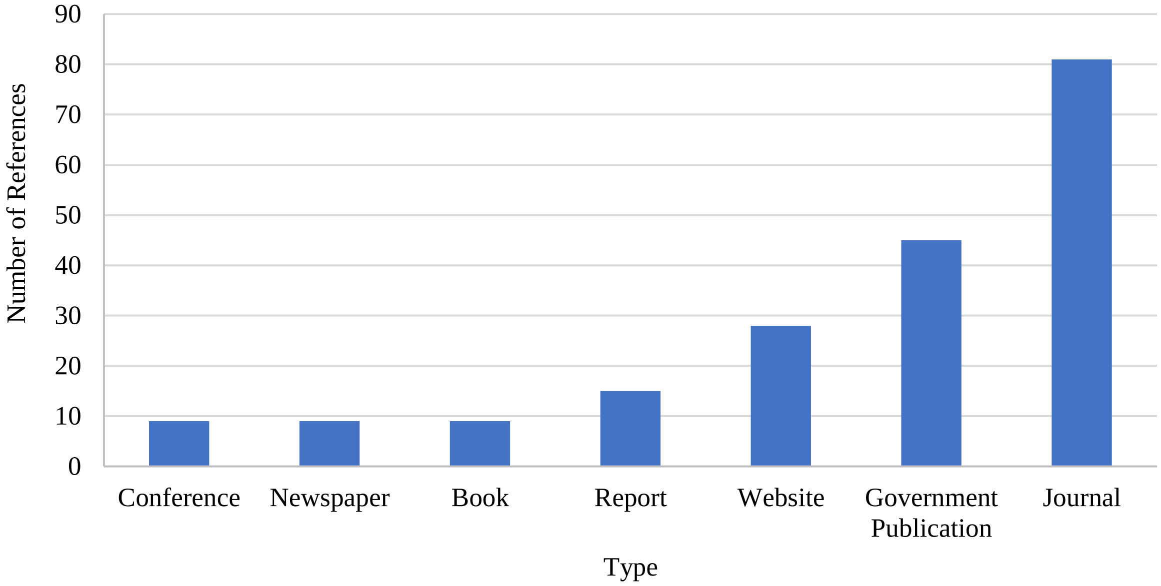


Figure 2.3: Literature split by Type of Source

2.2 Electric Vehicles

UK Government pressures have created a favourable landscape for the development and uptake of Electric Vehicles (EVs), which are now seeing increased adoption by consumers. Figure 2.4 depicts the change in number of licensed plug-in vehicles on UK roads since 2014, split by fuel type (GOV.UK, 2022a).

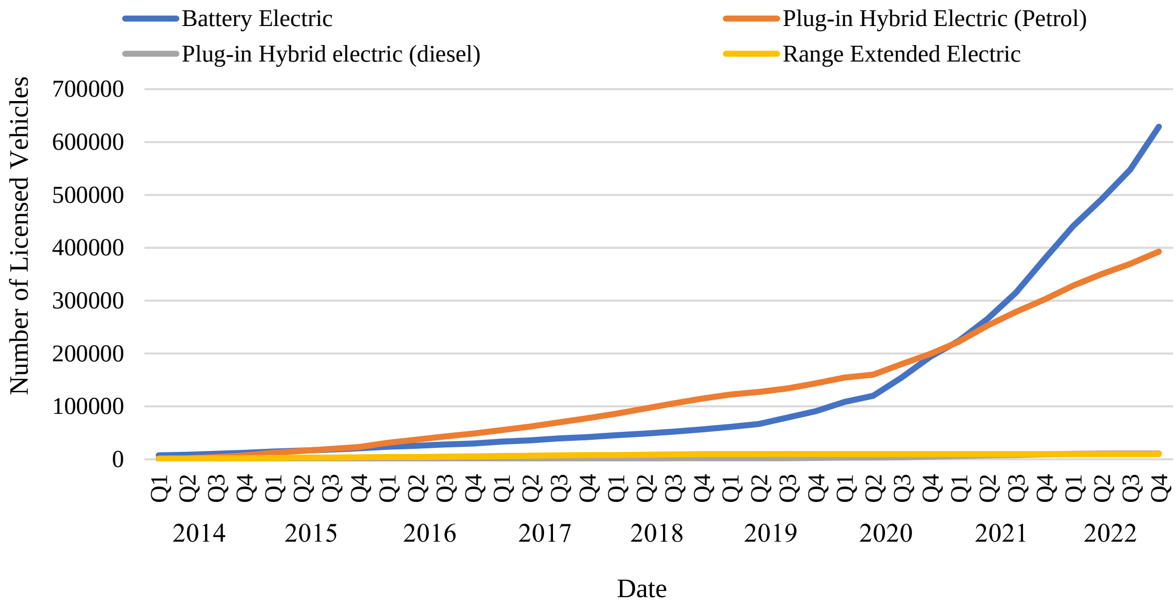


Figure 2.4: Number of licensed Plug-in vehicles across the UK

As shown in figure 2.4, Battery Electric Vehicles (BEVs) and Plug-in Hybrid Electric Vehicles (Petrol) (PHEVs) have seen large increases in adoption, in particular the BEVs. Considering the UK Governments timeline for the EV transition, this thesis will focus on investigating whether rural areas will be ready for when there are solely EVs on the roads, i.e. a future scenario. With the carbon savings of PHEVs currently under debate, the Climate Change Committee (CCC) are pushing for prioritising BEVs over PHEVs (CCC, 2023). With this in mind, BEVs will be the sole focus of work presented throughout this thesis.

At the end of 2022, there were 29,704,700 private cars registered on UK roads, this is predominantly made up of Petrol and Diesel vehicles, 17,531,000 and 10,765,700 respectively. Plug-in vehicles make up 1,114,000 vehicles, with 56.5% (629,000) of those being BEVs. Based on these numbers, a 3.75% market share, plug-in vehicles have just entered the 'Early Adopters' stage (Rogers, 2003). This will become a critical time for the EV transition, to overcome the 'chasm' (Moore, 2014). The chasm is a stage between the 'Early Adopters' and the 'Early Majority', split by the type of people who comprise these categories; visionaries and pragmatists, respectively (Moore, 2014). The trajectory of market penetration for EVs is determined by the drivers and barriers for this transition, as well as transport policy itself. These three themes will now be discussed.

2.2.1 Transport Policy

As discussed in Chapter 1, over recent years there have many been examples of new legislation and policies brought in by the UK government to influence this EV transition. This section aims to review these policies and their impact.

To provide an overview, Wang et al. (2019) reviewed both incentive (direct subsidies, tax breaks, road priorities etc.) and socio-economic factors (household income level, environmentalism, fuel and electricity prices etc.) across thirty countries, including the UK, in an effort to understand the key factors which promote EV adoption. Wang et al. (2019) focused solely on battery electric vehicles (BEVs) and plug-in hybrid electric vehicles (PHEVs), with Fuel Cell Electric Vehicles (FCEVs) and hybrid electric vehicles (HEVs) disregarded. Norway was found to have the highest market share of EVs, even though this country does not offer any direct subsidies (Wang et al., 2019). However, Norway did offer Value Added Tax (VAT) exemption for EVs, which equates to a significant amount of money compared to many other countries which often only exempt EVs from annual circulation taxes, amounting to little money. In general, Wang et al. (2019) found countries which offered higher tax breaks saw higher market shares of EVs, e.g. Norway and the Netherlands. As of 2015, Norway has an EV market share of 17.1% (Figenbaum, 2017). In comparison, the UK offers very little in terms of real monetary offsets, exacerbated by the recent revoking of the Plug-In Car Grant (PICG). The PICG offered consumers up to 35% off an EV purchase price, up to a maximum of £1500. This as well as the general lack of subsidies could explain the considerably lower EV uptake in the UK (3.75% as previously discussed). Although it is worth mentioning the difference in population, and thus corresponding fleet sizes. Norway's 17.1% EV market share equates to roughly 70,000 vehicles (Figenbaum, 2017), whereas the UKs 3.75% equates to over 1.1 million EVs.

The US, at one point in 2018, had 438 incentives for EVs, including tax rebates, sales tax or registration fee exemptions, reduction of parking fees, subsidies for charging infrastructure, and access to high occupancy vehicle (HOV) lanes (Stokes and Breetz, 2018). Stokes and Breetz (2018) looked at California's Zero Emission Vehicle (ZEV) mandate. This defined a certain percentage of vehicles that automakers sold had to be ZEVs, first starting in 1990. The mandate aimed for 2% of vehicles sold to be ZEVs by 1998, 5% by 2001, and 10% by 2003 onwards. There were various amendments over the years to account for the slow development of EVs compared to predictions, and the production of hybrid vehicles but decades later, as of 2018, EVs still only accounted for 3% of California's new vehicle sales. Although uptake levels are low, the mandate successfully forced automakers to develop and sell EVs (Stokes and Breetz, 2018).

However, with so many policies currently implemented across the US, there is a potential for these policies to fail in their attempts for facilitating the uptake of EVs (Carley et al., 2019). Elsewhere in the US, Carley et al. (2019) recognised that with the way current federal and state policies interact, the simultaneous goals of increasing EV market share and limiting GHG emissions are actually at odds of one another. The federal regulatory programs themselves, such as the Corporate Average Fuel Economy (CAFE) and the Environmental Protection Agency (EPA) GHG emissions standard, do not directly push for the development and uptake of EVs. The CAFE, for instance, acts a minimum limit to the miles per gallon (MPG) a vehicle needs to achieve, and EPAs GHG emissions standard sets the limit for tailpipe emissions of a vehicle. However, to meet these standards, an EV is not the most cost-effective technology for automakers to pursue, and so hinders the development of such vehicles. Compared to recent European GHG standards (part of the EV30@30 campaign), which are more stringent than these US standards, are expected to directly lead to almost 30% EV penetration by 2030 (IEA, 2017). The European GHG standards specify zero emission targets by the year 2030 (IEA, 2017), whereas the US standards only have the goal of 52.5 MPG (Carley et al., 2019) and 143 CO_2 g/mile by 2025. Thus enabling the car makers to develop other, more cost effective, technology solutions for their vehicles as opposed to EVs.

Having discussed various policies and their impacts in other countries, focus will now be on the UK. In the UK, ultra-low emission vehicles (ULEVs) are characterised by those that emit less than 75g of CO_2 per kilometre (km) (or 88.9 CO_2 g/mile) (Chen et al., 2020). Already this is far less than the US's 2025 standards for their vehicles as previously discussed. Furthermore, UK policies such as the 'Ten Point Plan' for a Green Industrial Revolution, as previously discussed in Chapter 1, act as a direct drive specifically for the development of EVs and their technology given the ban of sales of new petrol and diesel vehicles as of 2030.

Although the UK has set some of the most ambitious goals to achieve net zero targets re CO_2 emissions, which by extension has accelerated the uptakes of EVs and their development, the CCC (2020) highlighted future considerations and policies required to achieve a full EV transition by 2030. The alignment of incentives and mandates to targets, whilst also continuously monitoring impacts would ensure that funding is focused on the necessary preconditions for the petrol and diesel vehicle phase-out. Once targets are met, this would allow for funding to shift to the next priority at the appropriate time. Additionally, establishing this long-term clarity on future incentives and mandates will allow not just consumers, but also manufactures, automakers, and local authorities to plan for the various aspects of the EV transition, including chargepoint installations, EV uptake and infrastructure improvements. The CCC (2020) also suggest a Zero-Emission Vehicle Mandate which would require increasing shares of sales to be zero-carbon, reaching 100% by 2032 at the latest.

The CCC (2020) also suggest reinforcement of the distribution network now, ensuring networks are ready to meet future demand. Reinforcing today would be more cost-effective than implementing network reinforcements once demand outstrips capacity (CCC, 2020). This extends further to considering the development of a sufficient charging infrastructure across the UK. Further details of EV charging will be discussed in Section 2.4.

2.2.2 Emission Zones

Recent years have seen the expansion of Clean Air Zones (CAZ), Low Emission Zones (LEZ) and Ultra Low Emission Zones (ULEZ) across cities within the UK, including Birmingham, Bristol, Edinburgh, London, Oxford, Sheffield and York (solely for local bus services) (Motorway, 2023). These zones are geographical areas where certain vehicles travelling within must comply with emission standards, or pay a fine/daily charge (Motorway, 2023). They are designed to tackle air pollution within cities through discouraging high emission vehicles from entering, although there is debate on their effectiveness towards this goal.

Ma et al. (2021) studied the ULEZ in London, reporting minimal improvements in air quality directly due to the ULEZ in comparison to the overall, long-term, downward trend of London's air pollution levels. Mat et al. (2021) showed the relative changes in air pollution ranged from -9% to 6% for NO_2, -5% to 4% for O_3, and -6% to 4% for particulate matter. London itself has seen multiple air pollution mitigation policies in the past several years, which Mat et al. (2021) attribute to the declines in air pollution, stating that the ULEZ on its own is unlikely to be the most significant contributor to the air pollution reductions seen in recent years.

Peters et al. (2021) analysed data pertaining to the impact emission zones have on the uptake of Alternative Fuel Vehicles (AFVs), as well as CO_2 emissions in Madrid, Spain. As is the case in the US, low emission zones, as opposed to zero emission zones shift vehicle registrations towards fossil fuel powered AFVs and PHEVs, rather than zero emission vehicles (Peters et al., 2021). This in turn was found to fail at reducing the CO_2 emissions of the vehicle fleet itself due to the limited CO_2 reduction potential of AFVs and PHEVs (Peters et al., 2021). Peters et al., (2021) fail to suggest reasons for the vehicle registration shifts to AFVs and PHEVs rather than EVs, however, costs and availability of vehicles on the market are likely causes. To conclude, Peters et al. (2021) suggest that a zero emission zone would be required to foster the uptake of zero emission vehicles such as EVs.

The literature presented in this and the previous sections, (Sections 2.1.1 and 2.1.2) suggest that there must be other drivers promoting the uptake of EVs as opposed to various policies and vehicle mandates. These will now be discussed.

2.2.3 Drivers for EV Adoption

Surrounding this EV transition there are multiple positive factors which are driving the rate of adoption by consumers. It is important to understand these factors so as to capitalise on them when considering the facilitation of the uptake, as does this thesis. These drivers for adoption include environmental benefits, financial incentives and energy security. Each will now be discussed in detail.

ENVIRONMENTAL BENEFITS

In our increasingly eco-conscious society, individuals value the low carbon emissions of EVs (Tiwari et al., 2020), particularly given the growing health concerns that arise from transport emissions (DEFRA & DfT 2017). This has only been aided by recent scandals on the part of Internal Combustion Engine (ICE) vehicle manufacturers, such as the Volkswagen Scandal (Bailey, 2015). The Volkswagen Scandal, also known as Dieselgate or Emissiongate, saw the unearthing of Volkswagen intentional programming of their turbocharge direct injection (TDI) diesel engines to only activate their emission controls during laboratory emission testing (The Guardian, 2015).

EVs on the other hand are zero emission vehicles at the tailpipe (Karki et al., 2020). There is currently debate in the literature around the publicity of EVs being 'coined' as zero emission tailpipe or low emission vehicles in general due to the origins of generated electricity required for charge. Though, if the electricity used to recharge the EV is from renewable sources, EVs become a true green alternative to ICE vehicles (Tiwari et al., 2020). One study sought to calculate the impact on emissions if Scotland were able to switch all the current ICE light-duty vehicles to electric (Milev et al., 2021). With 2,240,000 light-duty vehicles, corresponding to 4065 GWh of energy required for their travelling patterns, Milev et al. (2021) found this would increase CO_2 emissions by 8.14% for the grid generated electricity alone (based on current generation mix). However, when combining these emissions increasing for the grid sector with the reduced tailpipe emissions of the transport sector, total emissions for Scotland would decrease by 11.4%, thus highlighting the benefits changing to EVs from ICE alone can have on emissions. With electricity generation also becoming greener, these numbers are only likely to improve further in the future. If Scottish electricity generation were to eliminate coal, utilising only the current other sources (Nuclear, Gas & Oil, Hydroelectric, and Other Renewable), this would further decrease the grids sector CO_2 emissions by 33.7% alone (Milev et al., 2021).

EVs also offer additional environmental benefits. EVs are much quieter than petrol and diesel vehicles, leading to improvements for noise pollution. In fact, EVs produce such little noise, they are now required by law to have an Acoustic Vehicle Alert System (AVAS) to emit a sound when reversing or travelling below 12mph (EDF, 2023).

FINANCIAL INCENTIVES

Incentives in the form of reduced sale costs for EVs (in particular cars) have recently been scraped by the UK Government. In part due to ongoing growth of EV sales (BBC, 2022), but also to release funds to expand the charging network and support other battery-powered vehicles (The Guardian, 2022c). However, they are still available for other types of low emission vehicles (motorcycles, mopeds, vans, trucks and taxis) (GOV.UK, 2023a). Last year the Office of Zero Emission Vehicles (OZEV) also ended the Electric Vehicle Homecharge Scheme (EVHS), a fund providing consumers with up to 75% the cost of installing EV smart charge points at domestic properties across the UK (GOV.UK, 2022b), it is now only available to persons living in flats and rented accommodation.

When considering maintenance and running costs, EVs are currently exempt from road tax (GOV.UK, 2023b), although this is scheduled to end after April 2025 (RAC, 2023). They are also exempt from chargers for Ultra-Low Emission Zones (ULEZ), including Clean Air Zones (CAZ) which multiple cities around the UK have recently introduced. On average, an electric car costs less than £1.30 to drive 100 miles (based on EDFs GoElectric 35 tariff during off-peak hours) vs. £17.16 for a Petrol car (EDF, 2023). However, this should be caveated by the fact that electricity prices are rising year on year, adding to the current cost of living crisis (Parliament, 2023). In addition, EVs also have the option to use dedicated parking bays, free of charge, at various locations around the country (Sheffield City Council, 2023).

ENERGY SECURITY

Energy security is "the uninterrupted availability of energy sources at an affordable price" (IEA, 2019). Following the emergence of the car, their popularity grew significantly. However, with this growth came an increasing dependence on petroleum, a cost-effective transportation fuel (Serra, 2012). The UK is not only a net importer of petroleum (Bolton, 2018), but oil reserves are predicted to run out by 2052 (MAHB, 2019). These factors stipulate that a petroleum-based ICE vehicle ecosystem is unsustainable in the future.

EVs offer a more secure alternative given the multiple fuel sources used in the generation of electricity. Although, the UK still relies heavily on fossil fuels for electricity production (Gridwatch, 2023), of which it is a large importer. Recent global affairs have exposed the threat of foreign dependency for electricity production, with results threatening the implementation of the UKs Electricity Supply Emergency Code (ESEC) (The Guardian, 2022a; GOV.UK, 2019). Although, as highlighted under the '*Environmental Benefits*', should electricity be sourced not just from renewable sources, but also domestic sources (Serra, 2012), the UK stands to have sovereignty over not just its energy supply for the transportation sector, but for all sectors.

There is an argument to make that the dependence for our transport sector would then move from petroleum to batteries. However, as outlined in Chapter 1, the UK Government is committing large sums of money into the investment of the EV supply chain, including the development of battery and gigafactories in the UK (BBC, 2023; The Guardian, 2021).

However, given these positive factors for the uptake of EVs, there are still multiple barriers for them to become mainstream and reach 100% market share.

2.2.4 Barriers to EV Adoption

The discussion of barriers to EV adoption within the literature is extensive. The ICE ecosystem is well established which makes this large socio-techno transition ever more difficult to "comprehend let alone achieve" (Berkeley et al., 2017). The most commonplace perceived barriers amongst consumers are as follows: driving range, charging, technology, financial, and pre-existing perceptions. These barriers will now be discussed in detail.

DRIVING RANGE

The leading factor hindering the uptake of EVs is driving range (Tiwari et al., 2020; Office for Low Emissions Vehicles, 2013). Carley et al. (2013) conducted surveys across multiple large U.S. cities and found over 70% of respondents reported driving range as either a 'major disadvantage' or 'somewhat of a disadvantage' of EVs.

Egbue & Long (2012) conducted an internet-based survey across students, faculty and staff at a technological university specialising in science, technology and engineering. Although the specific university is not stated, the authors of this paper belong to Missouri University of Science and Technology, and so suggests findings are from a US perspective. Egbue & Long (2012) found 33% of the 481 respondents to their survey identified battery range as their biggest concern with EVs. Due to concerns over range, drivers are less likely to attempt longer journeys with an EV, and that an EV is perceived as being more suitable as a second car (Graham-Rowe et al., 2012; Berkeley et al., 2018).

Although, when considering annual mileages driven, owners of EVs are actually driving more than those in petrol and diesel vehicles (RAC, 2021). Early EV models (circa 2009/10) were only capable of ranges of up to 100 miles, which in turn exacerbated this barrier for EV adoption. However, modern EVs are capable of ranges of 200-300 miles (Octopus, 2023), with cutting edge vehicles, such as the Telsa Model S reporting nearly 400 miles (Drive Electric, 2023). Many factors also affect driving range, including battery size, weight/design and driving style. In addition, this factor is intrinsically linked to another which deters consumers from buying EVs, and that is charging. The driving range concern is only exacerbated by not only the lack of public transportation options but also due to the fact utilities and amenities are spread further apart. This will be discussed further in Section 2.2.

CHARGING

The refuelling process for an EV is different to that of an ICE vehicle, and one that Berkeley et al. (2018) argues may not be understood clearly by consumers. However, existing EV owners indicate that the recharging process for an EV is simple and convenient, with the ability to recharge at many different types of location (home, work, shops etc) (Bunce et al., 2014). This suggests a lack of knowledge amongst the public and exposure to the technology alone would improve EV uptake (Tiwari et al., 2020).

The long duration of charging is another often cited deterrent against the adoption of EVs. Long charging times also deter individuals from long-distance trips, where the long recharge times add to the already long trip durations. However, reducing charging time would allow battery EVs to make these trips in near enough the same amount of time as with existing ICE vehicles, provided sufficient charging infrastructure is in place to accommodate the vehicle demand (Coffman et al., 2017).

The long charging times are also only exacerbated by an insufficient charging network (Berkeley et al., 2018). Egbue and Long (2012) found 17% of respondents identified lack of charging infrastructure as their biggest concern with EVs. As of May 2023, there were 43,626 public charge points across the UK (Zapmap, 2023b). Although this number is increasing year on year, the location of these charge points is already in favour of cities and urban environments, with rural areas receiving a lack of attention. This will be discussed further in Section 2.2.

TECHNOLOGY

Steinhilber et al. (2013) conducted interviews with key stakeholders within the automotive sectors of the UK and Germany, finding that EVs are often seen to be "inferior" compared to ICE vehicles. This is mainly due the limitations discussed previously; battery range and refuelling times (Steinhilber et al., 2013). This is also corroborated by Tiwari et al. (2020), hypothesising that these perceptions are a result of lack of exposure and knowledge of EVs.

Additionally, compared to an ICE vehicle, EV battery depletion is significantly affected by driving behaviours and environmental factors (i.e. temperature) (Hong et al., 2021; Jones et al., 2020). Although, it is worth noting, EVs have more responsive acceleration and regenerative braking when easing off the accelerator compared to a typical ICE vehicle. Coupled with their low centre of gravity, this improves handling, comfort, and safety (EDF, 2023), suggesting exposure to the technology is needed by consumers.

The technology behind EVs, primarily battery technology, is evolving rapidly. Although the current state of the art lithium ion is the basis for today's market EVs, new technologies such as sodium ion or solid state batteries may prove superior and provide EVs with even longer driving ranges, thus alleviating previous concerns highlighted. However, it should be noted that new technologies may also have their own nuanced issues. For example, solid state technology requires very high power, which given rural infrastructure is already an issue with today's power demands. For the work presented in this thesis, the current market technology only will be considered.

FINANCIAL

As detailed in the previous subsection (Section 2.2.3), there are financial gains to owning an EV, however, the higher initial purchase price is still a major deterrent (Berkeley et al., 2017; Carley et al., 2013). This can largely be attributed to the costs of current battery technology (Egbue and Long 2012). Graham-Rowe et al. (2012) found that people are unwilling to pay the higher upfront cost demanded by EVs, citing that the higher cost should reflect a superior vehicle, which most people feel EVs are not.

In addition to the higher upfront costs, there is debate within the literature regarding the lifetime costs of EVs compared to ICE vehicles. Dependent very much on location, Prud'homme and Koning (2012) found the Total Cost of Ownership (TCO) for BEVs to be €15,000 greater than an ICE vehicles in France, whilst Wu et al., (2015) predicted it won't be until 2025 for PHEVs and BEVs to become financially competitive with ICE vehicles. In the US, Tseng et al. (2013) reported EVs still costing 5% more than equivalent ICE vehicles with the US federal tax credits included.

However, Hagman et al. (2016) found that BEVs can have a lower TCO than ICE vehicles in Sweden. Depending on US fuel projections and costs for Colorado, Al-Alawi and Bradley (2013) also reported that PHEVs can have a lower TCO than ICE vehicles. Focusing on the UK, a recent study from Direct Line (2020) showed that an electric vehicle's average lifetime ownership cost in the UK is £52,133, compared to £53,625 for an equivalent ICE vehicle. This indicates that there is little financial incentive to switch EVs due to the similar lifetime ownership costs.

There is also anxiety over the re-sale value (Berkeley et al., 2018), however this is likely to change after 2030, following the ban of sales of new petrol and diesels, inflating ICE vehicle prices. Coupled with the purchase price of EVs falling more in line with ICE vehicle equivalents, as technology progress is made, these financial barriers may become mute in years to come.

PERCEPTIONS

The social barriers may pose as much of a problem as the technical barriers in the uptake of EVs, in any setting. Brase (2019) found ICE vehicles were perceived to be better than EVs in terms of safety, performance, suitability for long trips and availability of fuel/charging stations. Graham-Rowe et al. (2012) saw 40 UK citizens surveyed following a seven-day period of using an EV. Even after experience with an EV, many expressed dissatisfaction or lack of confidence with the vehicle, in comparison to their past experiences with ICE vehicles. One participant highlighted the lack of power compared to their previous 1.8 litre ICE vehicle, and another quoted it not feeling safe when taking the vehicle above 50mph (Graham-Rowe et al., 2012).

Lane and Potter (2007) conducted two research projects within the UK, finding that although consumers have economic concerns, their knowledge of actual car costs is rather low. Reiterating the theme highlighted by this literature review of the lack of knowledge on EVs amongst consumers. While consumers may know more about fuel costs, taxes, and insurance, issues of depreciation and government incentives for cleaner cars are not well understood (Lane and Potter, 2007).

Furthermore, as a rebuttal to some of the environmental driving points addressed in the previous section, some are unconvinced about the sustainability of the fuel source for EVs, i.e. the cleanness of the electricity grid (Egbue and Long, 2012). Though, the survey conducted by Egbue and Long (2012) is over 10 years old at the time of writing, even during this short time frame the cleanness of the grid has improved drastically and shall only continue to do so given the net zero targets of the UK. Others though, share concerns surrounding EV battery disposal (National Research Council, 2015). Verma and Kumar (2021) highlight this issue thoroughly, reporting EV battery recycling/disposal to be costly and detracting from the environmental benefits a zero-emission vehicle offers. Predictions see two million metric tons of used Li-ion batteries by 2030 (Verma and Kumar, 2021). A practical method for recycling and disposing of EV batteries (and other energy storage components from EVs) is essential for their successful implementation.

The understanding of these perceptions and their validity are crucial to facilitating the uptake of EVs, many of which can be overcome through awareness (Esmene and Leyshon, 2019). When considering rural areas, as does this thesis, these pre-conceived perceptions are ingrained deeper, and require additional resources for change (Stephens, 2016).

2.3 Rurality and Rural Transport

To ensure a smooth transition, numerous aspects need to be considered; grid integration, charging infrastructure, consumer requirements etc. These factors vary dramatically between areas, but one type of area often forgotten is rural. Rural areas are often left behind following large socio-techno transitions. Past examples include Internet and Mobile Phone connectivity (Williams et al., 2016). This would be detrimental to rural citizens if the same comes to pass for the EV transition due to the necessity of private vehicles in rural areas.

To provide a comprehensive understanding of the rural landscape in the UK, it is essential to delve into the historical evolution of rural classifications. Initially, in 2004, the ‘Rural Definition, was introduced by a collaboration between several UK Government departments and the University of London (DEFRA, 2005). This definition categorised Local Authority areas as either ‘rural’ or ‘urban’, based solely on the predominant population type they housed. However, this binary classification was soon recognised as oversimplified, failing to account for the nuanced mix of rural and urban characteristics within Local Authority areas. To address this limitation, the methodology was refined to delineate areas into six distinct groups: (1) major urban, (2) large urban, (3) other urban, (4) significant rural, (5) rural 50, (6) rural 80, offering a more granular understanding of the urban-rural continuum.

By 2014, further advancements were made by researchers at the University of Sheffield, who undertook new studies to evolve the Rural Definition (Rural Services Network, 2015). This led to a more sophisticated classification approach, reflecting the complex realities of rural urban intermingling's. The latest iteration, the Rural Urban Classification introduced by DEFRA in 2016, represents a significant leap forward in accurately distinguishing between rural and urban areas (DEFRA, 2016). This classification system differentiates rural and urban areas based on several criteria, with the primary factor being whether the location is outside of settlements with a population exceeding 10,000 residents. According to UK Government guidelines, the Rural Urban Classification is intended for use in statistical analysis and categorises areas into one of ten possible categories, as illustrated in Figure 2.5.

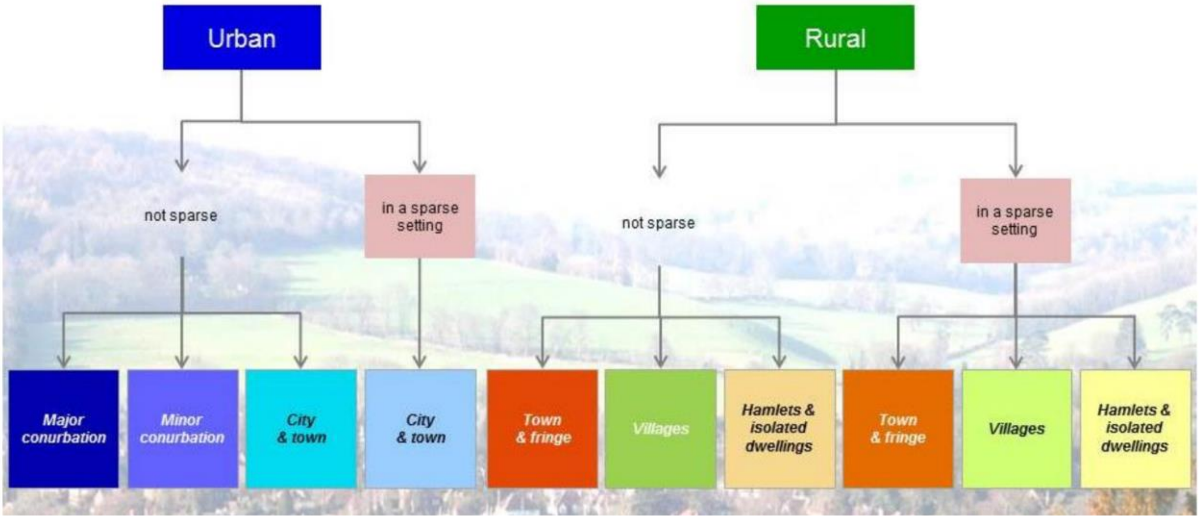


Figure 2.5: Rural Urban Classification Categories (Bibby & Brindley, 2013)

The Rural Urban Classification is the basis for the determination of rural areas to which to focus on for the work presented in this thesis. This is in part due to the crucial role this classification plays in the UK Census, the UKs largest data collection survey conducted by the UK Government. Due to the UK Census key role in the development of the ideas presented in this thesis, aligning our definition of rural with the UK Census also enabled smoother data acquisitions. Further details of the UK Census and its role within this thesis will be discussed in Section 3.1.1.

As per the 2018 mid-year population estimates for England, the population was recorded at 56.0 million, with 9.5 million people (approximately 17%) residing in rural areas, contrasting with the 46.6 million (83%) living in urban settings (DEFRA, 2020). Within this rural demography, 489,400 individuals (representing 0.9% of the total population) were located in rural settlements characterized by sparse settings. Despite their modest share of the national population, the focus on these areas is critical for two fundamental reasons. Ignoring the needs and challenges of these communities would only exacerbate existing disparities, contradicting the objectives of this thesis which aims to bridge such gaps through the application of stakeholder theory, a concept explored in greater depth in Section 2.8.2.

Moreover, rural areas, especially those with sparse populations, experience significant population flux due to tourism. This trend has been notably amplified post COVID-19, with the UK countryside witnessing unprecedented levels of visitation. Such variability introduces substantial demand on local infrastructure, presenting unique challenges for the EV transition. This thesis posits that addressing the fluctuating demand necessitates a robust and flexible infrastructure capable of supporting both permanent residents' transition to EVs and accommodating the surge from tourists, who are increasingly adopting EVs. Furthermore, tourism is not merely a contributor to local population dynamics; it can be the backbone of the economy in many rural areas. The sustainable integration of EVs into these regions is thus not only a matter of environmental or technological concern but also of economic survival. Ensuring that rural areas can effectively participate in the EV transition is essential to preventing further economic disparity and supporting these communities' resilience against the evolving landscape of mobility. Over the last 10 years, UK Government policies have reduced funding to public services. This includes in particular rural bus services and community transport schemes which have witnessed major reductions (Better Transport, 2018). Due to a lack of public transport options, car ownership has become a necessity in rural areas (Christie and Fone, 2003). Table 2.2 details the car ownership levels within various area classifications as set out by the Rural Urban Classification Methodology (DfT, 2018c).

Area Category	**Households with Car (%)**
Rural Village, Hamlet, and Isolated Dwelling	93
Rural Town and Fringe	86
Urban City and Town	79
Urban Conurbation	66

Table 2.2: Household car ownership by rural-urban classification

As shown by Table 2.2, car ownership is much more common in rural areas. Vehicles are crucial for rural communities, not just due to lack of public transportation options but also due to the fact utilities and amenities are spread further apart. This leads to considerably more car usage (Newman et al., 2014). Considering, 9.7 million people live in rural areas (within England alone) (DEFRA, 2021), who one day will have to change their vehicles to conform with government legislation (currently the only viable option being EVs), it is imperative these areas are considered appropriately for such change. Therefore, the focus of this thesis will be on the private passenger vehicle sector.

As outlined by the UK Governments 'Road to Zero' strategy, this transition is expected "*to be industry and consumer led*" (DfT, 2018a). With these forces alone, only locations with a strong business case will succeed. These types of locations are highly unlikely to be rural in nature due to the smaller customer base and much higher costs for electricity grid connections (House of Commons, 2018). To reinforce this argument, where rural areas are typically left behind in large socio-techno transitions, Graeme Cooper, at the time, project Director for EVs at the National Grid, states (Cooper, 2018):

"*Wherever you've seen a disruptive technology, if you leave it purely to market what generally happens is that towns and cities get done, and everybody else becomes a second-class citizen*."

This is already evident with the uneven geographical distribution of the UKs charging network currently in place. Begley and Berkley (2012) note the issues of charging infrastructure in rural areas of England as they are only sporadically available outside large urban areas. Figure 2.6 illustrates the total public charging points per 100,000 population, April 2023.

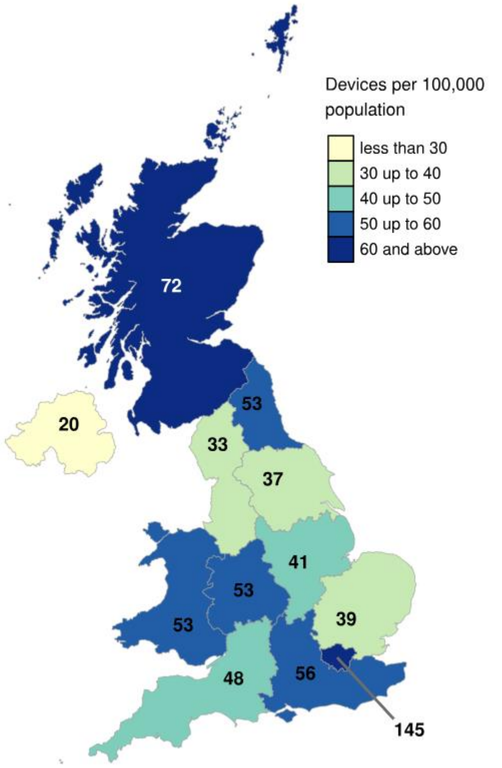


Figure 2.6: Public Charing Devices per 100,000 population by UK region (DfT, 2023a)

Looking at this distribution in more detail, the average provision in the UK is 60 devices per 100,000 population. London and Scotland have the highest levels, with 145 and 72 devices per 100,000 respectively. However, areas such as the Northwest and Yorkshire and the Humber only have 33 and 37 devices per 100,000 respectively. At the local authority level, over 100 local authorities have fewer than 30 public charging devices per 100,000 population (DfT, 2023b).

It is worth noting that the information presented in figure 2.6 relates to population and not population density, which in turn would relate to the rural-urban classification of an area. Although Scotland is shown to have a high number of devices per population, it is also imperative to remember the land size of Scotland in relation to its population size. Scotland has extremes of urban and rural areas, for example, Glasgow is a highly populated city whilst an area like Aviemore is very rural. These differences cannot be appreciated from figure 2.6. Previous effort has been made to understand the correlation between consumers and distances to their nearest public chargepoints. Figure 2.7 details the average distance to nearest public electric vehicle chargepoint for the UK, at the time of 2016. Figure 2.7 below highlights the disparity between population density of an area and the distance required to access a public EV charge point.

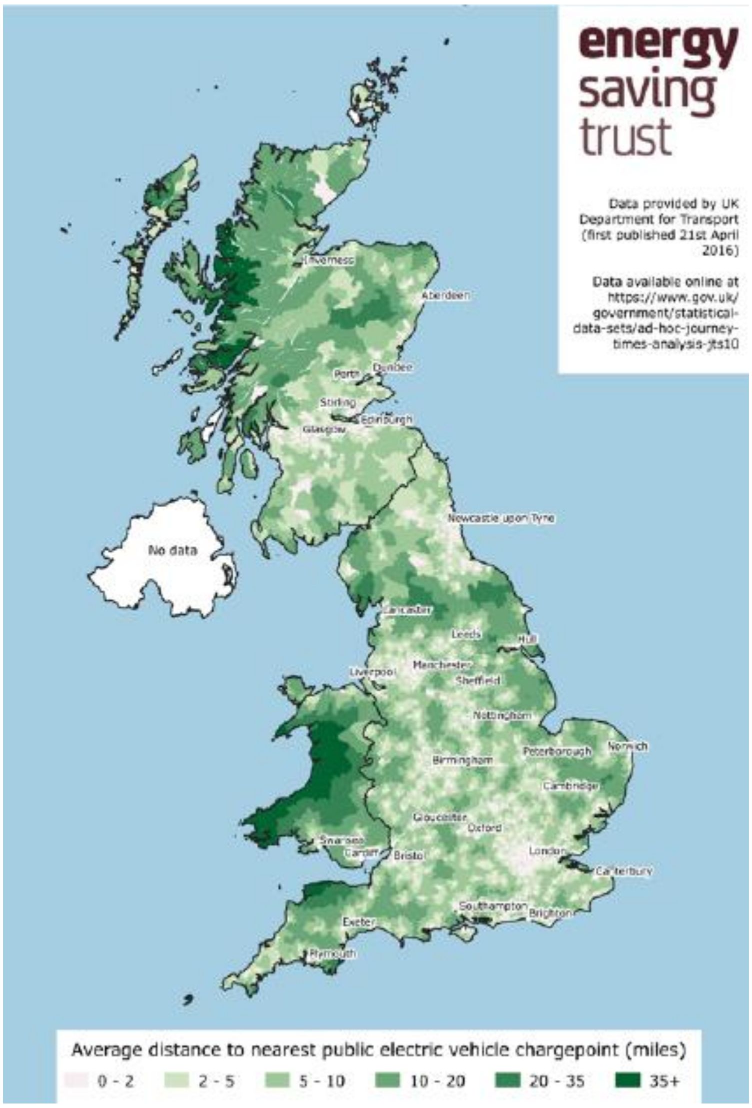


Figure 2.7: Average distance to nearest public electric vehicle chargepoint (miles) (Extracted from Parliament, 2018)

With regards to academic literature, there are far fewer studies pertaining to the EV transition in rural areas as opposed to urban locations. Cowie et al. (2020) highlights this lack of consideration regarding EVs in rural areas, as most technological developments, studies and considerations are centred on the urban scenario.

Compared to urban areas, rural locations and their communities experience different nuances when it comes to their vehicle usage. Rural vehicles are generally required to complete longer journeys (see figure 2.8 below), which gives rise to a much greater cause for concern amongst rural residents over range anxiety (Jones et al., 2020).

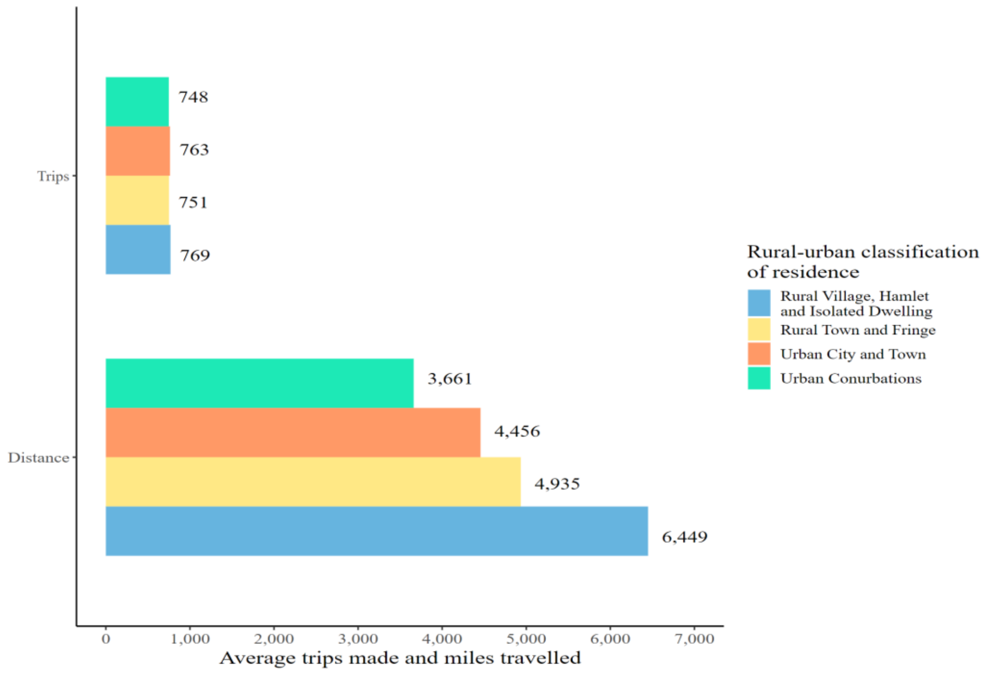


Figure 2.8: Average trips made, and miles travelled per person per year by rural and urban classification of residence: England, 2021 (GOV.UK, 2022c)

Additional nuances when considering the rural environment include the local electrical grid. Rural electrical grids typically consist of a less robust grid infrastructure in general (i.e. smaller substations, or transformers, possibly attached to wooden poles) (Western Power Distribution, 2022a). Coupled with the different travel patterns highlighted, should these then be conducted by an EV, the resulting charging profiles and associated grid impact will differ from the urban case.

The Mull and Iona Sustainable Transport Project (MICT, 2016) is an example of such an investigation into the feasibility of EVs in rural environments. Conducted by the local Community Trust, this project sought to promote EVs across these rural islands of Scotland. With a population of roughly 3000, this small-scale project resulted in an increase from 3 to 11 EVs on the islands, double the projects targets. However, such small numbers of EVs are highly unlikely to provide cause for concern for the local grid infrastructure. Therefore, as stated in the objectives (Section 1.1), the work presented in this thesis will consider large adoption rates of EVs to simulate potential future scenarios.

Jones et al. (2020) study of EVs and rural businesses, reports the promising suitability of EVs in a rural setting, given that the required support (infrastructure enhancement and technical developments) is provided. This study of the Warwickshire Rural Electric Vehicle (WREV) trial by Jones et al. (2020) also aimed to highlight the limited research on the impact of EVs on rural travel in the UK. Although the focus lay on rural businesses and the vehicles belonging to them, many findings are still applicable to the private passenger scenario in rural areas. Jones et al. (2020) for instance, found although the majority of trips undertaken by rural businesses were still comparatively short, the diversity of travel patterns and lack of available charge points meant range anxiety was a real concern. This resulted in users taking greater risks and in general, more dangerous driving styles to compensate. These findings only reinforce the nuances of the rural areas that have been previously discussed and by extension, highlight the importance of ensuring that pre-existing travel patterns of rural individuals can be met by EVs for a successful transition.

Another largescale EV trial in the UK was the ‘My Electric Avenue’ Project (2015). This was an 18 month EV trial project in various parts of Britain. Over 100 people, split across various clusters (groups of 8-10 people belonging to the same street) were recruited, with each receiving a Nissan Leaf to use for the duration of the trial. The project had three core aims, to understand customer driving and EV charging habits, to trial equipment in the hopes of mitigating the impact of EV charging and explore the possible opportunities EVs presented for the electrical network. The clusters included a street in Marlow, Chineham, Chiswick, Lyndhurst, South Gosforth, Wylam and two ‘workplace-based clusters’: Slough and Borough Council and Your Homes Newcastle. These locations provide a varied sample from across the country, north to south, and also includes some more rural locations such as Lyndhurst and Wylam. Although not solely focused on rural areas, this study still provides much to be considered. Broadly speaking, My Electric Avenue focused on how best to manage the network when a large number of EVs charge in the same street at the same time. This, in part, is very much the aim of this thesis, as set out in Chapter 1.

The ‘My Electric Avenue’ project (Ofgem, 2016) found the peak demand for residential EV charging did coincide with the traditional evening peak of the pre-existing grid load (Torriti et al., 2017). Both thermal and voltage issues were identified as a potential concern for increasing levels of EV uptake, with thermal issues arising first at lower penetration levels. The Demand Side Management (DSM) aspect of the project, which will be discussed in more detail during Section 2.5.2, was capable of mitigating these thermal constraints (Ofgem, 2016). With regards to sparsely populated networks (i.e. rural areas), Ofgem (2016) suggested the deployment of additional units for Powerline Carrier (PLC) communications is required to ensure reliable communications. PLC units were required for the DSM technology to work, indicating this option may not be viable for rural areas where the grid infrastructure is lacking, Ofgem (2016) found an exponential correlation between distance and reduced reliability of communications.

As highlighted by this literature review, and many previous (Jones et al., 2020; Begley and Berkley, 2012; Apronti and Ksaibati, 2018) the core gap in literature this thesis aims to fill, is research focused on the EV transition in rural areas. With this thesis' focus in mind, effort has been made to review literature specific or applicable to these areas. Though to provide a more holistic approach, it is beneficial to understand research which has also focused on urban areas. Thus, the following sections include such material.

To achieve the aims and objectives set out in Chapter 1, an understanding of current vehicle usage, corresponding EV usage, and potential recharging patterns for grid impact, are required. These form the building blocks for the work presented in this thesis. The following sections will now present the main findings and current state of the art in literature pertaining to each of these aspects.

2.4 Travel Demand Modelling

To assess the feasibility of the use of electric vehicles in rural areas, an understanding of how vehicles are used is required. With the knowledge of the journeys and distances driven by vehicles within rural areas, the corresponding energy requirements, should this activity be completed by EVs, can be calculated. This in turn enables the calculation for electricity requirements to support this rural EV population via potential EV charging patterns. Two approaches researchers can utilise for generating EV charging profiles have been identified (Pareschi et al., 2020; Brady and O'Mahony, 2016):

Public Trials – Researchers provide participants with actual EVs and Charging Stations. Over the course of some time period the researchers track and measure all information regarding their use. An example of this is the 'My Electric Avenue' project (2015).

Simulation Models – Researchers design a digital transportation system which emulates real life; however, the reliability of the results is always disputable.

Due to financial constraints with this project, the simulation pathway has been opted for. These models commonly utilise scenario modelling for charging behaviour built on top of a Travel Demand Model (TDM) (Pareschi et al., 2020). This is the process adopted by this work.

Travel demand studies originated in the USA during the period where transportation forecasts were developed following the sequential four-step model (McNally, 2007). This comprised of (1) Trip Generation, (2) Trip Distribution, (3) Mode Choice, and (4) Trip Assignment (Ahmed, 2012). Individual trips resulting from the Trip Generation step are often categorised by their respective purpose or destination, and hence referred to as trip categories. Apronti and Ksaibati (2018) developed a four-step TDM for estimating traffic volume for low-volume roads in Wyoming, with one key modification: the consideration of solely private passenger cars during the mode choice step. As mentioned previously, private passenger vehicles will also be the sole consideration for the work presented in this thesis.

Apronti and Ksaibati (2018) only considered three trip categories: Home-Base Work (HBW), Home-Base Other (HBO), and Non-Home Base (NHB) trips. This may be sufficient for an investigation into traffic volumes, however, for energy usage calculations of EVs a more detailed approach is required. Although the four-step model is still used today, as shown by Apronti and Ksaibati (2018), it is now considered an oversimplified representation of daily travel patterns, and an overly statistical/ad-hoc approach to modelling (i.e. not behaviourally oriented) (Goulias, 2021). Presently, five approaches to Travel Demand Modelling have been identified (Daina et al., 2017):

(1) **Vehicle Ownership and Annual Mileage Models (VOAMM)**: A high level model with low temporal resolutions (i.e. when yearly time scales are of interest) (Brownstone et al., 1994). Whilst it is possible to represent individual vehicles in this type of model, allowing for easy aggregation, it necessitates the use of substantial datasets. Brownstone et al. (1994) developed a forecasting model for annual vehicle demand, specifically for new and used vehicles, by fuel type (i.e. type of vehicle).

(2) **Summary Travel Statistic Models (STSM)**: This method relies on data pertaining to conventional ICE vehicles, sourced from national, regional, or metropolitan travel surveys. From these travel surveys, travel pattern summary statistics can be derived, which when used in combination with charging scenarios can generate potential EV Charging profiles. Again, this approach involves modelling individual vehicles, but it has been noted to yield inconsistent representations of car usage profiles (Diana et al., 2017). In another study, Wang et al. (2011) employed summary statistics from the US National Household Travel Survey to identify appropriate times for which vehicles arrive home after their last journey of the day to aid in the modelling of a PHEV population in Illinois.

(3) **Direct Use of Observed Activity Travel Schedules (DUOATS)**: Similar to the STSM approach, this approach utilises ICE vehicle patterns to simulate EVs. This can be accomplished through travel diaries, surveys, or Global Positioning System (GPS) data. This approach consistently produces car usage profiles that accurately represent real-world scenarios. Axsen & Kurani (2010) conducted their own techniques to capture driving patterns and identify potential recharging opportunities in California, US. This

survey involved participants completing a 24hr day travel diary, segmented into 15-minute intervals, and successfully collected data from 877 respondents.

(4) **Activity Based Models (ABM)**: Similar to the STSM modelling approach and building on the traditional 'four step model', these models are based entirely on simulation. In this modelling approach, individual vehicles are depicted as 'agents', offering a comprehensive and precise representation of usage patterns (Delhoum et al. 2020).

(5) **Markov Chain Models (MCM)**: A Markov Chain is a probabilistic model that characterizes a sequence of events by considering the likelihood of each event happening during each specific time interval. While this modelling technique offers the potential for great detail, it can lack realism in representing behaviours and requires substantial computational resources. Soares et al. (2011) employed a discrete-state, discrete-time Markov chain, with 30 minute intervals, to generate the movements of EVs over the course of one year.

While much of the research on EV transportation has primarily concentrated on modelling EV adoption and yearly usage patterns, a significantly finer time granularity, involving hourly or sub-hourly intervals, is essential for in-depth analysis of power systems, energy considerations, and their environmental impacts (Daina et al., 2017). Typical UK electricity meters, especially those used for businesses (business meters), are typically configured to record data at a 30-minte temporal resolution (British Business Energy, 2021). This temporal resolution was therefore chosen for the travel demand model to enable easy cross-analysis with the UK electrical grid when assessing EV impacts of rural grid infrastructure.

With regards to the TDM modelling approach, the VOAMM, STSM and DUOATS modelling approaches were disregarded as they do not align with the aforementioned requirements. Whilst both the ABM and MCM approaches provide adequate levels of detail and temporal resolutions for the TDM, the ABM approach has a lower computational complexity than the MCM approach, and hence was selected. A review of literature on Activity Based Modelling will now be presented.

2.4.1 Activity Based Modelling

At the core of Activity Based Models (ABMs) is the concept of representing individual processes in a disaggregated manner (Daina et al., 2017). In other words, ABMs function as micro-simulators or microscopic models where the behaviour for each individual is simulated to replicate that of each inhabitant within the studied area (Ridder et al., 2013; Weiss et al., 2017). This approach involves simulating individual components, referred to as agents, allowing for flexible aggregation. Further insights into microsimulations will be discussed in the following subsection, section 2.3.2.

Mattioli et al. (2019) used data from the 2016 UK National Travel Survey (NTS) to categorise cars based on their usage patterns throughout a week. This process entailed manipulating the NTS to create dataset resembling a 'vehicle travel diary', which was then subjected to sequence and cluster analysis to discern individual vehicle usage patterns. Mattioli et al. (2019) extracted six types of 'car day', with fewer than half conforming to the stereotypical, and commonly assumed, travel patterns associated with the conventional 9am – 5pm working hours. Mattioli et al. (2019) also showed how varied travel habits can depend on the day of the week. Understanding individuals can be grouped as per their travelling/driving habits is key to simplifying the computational requirements of an ABM. However, Mattioli et al. (2019) did not incorporate characteristics for the individuals comprising each of the six types of 'car day'. Such characteristics would include employment status, working hours, number of children etc would have enabled the development of a synthetic population comprised of detailed individual characteristics. This will be discussed further shortly. Inclusion of individual characteristics would have allowed for a TDM to reflect more accurately the heterogeneity nature of populations.

Although, for the scope of the work presented by Mattioli et al. (2019), it is possible any combination of characteristics for an individual is still capable of conducting all six types of 'car day', due to the dynamic nature of individuals and their mobility. Inclusion of population characteristics, as will be the focus for the work presented in this thesis, would yield not just a higher detailed modelled, but also more realistic and by extension more accurate results.

Zhang et al. (2020) modelled travelling patterns and corresponding EV charging load profiles with the focus on including these aforementioned characteristics (e.g. gender, age, education level etc.), factors which had not been incorporated by previous studies. Zhang et al. (2020) argued that exclusion of demographics when modelling travel patterns brings about hidden errors in the resulting charging profiles due to these diverse populations sharing identical travelling probabilities. They found that user demographics with collective social attributes have distinct travel patterns, which in turn affect the magnitude and peak time of the EV charging load profile.

Based on the 2009 US National Household Travel Survey (NHTS), Zhang et al. (2020) used the Monte Carlo method to simulate the travel profiles over the course of one day for 100,000 EVs. Coupled to this, a charging load simulator was applied to calculate the SOC over time, as well as energy and power demand from charge events scheduled. The assumption Zhang et al. (2020) incorporated into the charging simulations included a random assignment for energy consumption rate between 0.1 and 0.25 kWh/km, each vehicle is randomly assigned a battery capacity between 40 and 50 kWh, and to account for battery degradation, hard lower and upper limits, at 20% and 80% for the SOC are set. With these assumptions, Zhang et al. (2020) no longer required the development of an EV fleet to serve the synthetic population from the TDM, a much simpler methodology.

However, the work conducted by Zhang et al. (2020) fails to understand the longer-term implications for EV adoption in relation to pre-existing consumer travel profiles, due to the single day of investigation undertaken. Zhang et al. (2020) conclude with the need for future work to include long-term regional predictions, aiming to facilitate planning for a future where a significant proportion of vehicles within a system are electric. This gap will aimed to be filled by the work presented in this thesis.

Another example of a data led TDM was developed by Kang and Recker (2009) who analysed trip diaries from California’s 2000-2001 Household Travel Survey and evaluated the effects of changing vehicle types to various PHEV’s. From this, they were able to construct 1-day trip/activity chains for over 15,823 vehicles across 11,385 households. Kang and Recker (2009) investigate multiple charging scenarios for two classes of PHEVs (those with all-electric ranges of 20 miles (PHEV20), and those with 60 miles (PHEV60)). Simulations only lasted 48 hrs, which may prove disadvantageous when considering energy requirements over long periods of time. The average trip distance was 7.16 miles, with standard deviations of 14.46 miles, which neglects to account for the impact longer trip journeys have, which, as shown previously, are more likely to be conducted in rural areas.

Concerning the EV charging model by Kang and Recker (2009), which examines two types of PHEVs to evaluate their suitability for such travel, it was determined that home charging could sustain 40-50% of the distance covered by equivalent ICEs using the electric power of the PHEV20, and 70-80% for the PHEV60. Improving public charging facilities should only improve these findings. Although Kang and Recker (2009) provide much to be considered, particularly in terms of the development of their TDM, they again, fail to capture longer term travel patterns. This only then extends to the impact assessment of EVs. Additionally, their study solely focuses on PHEVs, which although were a more popular vehicle choice at the time of this study, more recent statistics indicate the prevalence of pure EVs (see figure 2.1).

What the previous examples of literature detailed above have failed to capture are the differences between rural and urbanised areas with relation to travelling patterns. These prominent studies (Mattioli et al., 2019; Zhang et al., 2020; Kang and Recker, 2009) have utilised national datasets which, although can capture data from both urban and rural areas, are more often than not biased towards urban areas. This can be seen by the split of data between rural and urban areas within the 2021 UK National Travel Survey. To fill this gap, other practices have sought to adapt methodologies that have been designed predominantly for urban areas (Apronti and Ksaibati 2018). However, with urban areas witnessing higher traffic volumes, smaller distances and different driving habits, EV viability in rural areas cannot be based on this approach. Apronti and Ksaibati (2018) highlight the need for rural specific model due to the lack of consideration these areas receive, reinforcing the need for a rural specific TDM.

2.4.2 Spatial Microsimulation

Microsimulations refer to a methodology whereby individual agents (e.g. a vehicle) are modelled with their own distinct behaviours (Raney et al., 2003), as opposed to previous methods which aggregate behaviours collectively. This approach provides a means for researchers to overcome constraints stemming from the lack of available geocoded micro-data in the context of travel research (Lovelace et al., 2014).

The initial phase in spatial microsimulation methods revolves around generating populations (Raney et al. 2003). The objective is to disaggregate demographic data to derive individual households and their respective members. Typically, this process relies on census data. For example, a model assessing CO_2 emissions from passenger transport in urban Guangzhou utilised data from the 2010 sixth population census of Guangzhou (Ma et al. 2018). Cullinan et al. (2011) used the Simulation Model of the Irish Local Economy (SMILE) to create a synthetic population for investigating visitor numbers at outdoor recreation sites in Ireland; and Ma et al. (2014) used the year 2000's population census data at a sub-district level to create a synthetic sub-district population for analysing urban travel-related CO_2 emissions in Beijing.

Disseminating a population into its aggregates, and developing a synthetic population, allows for high fidelity and realism when it comes to simulations. With this method, each individual (vehicle in the case of a TDM) can be investigated separately or as an entire fleet. With this approach employed, the travel patterns of vehicles can be understood and used to overlay EV charging scenarios (Pareschi et al., 2020), the next step in anticipating the impact of EVs.

2.5 EV Charging

As discussed in the previous subsection, for determining EV charging profiles the simulation approach has been deemed the most feasible of the two methods. This is also reinforced by the lack of publicly available EV trial empirical data (Jones et al. 2020). Having reviewed the state of TDMs, and highlighting methodologies which can be utilised for this thesis, focus now turns to simulating the charging of EVs.

The initial phase work conducted by Brady and O'Mahony (2016) used simulation to generate the daily travel of a population of vehicles, with this they were then able to calculate the State of Charge (SOC) of these vehicles (as if they were EVs). With a blanket energy consumption of 0.265 kWh/km for all vehicles within the simulation, Brady and O'Mahony (2016) used a probabilistic charging decision model to determine when charging takes place. This decision was based on three core factors: (1) the State of Charge (SOC) of an EV at a destination, (2) the duration a vehicle is parked for, and (3) the current journey number (i.e. how many trips the car has already undertaken that day, given the assumption that a higher probability will be given to charging following the last journey of the day. A noteworthy consideration is Brady and O’Mahony’s (2016) simulation period, only two consecutive days are modelled, with all vehicles beginning this simulation period with 100% SOC. With such a short timeframe modelled, Brady and O’Mahony (2016) fail to address the impacts on charging behaviour, and by extension the impact on the grid, witnessed over longer simulation periods. For instance, there is large variation in activity between different days of the week alone; weekend travel activity is significantly less than weekday activity (GOV.UK, 2020).

Brady and O'Mahony's (2016) research provides significant insights into electric vehicle (EV) charging behaviour, including considerations related to the availability of charging infrastructure. While they do not explicitly address scenarios where an EV is scheduled to charge but cannot due to unavailable charging points, their simulation implicitly assumes that each vehicle has access to a dedicated charging point whenever needed. This assumption is based on modelling charging events determined by three key factors: the current state of charge (SOC), available parking time, and the journey number. These criteria indirectly suggest a variable probability of charging point availability, a methodological choice influenced by data limitations and the challenges of explicitly simulating every potential charging obstacle. The study highlights the complexity of integrating charging point availability into EV charging models, opting for a simplified approach where each vehicle is assumed to have its own charger for the sake of the model's feasibility and due to constraints on time resources. This simplified assumption, although not capturing the intricacies of charging infrastructure constraints, emphasizes the crucial importance of accessible charging infrastructure in accurately modelling and understanding EV charging behaviours. The initialisation of the SOC on the first day of simulation is a common challenge encountered when modelling EVs over multiple days. Pareschi et al. (2020) devised a solution by introducing a ‘Day 0’, an additional day at the outset of the simulation period. On Day 0, all EVs begin with a full charge, and the ending SOC values were employed as the initial SOC’s for the actual first day of simulation. This approach mitigated the impact of initial assumptions and conditions.

Crozier et al. (2021) investigated various methods for modelling the variability of EV charging patterns and classified these methods into three distinct categories: (1) bottom-up charging models applied to varied vehicle use, (2) stochastic bottom-up charging models applied to a fixed set of vehicle usage, and (3) top down stochastic charging models.

The first group involves the utilisation of predefined rules that determine when charging occurs, the most common rule being to initiate charging after the final journey of the day (Pashajavid and Golkar, 2012), typically at the EV owners’ home (Kang and Recker, 2009; Hardman et al., 2018). Some extensions to this approach include incorporating charging events whenever the vehicle is at home irrespective of its future travel patterns (Grahn et al., 2013; Wu et al., 2011).

The second group of models operates on given vehicle usage patterns and generates stochastic charging estimates. Developing these models requires substantial datasets pertaining to EV usage and charging. Monte Carlo simulations can be employed to capture charging variability, although this approach can overestimate the peak aggregated charging demand when considering many agents (vehicles) concurrently (Crozier et al. 2021).

The third group focuses directly on modelling charging itself, rather than the relationship between vehicle use and charging. These are known as top-down models for EV charging and are particularly suitable for investigations pertaining to public charging, where questions of charge point numbers and availabilities are the focus (Crozier et al. 2021).

However, reviewing literature focused on empirical data collected via Public Trials, the other approach to generating EV charging profiles, also offers much to be considered. Kim (2019) analysed empirical meter-level data to investigate the energy load profiles of residential customers under the Time of Use (TOU) rate with and without EV charging. When considering the TOU tariffs, a high correlation was found between charging schedules and the electricity rate tariff structure participants were contracted to. Indicating individuals are heavily influenced by the pricing structure of their electricity tariffs to dictate when they would charge their vehicles. TOU and smart charging tariffs have been recognised as a method to not only shift peak demands to off-peak times and by doing so alleviate pressures on grid infrastructure, but also lower the cost of charging an EV (Hardman et al., 2018).

Turning focus to consumer preferences regarding EV charging and its infrastructure – crucial factors in promoting EV adoption – Hardman et al. (2018) sought to understand the interaction of existing EV owners with charging infrastructure. Hardman et al. (2018) found home charging to be the predominant choice among EV owners, with 50-80% of all charging events taking place at home. Following home charging, work and public locations (i.e. supermarkets) were the next most popular charging locations (Hardman et al., 2018).

This strong preference for home charging ties the refuelling process of EVs closely to the vehicle's home and, by extension, to the residential energy sector and its demand, as noted by Ofgem (2018). Adderly et al. (2018) support this, reporting that 81% of EV charging in the US occurs at home. Moreover, Hardman et al. (2018) suggest that home charging could mitigate issues like congestion that arise with extensive public charge point usage.

Building on this understanding of home charging's prominence, it is important to consider the distinct advantages in rural settings, a highlighted by Newman et al. (2014). Rural households, often with more available space and features such as designated off-street private parking (driveways, garages, carports etc) (Newman et al. 2014), are well positioned to accommodate home charge points. This contrasts sharply with urban areas, where the lack of off-street parking for many types of properties in these areas (flats, terraced houses etc.) hinders the transition. In rural areas, the dispersed nature of amenities, such as shops and utilities, further bolsters the case for home charging, as charging points at public locations become more valuable and practical, improving their business case according to Newman et al. (2014). This rural context provides a deeper understanding of the varying degrees of feasibility and necessity for home charging in different geographic areas, complementing the findings of Hardman et al. (2018).

2.6 Electrical Grid

It is widely understood and expected that EV uptake will lead to a greater demand for electricity. From a grid perspective, large-scale deployment of EVs pose multiple challenges in terms of changes to current load profiles (Shahriar et al., 2020; Ridder et al., 2013). Ashfaq et al. (2021) highlighted the largest threat comes from uncoordinated charging behaviour, as this would deteriorate the distribution system's functioning (i.e. transformer overloading, voltage instability, power loss, and frequency variations), which may collapse the power system (Martinenas et al., 2016). This has also been advocated by the works of Clement-Nyns et al. (2010) and Wang et al. (2018). The 'My Electric Avenue' project predict 32% of local electricity networks (312,000 circuits) will require intervention when 40-70% of customers have EVs (My Electric Avenue, 2023). These susceptible networks were distinguished by any with an available capacity less than 1.5kW per customer and based on 3.5 kW (16amp) charging.

These challenges are only heightened in rural areas where, as mentioned previously, resides typically weaker grid infrastructure (Western Power Distribution, 2022a; Nutley, 2005). However, studies have shown that if charging/discharging of EVs was sufficiently utilized, they could be employed to actually aid and improve the grid (Pang et al., 2012).

Hartvigsson et al. (2022) conducted the first national coverage of EV charging impacts in residential areas for Sweden. Results showed that the risk of power system violations due to EV charging are greatest in cities and smaller in urban areas, while rural areas show significantly fewer violations. This only holds true if the infrastructure is built to the same level across urban and rural areas, as is the case in Sweden and the areas investigated by Hartvigsson et al. (2022). In this case, the number of customers in a low-voltage grid decreases, the designed grid capacity per customer increases and so reduces the likelihood of voltage violations to occur when adding EV charging loads. However, this is not the case for UK grid infrastructure amongst urban and rural areas. As highlighted previously, the grid infrastructure in rural UK areas is much less robust. Hartvigsson et al. (2022) also showed that even pricing points from chargepoint operators could cause grid instabilities. If charging rates are changed too quickly and the grid does not have the capabilities to respond fast enough to these changes, this could also result in potential grid failures (ADE, 2020; Hartvigsson et al., 2022).

Two large aspects this thesis aims to investigate in relation to the grid are (1) the effects of power outages and (2) demand side management, a technique to aid the grid in times of voltage violations and prevent power outages. Literature surrounding these two topics will now be discussed in more detail.

2.6.1 Power Outages

In this electrified vehicle future, a potential major cause for concern is the impact of power cuts, due to increasing numbers of motorists becoming dependent on an unfailing electrical grid to keep their vehicles operational. Although power cuts are an infrequent occurrence in the UK, natural disasters (i.e. storms and extreme weather) can still cause longer term power outages, particularly in more rural and remote locations. On the 9th of August 2019, a large scale power outage caused interruptions to over 1 million UK consumers' electricity supply (Ofgem, 2020). This power blackout was the result of a lightning strike in Cambridge, UK, exposing fault lines brought about by the rapid changes due to the decarbonisation drive and penetration of smart grid technologies (Bialek, 2020). Although the voltage disturbance due to the lightning strike was within expectations, it caused three infeed losses from surrounding wind farms and power stations.

In addition to unplanned power outage scenarios, recent global affairs have exposed the threat of energy generation difficulties in the UK. This has led to the UK Government considering invoking the Electricity Supply Emergency Code (ESEC) as mitigation, receiving large media attention (The Guardian, 2022a). The ESEC details supply plans should prolonged electricity shortage affect a specific region, or the whole country. Understanding the impact power outages will have, from not just a grid perspective but also consumer requirements of their vehicles is vital for success of the EV transition.

Research has not yet explored or predicted the performance of EVs during power outages, concentrating instead on the possible solutions that's EVs offer for grid instability. Zheng et al. (2019) examined Vehicle-to-Grid (V2G) technology, noting is potential as an effective and economical approach to accommodate the increased charging demands EVs will impose on current electrical grids. V2G technology facilitates bidirectional energy exchanges between EVs and the grid, enabling the storage of surplus power during periods of lower demand and its injection back into the grid during peak demand times. In this context, EVs function not only as consumers of electricity but also as a distributed energy storage system. However, it is important to note that this technology remains in the experimental phase, and numerous technical and regulatory challenges must be addressed before it can be widely and effectively implemented (Zheng et al., 2019).

Tian & Talebizadehsardari (2021) considered shared parking stations (car parks) with V2G capabilities to provide energy resilience for local buildings near to the parking station during times of power outages. Through their simulations, Tian & Talebizadehsardari (2021) found that the EV V2G parking stations could only supply the loads of the buildings for a duration of up to 6hrs depending on the time of day of the outage. This is not a long period of time for a power outage to occur, especially if said power outages are caused by natural disasters which damage infrastructure leading to long repair times, and thus longer power outages. Adderly et al. (2018) sought to highlight this risk for EV owners during natural disasters in the US which require evacuations. Looking at a hurricane scenario from Florida, US, Adderly et al. (2018) point out the distances for escaping an evacuated zone may exceed the range of an EV on a single charge. With the increase in uptake of EVs, this issue would only become exacerbated by charging stations upon evacuation routes becoming saturated or unavailable themselves due to power outages. As a note for the EV transition as a whole, Adderly et al. (2018) also highlighted that EVs have now become widespread enough to warrant this concern.

For power outage cases which do not require evacuations, Rahimi & Davoudi (2018) looked at the opportunity EVs present for residential customers during periods of unavailability of distribution systems. The unavailability of a distribution system could still be due to natural disasters such as hurricanes for instance. Through first understanding the electricity requirements of a household, various models of EVs and Hybrid vehicles were investigated to calculate how long they would be able to provide power and energy to the household. Rahimi & Davoudi (2018) found hybrid vehicles out-performed the EVs when it came to duration of serving time (the time for which the buildings could rely on the vehicles acting as generators), due to the larger amount of energy capacity from both the battery and fuel. For example, a Tesla model S could serve between 0.9 and 2.9 days depending on available battery capacity and season of the year, whereas a 2017 Prius offered between 2.0 and 6.5 days.

Kuchta (2022) suggests that in households equipped with solar panels - a common scenario today, with many studies examining situations where EV charging energy is generated on-site (Yang and Wang, 2021; Richardson, 2013) – it might be feasible to channel this electricity directly to their vehicles. Yang & Wang (2021) investigated just that, a resilient home energy management strategy to enable residential houses to implement self-power supply during a planned grid outage period. Their proposed strategy incorporated the energy backup capability of PHEVs and residential solar photovoltaic (PV) sources. Through also scheduling home energy consumption patterns, they significantly reduced the impact of a grid outage.

However, these studies are all mute considering V2G technology is still in its developmental stage. Additionally, for V2G to work, EVs need to remain stationary, rendering the EV as a vehicle useless when engaged in V2G. As mentioned in Chapter 1, for rural areas, this approach is less viable due to the higher vehicle usage observed in these areas. Although it does present interesting opportunities and potential solutions, consideration should be given to the impact of power outages with today's standards (todays infrastructure limitations etc.). As presented in Chapter 1 (section 1.1), one of the aims of this thesis is to understand just that.

2.6.2 Demand Side Management

Demand-side Management (DSM) refers to a range of technologies and interventions designed to create greater efficiency and flexibility on the demand side of the energy system. With households being increasingly equipped with smart metering, this potential is already receiving a lot of attention for household use.

Mohanty et al. (2022) identified two main classes of DSM strategies, based on the behavioural changes of the agents, in this case consumers: incentive-based or price-based strategies. Price-based strategies being those which feature reactions to electricity tariff signals (Gottwalt et al., 2011), including Time-Of-Use (TOU) pricing, Critical Peak Pricing (CPP) and/or Real-Time Pricing (RTP). Whereas in incentive-based programs, the consumers are incentivized independent of electricity tariffs (Mohanty et al., 2022). Examples of these strategies include Direct Load Control (DLC); a utility's program to remotely shut down customers electrical equipment in exchange for an incentive payment or bill credit, Load Curtailment; the deliberate reduction in power output to balance energy supplies, lessening the stresses on the grid, and Demand Response (DR) bidding; encouraging customers to shift electricity demands to times when electricity is more plentiful or other demand is lower, typically through price incentives.

Gottwalt et al. (2011) identified considerable amounts of flexibility in residential demand when utilising DSM techniques with smart appliances and variable prices. Through simulation, Gottwalt et al. (2011) developed an artificial load profile for individual household appliances (examples include but not limited to: dishwasher, washing machine, Information and Communication Technology (ICT), Consumer electronics, stove, lights, circulation pump), which in turn are aggregated together to form household load profiles. Based upon German national statistics for utilisation of appliances, i.e. number of yearly uses and appliance run times, Gottwalt et al. (2011) generated household load profiles for a whole year, split into 15 minute intervals. This allowed Gottwalt et al. (2011) to integrate factors such as holidays, vacations, and seasonal impacts. With these developed load profiles, congregated from individual appliances under a flat electricity tariff (i.e. a flat rate pricing structure), simulations then sought to replace the appliances with smart appliances, and incorporate time-based electricity prices. Gottwalt et al. (2011) actually found there to be no improvement on peak loads. As the time-based electricity price structures simulated were day-ahead TOU tariffs, original demand peaks are eliminated, but alternative peaks occur, increasing in size with adoption rate of smart appliances. In terms of the consumers monetary gain from investing in smart appliances, to enable DSM techniques, Gottwalt et al. (2011) showed that households save very little over the course of a year, with the savings in electricity bills hardly exceeding the cost of smart appliances. However, from a grid operators perspective, DSM technology increased demand responsiveness and thus a better ability to adjust to intermittent supplies. The work presented by Gottwalt et al. (2011) highlights the unintended impact of peak shifting technologies if large numbers of households are simulated, i.e. the generation of new peaks, replacing the old ones. Effort may be required to limit the grids capacity over time so as to eliminate the possibility for other peaks to form when originals are dissolved.

One model presented in literature uses a global charging power cap, within which selection criteria, including State-of-Charge (SOC) and availability, are used to develop a priority ranking system from which vehicles are picked to determine charging order (Ciabattoni et al., 2021). The work of Ciabattoni et al. (2021) focuses on the development of their cloud-based tool, a fully customisable EV population simulator to fill the lack of large-scale data sets available for EVs, upon which a peak-shaving (DSM) case study is presented to illustrate the simulators potential. Each driver (EV) is randomly assigned a charge point, either 3, 4.5 or 6 kW. Although the output from Ciabattoni et al. (2021) simulator provides power and energy requirements from the charge point, SOC and minimum SOC (the minimum amount of SOC required during recharge for each EV to successfully complete the following travel requirements until the next charge) of the EVs continuously throughout a pre-defined simulation period, only commuting trips are considered. Thus, lacking the ability to capture the heterogenous nature of vehicle usage, and by extension, accurate reflections of an EV's SOC over time.

Nevertheless, Ciabattoni et al. (2021) go on to present a DSM strategy applied to the output of the simulator; a cap for the global charging power absorbed from the grid. The commuting distances and minimum SOC are still enforced and a population of 100 EVs are simulated. Ciabattoni et al. (2021) explored multiple power caps (70, 50, 23, 18, 14 and 10% of the maximum power required should all vehicles want to charge at the same time. For this simulation run, this yielded a maximum power demand of 450 kW from all 100 various charge point powers. For all scenarios, apart from the 10% power cap), all travel requirements for each EV are met. For the DSM simulation conducted by Ciabattoni et al. (2021) to determine which EVs can and cannot charge at any one particular time, when the total number of EV chargepoints plugged in exceeds the power cap of the current scenario being investigated, a priority mechanism has been developed. EVs whose State of Charge (SOC) falls below their specific minimum required SOC are given the highest priority. This priority diminishes once the EV reaches this minimum SOC threshold. This method, reflecting a lowest SOC has priority approach in some ways is an interesting equitable approach to the determination of charging schedule.

One core assumption should be noted from the work by Ciabattoni et al. (2021), each vehicle has its own charge point. Households are not considered within the simulator presented by Ciabattoni et al. (2021) and thus neither are multi-vehicle households, households which may only have one charge point between multiple vehicles. However, Ciabattoni et al. (2021) approach does yield lower computational requirements and complexity from this simplification.

Furthermore, as highlighted previously, the 'My Electric Avenue' project found 32% of Britain's low voltage (LV) feeders will require intervention once larger EV market shares are achieved. Traditionally, these findings would mean the replacement of underground cables, however, another aspect of this project saw the trialling of DSM technology; Esprit (My Electric Avenue, 2023). Esprit represents a cutting-edge technological solution capable of managing EV charging activities in response to elevated demand levels within the local electricity grid. By incorporating Esprit into networks, the 'My Electric Avenue' project is the first real-life trial that has directly controlled domestic EV charging to prevent underground cables, overhead lines and substations being potentially overloaded. The project found that the adoption of Esprit has the potential to yield significant cost savings, estimated at approximately £2.2 billion in infrastructure reinforcement expenses by the year 2050 (My Electric Avenue, 2023). The installation of Esprit and idea of curtailment was accepted by participants of the

My Electric Avenue project beforehand, with Fisher et al. (2015) reporting participants were comfortable because "…they only had short journeys to complete each day, with available charging periods of 10-12 hours overnight", and "…they could always use another vehicle if necessary". The reactions to DSM and the power capping of chargers may be different if the EV was your only option for mobility, as would likely be the case for rural households, especially one vehicle household.

Likewise, to power outages, EVs also present opportunities for aiding DSM measures. With V2G technology, an EV could be used as an energy source during times of peak demand on the grid (Pang et al., 2012; Mesaric and Krajcar, 2015). However, Cowie et al. (2020) actually highlight the "lack of thinking" behind using EVs for DSM in rural areas. Rural vehicles are much less likely to spend as much time parked compared to their urban counterparts and thus reduce their feasibility for use in DSM projects. In addition, there are also significant issues with utilising EVs for DSM strategies in terms of both consumer acceptance (exacerbating range anxiety issues), and battery degradation/health from additional charge/discharge cycles (Mohanty et al., 2022).

2.7 Real-World EV Studies

The focus of this literature review thus far has been predominantly technical. To ensure both a quantitative and qualitative approach to the work presented in this thesis the following section will focus on real-world studies which have been conducted on the EVs and the transition.

The business case for rural areas under current circumstances, including lower population densities, longer journey distances, and lower return on investment (ROI) seen by companies and investors installing EV and charging infrastructure, leaves rural communities with a high possibility of being 'left behind' (House of Commons, 2018). This thesis intends to take a stakeholder approach to help mitigate this possible scenario. This approach will ensure the implementation of EVs, and its necessary support infrastructure yields benefits for all stakeholders in these rural environments, in particular the rural community.

Although there is a general lack of consideration for the EV transition in rural areas from an academic aspect, and even less so from a political aspect, there have been some studies conducted which focus on it. Newman et al. (2014) challenged the widely held belief that EVs are ideally suited for urban setting, suggesting instead that they could be equally, if not more, effective in suburban and rural areas. They highlight the typically longer commuting distances in these areas (30-80 km round trips), which Newman et al. (2014) argue align better with the discharge-recharge cycle of EV batteries. However, this could mean that after a typical day's travel, an EV might have limited capacity for additional trips without recharging, potentially delaying the onset of further travel. In addition, the longer average travel distances in rural settings, as opposed to urban ones, could lead to a more significant cost benefit of using an EV over an ICE vehicle.

Additionally, literature highlights the importance of an inclusive approach (i.e. open communication between all stakeholders of the rural EV transition) when tackling the EV transition in rural areas (MICT, 2016; Esmene and Leyshon, 2019). To involve the rural community as an active stakeholder and participant in the transition to EVs in their area, and to facilitate a smoother shift, data collection from these areas will be conducted. In preparation for this, examples of previous EV surveys have been reviewed and are presented below.

One survey, conducted by the Electric Power Research Institute (EPRI), based in the US, developed a web-based survey which was active from 2011 till mid-2014. Dunckley and Tal (2016) surveyed over 4,000 EV owners across 11 states in America to investigate the attitudes and perceptions of EV owners with regards to the roles of electricity companies and grid operators in this transition and the market itself. Dunckley and Tal (2016) found most US based EV drivers only charge at home, with some charging at home and work. The only criteria for participation was ownership of an EV, with no published statistics on their location (i.e. if participants lived in a rural or urban environment). Although from the demographics they did collect, 98% reported living in detached houses (Dunckley and Tal 2016). As highlighted previously, rural households typically have more space and off-street parking (see Section 2.5), which usually presents itself as detached houses. Given the high proportion of detached households within the Dunckley and Tal (2016) study, findings from this study can be applicable to rural areas. For comparison, figure 2.9 presents housing stock statistics for England, categorised by building type and location (rural to urban). As shown by figure 2.9, rural areas by far have the highest percentage of detached and semi-detached houses, which typically will have off-street parking, compared to Flats for instance which are shown to be much more prevalent in urban areas.

Figure 2.9: Percentage of residential properties, by building type (Figure A-1 extracted from DEFRA, 2023)

The survey conducted by Dunckley and Tal (2016) also explored how incentives impact consumer decisions to purchase EVs. By categorisation responses according to the make and model of the EVs owned by participants, they shed light on the popularity of specific models like the Nissan Leaf and Chevrolet Volt. The findings revealed that the federal tax credit, which was applicable to most buyers due to its criteria, held significant importance, especially for owners of the Nissan Leaf and Chevrolet Volt, as these vehicles qualified for the maximum credit of $7500 at the time of the survey. This insight could account for the Nissan Leaf's popularity observed in prior surveys discussed and its frequent inclusion in simulations and models developed in literature presented previously in this review.

Conversely, Dunckley and Tal (2016) also reported the minor impact home charging installation incentives had for EV uptake, irrespective of the model. Considering the UKs only grant for purchasing an EV currently is for chargepoint installation this financial incentive offered by the UK Government may not do much for EV uptake levels.

Dunckley and Tal (2016) also asked participants about charging behaviours and likewise to many other examples of literature presented in this review, saw Home charging as the most widespread. Responses showed 57% only plugged their EV in at home. Whilst 40% of respondents utilised home and public locations (including work) for recharging events. Only 2% charge their EVs solely away from home. Finally 1% did not plug their vehicle in during the last 30 days (Dunckley and Tal, 2016).

When vehicles were actually plugged in, the majority of participants reported that their EVs begin charging immediately, however 20% use a timer to shift the load to off-peak hours. Dunckley and Tal (2016) found a high correlation between using a timer to shift the EV charging hours and the respective household being on a TOU electricity rate. In total 35% of households on a TOU rate use a timer, but contrary to intuition, 13% of households on a flat, standard electricity tariff also use a timer. Thus, moving their charging hours without any financial incentive. These individuals are most likely actively changing their charging behaviour due to their understanding of the electrical grids natural demand curves; however, this cannot be proven. Dunckley and Tal (2016) go on to advocate the opportunity EVs present to shift electric loads through encouraging customers to adopt TOU electricity tariffs. However, as highlighted by Gottwalt et al. (2011), during the discussions of Section 2.5.2, work is required to understand the implications of large number of households adopting TOU electricity tariffs as new peaks may be formed.

Graham-Rowe et al. (2012) highlights the need for infrastructure investment to convince consumers to adopt EVs. This came following a questionnaire conducted with 40 UK private passenger vehicle drivers at the end of a 7-day period using an EV, the first UK EV trial focused on mainstream consumers. Participants were recruited from areas including the Berkshire, Hampshire, and Surrey regions, with the survey itself including a location question which options for participants to indicate the type of area from which they reside (rural, urban, or suburban). Of the 40 participants, 20 lived in a suburban environment, 13 in urban and 7 in rural locations (Graham-Rowe et al., 2012). As is the case for many individuals still today, the prioritisation of personal mobility outweighs environmental benefits (Graham-Rowe et al., 2012), a finding also corroborated by Bailey and Axsen (2015) and Skippon and Garwood (2011).

The participants of Graham-Rowe et al. (2012) study did note the environmental benefits and righteousness of operating an EV, however participants had multiple complaints. Ranging from embarrassment of driving EVs, compared to the ICEs on the road, adaptation requirements for operating an EV, lack of confidence in the vehicle to financial and range anxiety. However, this study is over 10yrs old at the time of writing and the date the actual data collected itself was not presented, since which EVs have come on considerably in all these departments. It would be beneficial to conduct a similar questionnaire today for comparison.

Carley et al. (2013) also surveyed 2302 consumers from over 21 major US cities on their intent on purchasing EVs, with questions focused on driving range. With this study concentrating solely on consumers in major urbanised areas only, it inherently carries a bias towards a demographic likely less worried about driving range compared to rural inhabitants. Consequently, this may lead to an underestimation of the genuine concerns regarding EV driving range. The survey developed by Carley et al. (2013) went live during the fall of 2011, before vehicle manufacturers and dealers began marketing campaigns, thus Carley et al. (2013) was able to capture true pre-conceived notions regarding EVs. This peer-reviewed journal from Carley et al. (2013) reported that the perceived disadvantages of EVs are significant deterrents which need to be overcome, however, many can be addressed via public policy and investments. For example, range anxiety could be alleviated through the installation of more public chargepoints. A course of action which is currently a priority of the UK Government (DfT, 2023c).

As detailed, there are many examples of conducted surveys which have aided the understanding of the EV transition. However, few examples of surveys focus on rural areas alone, attempting to capture any nuances these environments pose towards the transition. The work presented in this thesis aims to fill this research gap through the development of a survey, specifically for rural data collection, and by extension validate the rural focused simulations which shall be presented (Section 1.1).

2.8 Research Approach

To achieve the multi-disciplinary nature of this thesis and the topics within, focus will now be placed upon the theoretical underpinning of this research. The transition of rural communities towards EVs adoption necessitates a methodological foundation that is not only practical but is also supported by a solid theoretical framework. With this in mind, it will explore the principles of pragmatism, stakeholder theory, and the case study methodology. These theoretical perspectives have been carefully selected for their relevance and potential to provide a comprehensive, multidimensional lens through which the complexities of rural EV adoption can be analysed and understood. Through this theoretical exploration, this thesis aims to forge a robust foundation that not only informs the empirical investigation but also enriches the analytical depth of the research findings.

2.8.1 Pragmatism

In response to the complex, multifaceted nature of transitioning rural communities to EVs, the research presented in this thesis adopts a pragmatic philosophical foundation. Pragmatism, as a philosophical tradition, prioritizes the practical application of ideas and the real-world impact of research outcomes over rigid adherence to any one methodological approach (Morgan 2014). It is particularly suited to addressing the interdisciplinary nature of the rural EV transition, as it allows for flexibility in research design and methodology.

Pragmatism is grounded in the belief that the truth of an idea or theory lies in its practical effects and its ability to solve problems (James and Sheffield 2019; Dewey 1938). This philosophy advocates for a pluralistic approach to research, where methods from both the positivist and interpretivist paradigms can be employed together to gather a comprehensive understanding on the research problem. As such, pragmatism inherently supports the use of mixed methods, enabling researchers to draw upon the strengths of both quantitative and qualitative research (; Johnson and Onwuegbuzie, 2004; Tashakkori and Creswell 2007; Creswell and Creswell 2018). This aligns with the interdisciplinary approach necessary for examining the socio-techno transition to EVs in rural areas, where understanding the nuanced interplay between technology, policy, and human behaviour is crucial.

The pragmatic approach in this thesis is manifested through the development and application of a novel Travel Demand Model and an EV Charging Model, which together provide a multifaceted view of the potential impacts of EV adoption in rural communities. The quantitative data generated by these models will be complemented by qualitative insights from the survey distributed among rural individuals. This mixed methods approach, underpinned by pragmatism, allows for a more nuanced analysis of the feasibility, capabilities, and impacts of transitioning to EVs on both communities and grid operators.

The decision to adopt a pragmatic approach is justified by the complexity and broadness of the research problem, which spans technical, environmental, social, and policy dimensions. Pragmatism offers the flexibility to adapt to methods as the research progresses, ensuring that the methods chosen are fit for purpose and sensitive to the evolving nature of the research. This adaptability is crucial for exploring new and evolving trends, like the shift towards EVs in rural areas, where existing models and theories may not adequately reflect the intricacies of the scenario (Feilzer 2010).

By grounding this research in pragmatism, it contributes not only to the body of knowledge on the rural EV transition, but also to the methodological discourse on the application of pragmatic principles in interdisciplinary research. This approach demonstrates the value of pragmatism in aligning theoretical constructs and practical concerns, thereby offering insights that are both academically robust and practically relevant.

2.8.2 Stakeholder Theory

As highlighted previously, the business case for the EV transition in rural areas, under current circumstances, leaves rural communities with a high possibility of being 'left behind' (House of Commons, 2018). This disparity uncovers a critical research gap – the need for inclusive strategies that ensure rural communities are integral to the EV transition narrative. Addressing this gap necessitates a theoretical lens that accommodates diverse interests and facilitates equitable value creation across all stakeholder groups.

Stakeholder theory, as articulated by Freeman (2010), provides a robust framework for this endeavour. The stakeholder refers to "any group or individual who can affect or is affected by the achievement of an organization's purpose" (Freeman, 2010). These groups have a stake in a particular issue or system and the stake (concern, issue, or claim) may be regarded as the driver of the relationship between a stakeholder and an organization. Stakeholder theory argues that an organisation should create value for all stakeholders, not just shareholders (Freeman 2010). This inclusive approach aligns with the ethical standpoint of utilitarianism, emphasising outcomes that maximize overall well-being (Jones et al., 2007).

The discourse on stakeholder theory reveals its evolution into three primary variants: descriptive/empirical, instrumental, and normative (Hörisch et al. 2014). The research presented in this thesis is anchored in Normal Stakeholder Theory (also known as Moral Stakeholder Theory), which advocates for stakeholder consideration as a moral imperative, irrespective of the direct benefits to the organisation (Jones et al., 2007; Gooyert et al., 2017). This is opposed to the Instrumental stakeholder theory approach which take stakeholders into account because of perceived benefit for the organisation. The implications of this decision come down to the process of identifying stakeholders. A Normative (Moral) stakeholder approach will develop a wider set of stakeholders as those without power and influence on the organisation are considered to find the optimal solution going forward. The rural community, on which this research project is based, is the embodiment of this type of stakeholder – without power and influence. This has resulted in the 'left-behind' stereotype determined by past socio-techno transitions. The morally correct approach is to make sure they are accounted for and thus this theory resonates with the ethos of this research more so.

The Normative Stakeholder Theory underpins the methodologies used by this thesis, guiding the identification and inclusion of a broad spectrum of stakeholders, particularly emphasising those traditionally marginalised – rural residents. This theoretical stance is operationalized through a mixed-methods approach comprising of a case study and survey. This approach aims to centre the perspectives and experiences of rural individuals – customers who are often overlooked in large-scale transitions.

2.8.3 Case Study Approach

To ensure the findings of this thesis are routed with real-world applicability, a case study research approach was adopted. The case study method is ideally suited for investigating complex phenomena within their real-life contexts, particularly when the boundaries between phenomenon and context are not clearly evident (Yin, 2014). The decision to adopt a case study approach was driven by the need to understand the intricacies of EV adoption in rural settings – a topic that benefits from a detailed, contextual examination. Case studies enable a holistic analysis of the socio-technical and environmental variables at play, allowing for the exploration of processes, impacts, and experiences from multiple stakeholder perspective.

A case study is defined as an empirical inquiry that investigates a contemporary phenomenon in depth and within its real-world context (Crowe et al., 2011). It is a methodological approach that stands on the foundational belief that complex issues cannot be fully understood without considering the context in which they occur, thus emphasising the importance of situational analysis for generating insights. Multiple definitions of case studies exist and can be seen in Table 2.3 below.

Author	**Definition**
Stake	Focuses on the complexity and particular nature of the case in question. *"A case study is both the process of learning about the case and the product of our learning"* (p.237)
Yin	Emphasises the contextual analysis of a limited number of events or conditions and their relationships.
Miles and Huberman	Considers the case as a phenomenon occurring in a bounded context
Green and Thorogood	Views the case study as an approach to obtain an in-depth understanding of a specific issue, entity, or process.
George and Bennett	Defines case studies as detailed examination of an individual case within a real-world context.

Table 2.3: Definitions of a case study (Extracted from Crowe et al., 2011)

Ensuring the validity of case study research is paramount to generating credible and reliable findings that can inform theory and practice. Robert K. Yin's (2014) approach to case study methodology provides a comprehensive framework for addressing validity concerns, encompassing construct validity, internal validity, external validity, and reliability. This section will now elaborate on these validity factors are applied in the context of investigating the transition to EVs in rural settings.

The methodological framework for this thesis draws heavily on the principles outlined by Robert K. Yin (2014), which advocates for a systematic approach to case study research. This includes the development of a clear research framework, the use of multiple sources of evidence, and the creation of a compelling narrative to present the findings. Yin's approach is particularly well-suited to examining the technological and social dimensions of EV adoption in rural communities.

The practical application of Yin's case study methodology in this thesis is demonstrated through the examination of EV adoption within the Peak District, UK – an applied example. This specific case was chosen due to its representative nature of rural communities facing the challenges of transition to EVs – this will be discussed in more detail in the following chapter. The case study involved an integrated method of data collection, including surveys, analysis of secondary data and infrastructural challenges.

Adopting a case study approach will enable a detailed exploration of the EV transition in rural areas. By grounding the research in real-world applicability, this thesis contributes valuable knowledge to the field and will provide a solid foundation for future research and policy development in the context of sustainable rural mobility.

CONSTRUCT VALIDITY

Construct validity refers to the accurate identification and operationalisation of the concepts under investigation. Yin (2014) emphasises the importance of using multiple sources of evidence and establishing a chain of evidence to enhance construct validity. In the applied example of rural EV adoption, construct validity was ensured though the triangulation of data collected from multiple sources. This multiplicity of viewpoints and data types allowed for a robust operationalisation of the concepts or interest, such as "EV Adoption Barriers" and "Rural Mobility".

INTERNAL VALIDITY

Internal validity, which is primarily a concern in causal (explanatory) case studies, deals with establishing a causal relationship between variables. While the focus on rural EV adoption may not strictly seek to establish causality, Yin's framework suggests the use of pattern matching, explanation building, and addressing rival explanations as strategies to enhance internal validity. In this research, pattern matching can be employed by comparing observed patterns in the data (from the survey) with predicted patterns derived from the simulations (Travel Demand Model and EV Charging Model). This approach helps to solidify the internal logic of the case study.

EXTERNAL VALIDITY

External validity concerns the extent to which the findings from a case study can be generalised to other contexts. Yin (reference) advocates for the use of theory in case study research as a means to enhance external validity. Rather than relying on statistical generalisation, case studies aim for analytical generalisation, where the researcher generalises findings to theory rather than to populations. Therefore, this thesis aims to generate findings for rural EV adoption that are applicable to all rural areas, this focus will be implemented through the adaptability of the novel models presented. In turn, these models can be utilised with any other case study area, thus facilitating the transferability of insights to a broader range of rural settings than solely the case study presented here.

RELIABILITY

Reliability in case study research ensures that another researcher could follow the same procedures and arrive at the same findings. Yin suggests the development of a detailed case study protocol and the maintenance of a case study database as key strategies for enhancing reliability. This thesis in itself can serve as a protocol outline for the studies procedure, from case selection through to data collection, modelling and analysis. A case study database, including raw data, survey responses, simulation code was maintained throughout, ensuring that the research process was transparent and replicable.

2.9 Chapter Summary

Initially, this chapter outlined a somewhat new, hybrid approach to literature analysis, merging narrative and systematic review methodologies. This approach was designed to accommodate the broad spectrum of research questions, enabling the identification of key themes and empirical evidence within the complex domain of rural EV transition. Various source types, including peer-reviewed articles, government reports and online materials provided a comprehensive pool of information from which to discuss. However, this approach may have neglected to include more grey materials which has been discussed previously. Despite this initial oversight in directly searching for grey literature, this expansive hybrid approach facilitated a nuanced understanding of rural EV adoption, setting a solid foundation for the thesis' contributions to the field.

This chapter has illustrated how the uptake of EVs are increasing. Although, there is still a way to go in terms of reaching a market penetration level whereby the number of EVs on UK roads will achieve UK Government targets. BEVs have been shown to have the highest rate of uptake within the UK and therefore shall be the focus for this thesis. However, given this increased rate of uptake, the reviewed literature on EV policies has shown the UK lacks incentives to promote the EV transition. Building upon this further, Section 2.2.2 reviewed emission zones, which were also shown to not foster the uptake of zero emission tailpipe vehicles such as BEVs. In addition, both the drivers and barriers EVs have to contend with to reach these goals have been reviewed. Range anxiety, public charging infrastructure, upfront costs and preconceived perceptions are all still barriers to the EV transition.

Section 2.3 reviewed rural areas in general, the crux of this thesis, highlighting how vital vehicles are to the inhabitants of these areas, as well as a larger proportion of this population. They have been shown to conduct different trips with their vehicles to their urban counterparts, highlighting the need for rurally focused research to aid this transition in these areas. However, given past socio-techno transitions and the current trajectory of this one, they are already falling behind their urban counterparts.

The methodology for investigating the impact of EVs, and therefore predicting the changes/work that need to be done was discussed. This involves creating a travel demand model, based upon a synthetic population, and then applying various charging scenarios. Following this simulation pathway the activity based TDMs were identified to be most suitable given the aims and objectives of this thesis. The literature reviewed revealed several gaps and novelties that will be filled by the research presented in this thesis. This includes creating a longer term model to capture changes witnessed in car usage/travel over a longer period of time, incorporating a combination of social and demographic characteristics with these various models, and developing said models dedicated to capturing rural nuances; reflecting the differing travel patterns and vehicle requirements of rural areas compared to urban.

This chapter then moved to discuss EV charging in Section 2.5. Noting a key feature, that will be employed by the models developed in this thesis, to incorporate a ‘Day 0’ to the simulation for initialisation. Additionally, weight needs to be given to understanding the impact of electricity tariffs (vis-à-vis pricing structures) and human behaviour itself when it comes to EV charging. To fully understand the impact of large-scale deployment of EVs in rural areas, integration with the electrical grid needs to be explored. Given the typically weaker infrastructure of the grid in rural areas, two further topics were discussed: power outages and demand side management.

Given the predominantly technical/quantitative discussion thus far through, the Chapter sought to incorporate a qualitative aspect to balance the narrative and direction of the forthcoming work presented in this thesis. Literature on EV surveys was reviewed so as to ensure the work presented in this thesis engaged the stakeholder so often overlooked, the rural community. This thesis aims to conduct its own survey focused on this stakeholder and so sought to understand past examples of EV surveys.

Finally, Section 2.8 established a multi-disciplinary framework to explore the transition of rural communities towards EV adoption, utilising a robust theoretical foundation that includes pragmatism, stakeholder theory, and a case study methodology. Together, these methodologies provide an adaptable framework that aims to enrich both the academic and practical understanding of rural EV adoption.

2.9.1 Overview of Key Findings from Literature Review

- The UK Government has now revoked many of the previous grants which were available to potential EV consumers, a decision shown by the literature reviewed to hinder the uptake of EVs in any country – more financial incentives are needed.

- If legislation specifies only low emission targets, as is the case with many Clean Air Zone projects across the UK, not zero emission targets, this too also does not lead to promoting EV uptake, if anything draws out the transition longer to actual zero emission vehicles such as EVs.
- From an individual consumer perspective, the transition to EVs offers very little incentive, as a whole collective though there are the environmental aspects which will benefit all. The drivers for adoption are largely from the state's perspective – energy security, environmental benefits and meeting targets.
- However, EVs need to overcome very real driving range concerns, charging infrastructure issues (public and private), financial and pre-conceived perceptions due to the poor marketing and headlines EVs have received over the last 10 years.
- Vehicles are far more of a necessity to rural dwellers than urban, primarily due to the lack of public transportation options and the spread-out nature of utilities and amenities.
- Rural areas in the UK are classed as such based upon the Rural-Urban Classification
- Rural areas have been left behind after previous large-scale socio-techno transitions, given the importance of mobility for rural dwellers this can't happen with the EV transition. Current progress in the EV transition in the UK is already leaving rural areas behind, based on public charge point installation statistics.
- A particular EV has been the focus of many pre-existing pieces of literature – the Nissan Leaf. (My Electric Avenue Project; Jones et al., 2020; Adderly et al., 2018)
- Highlighted a methodology which could be utilised to facilitate the uptake of Electric Vehicles, from a technical infrastructure standpoint – A Travel Demand Model with EV Charging scenarios built on top to assess EV integration with local grid infrastructure.
- Identified the Activity Based Travel Demand Model (a form of Agent Based Modelling) as the most suitable approach to achieve the Aims of this thesis.
- Identified the National Travel Survey (Mattioli et al., 2019) as a potential source of data for this thesis.
- The important of home charging EVs (Kang and Recker, 2009; Hardman et al. 2018; Adderly et al., 2018; Dunckley and Tal, 2016).
- A lack of rural focused Travel Demand Models, i.e. ones that consider the nuances of rural vehicle travel compared to urban (Apronti and Ksaibati, 2018).
- Many current EV Charging models and scenarios fail to consider longer-term durations of simulation/investigation. Most are just 1 or 2 days.
- The Day 0 approach from Pareschi et al. (2020) for initialising the simulation parameters and mitigate the impact of transient behaviour in the system.
- Should EVs reach 40-70% market penetration, an estimated 323% of the UKs distribution system will be unable to cope. It is therefore vital to understand what the impact is and develop mitigation strategies.

- No evidence could be found reviewing the impact of power outages on EVs charging/usability.
- With such a globalised energy dependency, the UK is at risk of potential planned long-term power outages – what are the implications for the EV transition?
- Ciabattoni et al. (2021) proposed a hierarchy methodology for DSM – lowest SOC has priority.
- Charging takes place following last trip of the day (Kang and Recker, 2009).
- Likewise, to previous examples of Travel Demand Models, no evidence of rurally focused data collection surveys could be found.
- Identification of pragmatism as the most appropriate framework to continue the work of this thesis with and with this the Case Study approach. This will manifest as an empirical inquiry into the EV transition in rural areas.

Having reviewed past research on the topics surrounding the research question and this thesis, the following chapters will present the development of novel models, building upon past works presented in this review. This includes a travel demand model, EV charging model, the grid impact and conduction of a survey on rural communities. This chapter has achieved '*Objective 1a and 1b*', and by extension the first Research Aim, as presented in Chapter 1. In addition, the literature presented in this chapter sets the background for the other Research Aims and Objectives of this thesis.

CHAPTER 3: TRAVEL DEMAND MODEL

As highlighted by the previous chapter, understanding EVs and their charging profiles can be achieved through the simulation approach (Pareschi et al., 2020). This approach requires a Travel Demand Model (TDM) and EV charging scenarios. With the pre-existing travel patterns of vehicles simulated by a TDM, effort can then be made to understand the impact should this travel be conducted solely by EVs. The focus of this chapter shall be the development of a novel TDM for rural areas.

The chapter starts with detailing the selection process employed to find a suitable rural community on which to base this model, ensuring the rural focused requisite is achieved. For this community, key parameters for the model were extracted from public datasets. The literature reviewed in Chapter 2 found no prior models available that could be applied to serve the purpose set out for this thesis. Section 3.2 details preliminary work which was conducted to develop a smaller, 1-day TDM. This will henceforth be referred to as the 'One Day Model' and was developed as part of the pathway for developing a 7-day TDM. A short evaluation of the One Day Model will also be presented, which led to the development of criteria for the 7-Day TDM. Section 3.3 presents the novel 7-day TDM, a predictive travel model specific to rural areas for private passenger vehicles. This section includes the data driving the model's methodology, how it works, and the results. This is followed by a discussion of results and a short model validation using a previous year's data from the publicly available, UK National Travel Survey (NTS) (GOV.UK, 2021). This chapter concludes with a short summary, Section 3.5.

To note, material presented in this chapter has been published, or is currently under review at the time of writing, in conference and journal papers (McKinney et al., 2022; McKinney et al., 2023b).

3.1 Case Study Location

This project is, in part, investigating the impact electric vehicles will have on rural areas, which includes their impact on the electrical distribution grid of rural areas. To ensure applicability for the work presented in this thesis, a real-world rural location was chosen to act as a case study area. This section includes an overview for the selection of this rural location, as well as various demographic statistics pertaining to the area which will act as the preliminary set up for the TDM.

3.1.1 Bradbourne

The village of Bradbourne was identified due to its small population size (and by extension the number of vehicles and households) to allow for a lower computational requirement, supporting an in-depth analysis of the rural community requirements, as well as being easily accessible from the university base. Additionally, Bradbourne has readily available public data on various aspects of the community, which is key to the development of a realistic TDM. Bradbourne is located in Derbyshire on the outskirts of the Peak District National Park, as shown in Figure 3.1.

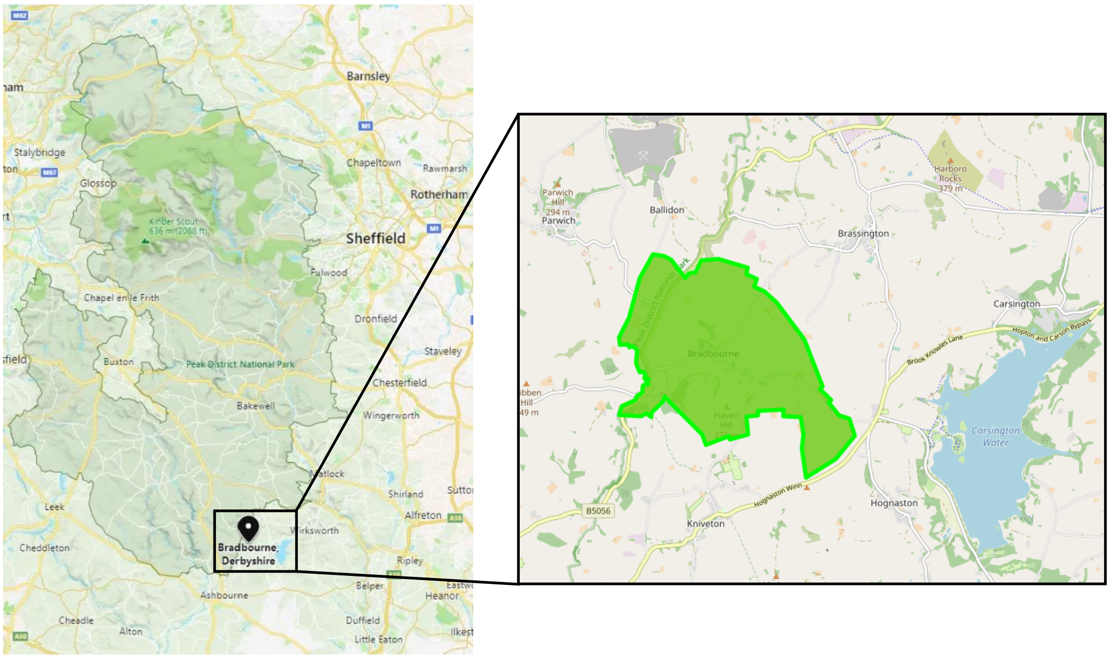


Figure 3.1: The Location of Bradbourne, England, UK (Left: Bing, 2021, Right: City Population, 2021)

The village of Bradbourne, although rural, can be classed as an affluent area. Taking the local house prices as a determination for affluency, the average sold price in Bradbourne over the last 12 months was £588,333 (Zoopla, 2023). This is almost double the UK average house price of £286,000 as of May 2023 (GOV.UK, 2023d). Current housing surveys of Bradbourne and the local surrounding areas (Parwich, Ballidon, Newton Grange etc.) have highlighted the need for more affordable housing in the area (Parwich Parish Council, 2022). Given Bradbourne's affluent status, there is a higher likelihood residents in this village will be able to afford the higher initial price tags currently attached to EVs. Therefore, overcoming a large barrier to entry for a 100% EV population in a rural settlement, the focus of this thesis.

This thesis aims to facilitate the uptake of EVs in rural areas, and the approach adopted to do this is a focus on local infrastructure and how this will cope with an EV future. The affluency of a rural area does play a pivotal part in the EV transition, for instance on the ability for locals to purchase EVs themselves and the installation of home charge points. This approach would require extensive financial analysis of an area on the local purchasing power of rural inhabitants; however, this is outside the scope of this thesis. For the approach of investigating local infrastructure, this will be the same regardless of a rural areas inhabitants purchasing power, a factor which also changes over time. Whether it's a poor rural area of a rich rural area will have little impact on the level of the local electrical grid infrastructure. Though it is true different rural areas can and will have varying levels of local grid infrastructure (power line ratings, transformer sizes etc), the work presented in this thesis is applicable to all rural areas, as the level of the local electrical grid will be considered, this will be discussed more in Chapter 5.

A final note for the impact of an areas affluency on the EV transition in rural areas, will be the local public transport options. This thesis has already shown the high necessity of owning your own vehicles in rural areas, due in part to the reduced funding for public transport in rural areas. Therefore the use of Bradbourne as the basis for the investigation in this thesis can be seen as a placeholder for any rural area across the UK. As long as data is available for the area of interest from the UK Census survey, a primary source of data for the work presented in this thesis, the methodologies described in this Chapter and the following can be applied.

The UK Census is a survey, conducted by the Office for National Statistics (ONS), every 10 years across England and Wales. It provides the most accurate estimate of all the people and households, building a detailed snapshot of our society. For UK Census statistics, the area of the UK is split into geographical areas, called Outputs Areas (OAs). A typical OA is comprised of between 40-250 households, or 100-625 persons (ONS, 2023). Bradbourne has the census output area code E00099163 (ONS, 2021), which has been used to determine the housing stock from the UK Census. The number of households (including their occupancy levels) and car availability data for Bradbourne was obtained from the 2011 UK Census Survey, Table QS406EW (Nomis, 2013a) and QS416EW (Nomis, 2013b), respectively, shown in Table 3.1 and Table 3.2.

Household Occupancy	No. of Households
One Person	15
Two People	14
Three People	13
Four People	3
Five People	2
Six People	1
Seven People	1
Total	**49**

Table 3.1: Household Occupancy in Bradbourne (NOMIS, 2013a)

Car or Van Availability	No. of Households
No Cars or Vans	4
1 Car or Van	17
2 Cars or Vans	18
3 Cars or Vans	9
4 or more Cars or Vans	1
Total Number of Vehicles	**84**

Table 3.2: Car Availability for Bradbourne (NOMIS, 2013b)

3.1.2 Household & Car Distribution

To approximate how many cars at each household, table 1 and table 2 were combined based on the premise that ‘the larger the household, the higher the number of cars that will be available’. Each house was then given its own ID number ranging from 1 to 49. This resulted in the following household compositions, shown in table 3.3. As per the UK Census definitions, ‘Car or Van’ includes pick-ups, camper vans and motorhomes but does not count motorbikes, trikes, quadbikes, and Statutory Off-Road Notification (SORN) vehicles (Census, 2021).

Household Occupancy	House ID	No. of Cars
One Person	1	0
	2	0
	3	0
	4	0
	5	1
	6	1
	7	1
	8	1
	9	1
	10	1
	11	1
	12	1
	13	1
	14	1
	15	1
Two Person	16	1
	17	1
	18	1
	19	1
	20	1
	21	1
	22	2
	23	2
	24	2
	25	2
	26	2
	27	2
	28	2
	29	2

Household Occupancy	House ID	No. of Cars
Three Person	30	2
	31	2
	32	2
	33	2
	34	2
	35	2
	36	2
	37	2
	38	2
	39	2
	40	3
	41	3
	42	3
Four Person	43	3
	44	3
	45	3
Five Person	46	3
	47	3
Six Person	48	3
Seven Person	49	4

Table 3.3: Households of Bradbourne composition

3.2 Development of the Travel Demand Model

Preliminary work saw the development of a simple 1-day Travel Demand Model, acting as a ‘stepping-stone’ for the development of the final, 7-day model. This section will describe this initial model, henceforth referred to as the ‘One Day Model’, followed by an in-depth evaluation. This evaluation reinforced the issues with short term TDMs discussed in the previous chapter, as well as highlighting important considerations for the development of the 7-day model.

3.2.1 One Day Model

Based upon the composition of each household (number of occupants and number of cars available), coupled with consideration of how those factors reflect potential occupant(s) ages, and their employment or education status, numerous lifestyle scenarios were developed. These can be seen in table 3.4.

Household Composition	Description	Lifestyle Scenario
One Person & No Car	N/A to this study	1
One Person & One Car	Retired Individual – Uses vehicle for ‘Other’ use	2
	Individual living alone - Working Full Time	3
Two Person & One Car	Retired Couple – Uses vehicle for ‘Other’ use	4
	Two Adults - One Works Full Time, One Does Not	5
	Two Adults - Both Work Full Time (Car Share)	6
Two Person & Two Car	Two Adults - Both Work Full Time	7
	Two Adults - One Works Full Time, One Works Part Time	8
	Two Adults - One Works Full Time, One ‘Other’	9
Three Person &Two Car	Two Adults & 1 Children (<5yrs) - One Works Full Time, One ‘Other’	10
	Two Adults & 1 Children (5-18yrs) - One Works Full Time, One School + Other	11
	Two Adults & 1 Children (5-18yrs) - One Works Full Time, One School + Part Time Work	12
	Two Adults & 1 Children (5-18yrs) - Two Work Full Time	13
Three Person & Three Car	Two Adults & 1 Children (17-18yrs) - Two Work Full Time, One School	14
	Three Adults - Three Work Full Time	15
	Three Adults - Two Work Full Time, One Car sits idle	16
Four Person & Three Car	Two Adults & Two Children (5-18yrs) - Two Work Full Time, One School	17
	Two Adults & Two Children (5-18yrs) - Two Work Full Time, One Car sits idle	18
Five Person & Three Car	Two Adults & Three Children (5-18yrs) - One Works Full Time, One ‘Other’, One School	19
	Three Adults & Two Children (5-18yrs) - Two Work Full Time, One Works Part Time	20
Six Person & Three Car	Three Adults & Three Children (5-18yrs) - Three Work Full Time	21
Seven Person & Four Car	Three Adults & Four Children (5-18yrs) - Three Work Full Time, One School	22

Table 3.4: ‘One Day Model’ Lifestyle Scenarios

Households with children have been categorised by three categories based on the age, ‘<5yrs’ or ‘5-18yrs’, or ’17-18yrs’. This is to differentiate between households that would likely have children in education or not, and if the child themselves is capable of driving. Considering the driving age for the UK, the location of research for this thesis, is 17 (GOV.UK, 2023c), the age category '17-18yrs' represents those children who will have their own vehicle and drive themselves to School.

From these lifestyle scenarios, a combination of trip purposes that each household might reasonably undertake in order to fulfil its lifestyle requirements (i.e. full time work – commuting trip purpose), was determined. These trip purposes were derived from those defined by the UK National Travel Survey (DfT, 2018b). The NTS is an annual survey by the Ministry of Transport, first commissioned in 1965 (Cornick et al., 2018) and one of the largest surveys completed in relation to travel in England. Approximately 16,000 individuals across 7,000 households are randomly selected to participate each year (DfT, 2020a) in the survey that consists of a face-to-face interview and a written travel diary. Annually, the Department of Transport published summary statistics tables (GOV.UK, 2021). For the model's creation, the most recent data available at the time, from the year 2018, was utilized (See Appendix A for NTS Summary Table NTS0403).

For simplicity, the number of possible trip purposes was reduced (through combination) from the 14 categorised by the NTS to 3 for use in this 1-day model. For example, the trip purpose categories '*Commuting*' and '*Business*' were combined into '*Work Commute*', as it was deemed these to be similar in terms of travel pattern and hence charging requirements for the purposes of modelling scenarios.

When considering the time resolution for this TDM, a 30 minute resolution was chosen to best serve the requirements for this thesis. With the EV charging model building upon a TDM, consideration was given to aligning the resolution of the TDM to one that would be beneficial for EV and household energy calculations, and by extension, grid integration. Although residential electricity meters are not monitored, business meters (often found on rural premises) are monitored half-hourly (British Business Energy, 2021). Therefore, to reduce computational complexities, a blanket duration of 30 minutes was set for all trip purposes. The resulting 'trip purpose' categories and their associated duration and distance are shown in table 3.5.

Trip Purpose	**Trip Duration (mins)**	**Trip Distance (miles)**
Work Commute	30	14
Education Commute	30	2.7
'Other' use	30	6.6

Table 3.5: Derived Trip Duration and Distance by Trip Purpose

The resulting passenger vehicle usage profiles, required to fulfil the lifestyle scenario of a particular household, will henceforth be referred to as 'Car Days'. These proposed 'Car Days' have been adopted as the basis for the TDM, attempting to capture the travel patterns of individuals by mimicking the results of a travel diary. This methodology was opted for to acquire information similar to that captured by the NTS - travel diaries - which at the time of development of this one day model was inaccessible. Additionally, another method to acquire this information would be to conduct primary data collection, however, due to time and resource restrictions, this was not practical at this stage. Seven different Car Day Scenarios (A - G) have been proposed which are presented in table 3.6. The Vehicle Location and Mileage Driven through the day for each devised Car Day Scenario is graphically represented in figures 3.2 and 3.3, respectively.

Car Day	Premise	Description	Total Miles Driven
A	Full Time Work	Full Time Work (09:00-17:00) Car leaves at 08:30, Returns at 17:30	28
B	Part Time Work	Part Time Work (09:00-13:00) Car leaves at 08:30, Returns at 13:30	28
C	Education Commute	Student commutes to School (08:30-15:30) Car leaves at 08:00, Returns at 16:00	5.4
D	‘Other’ Activity	‘Other’ Activity (10:30-14:30) Car leaves at 10:00, Returns at 15:00	13.2
E	Car Share (Full Time Work)	Car share to two different working locations (09:00-17:00) Car leaves at 08:00, drop-off at 08:30, arrives at 2nd work location for 09:00. Car returns at 18:00, after pick-up from work location 1 at 17:30	56
F	School Commute + ‘Other’	Car used to commute to school (08:30-15:30), drop-off student(s), then continues on to complete an ‘Other’ activity before returning home Car leaves at 08:00, drop-off student at 08:30 before continuing on and arriving at ‘Other’ trip destination at 09:00 Car returns from ‘Other’ trip at 12:00 Car leaves at 15:00, Returns at 16:00	21.3
G	School Commute + Part Time Work	Car used to commute to school (08:30-15:30), drop-off student(s), then continues on to Part Time Work (09:00-13:00) Car leaves house at 08:00, drop-off student(s) at 08:30 before continuing on to Part Time Work destination at 09:00 Car returns from Part Time Work at 13:30 Car leaves at 15:00 to pick-up student(s) from school at 15:30 and returning at 16:00	36.1

Table 3.6: Car Days Scenarios

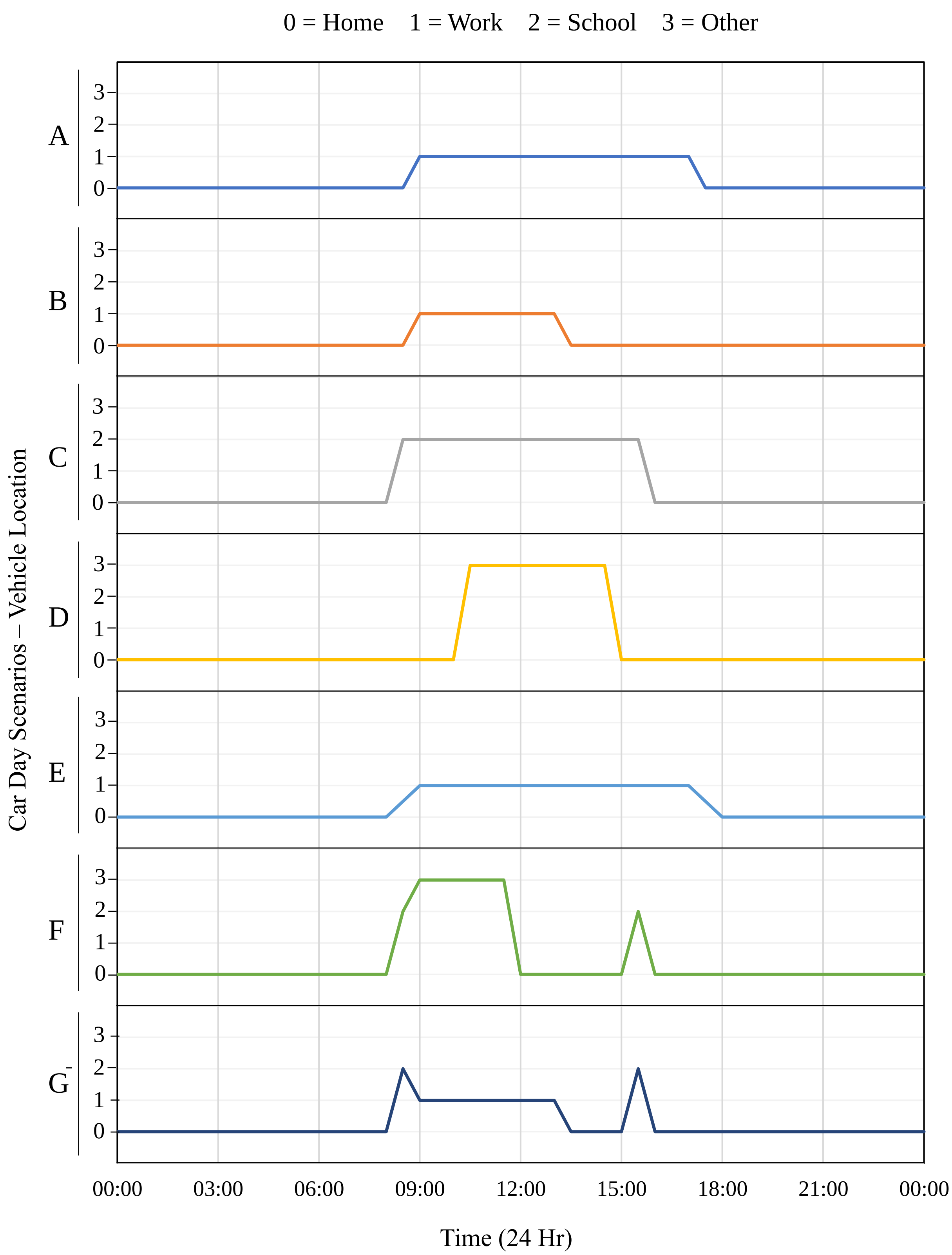


Figure 3.2: Car Day Scenarios – Vehicle Locations

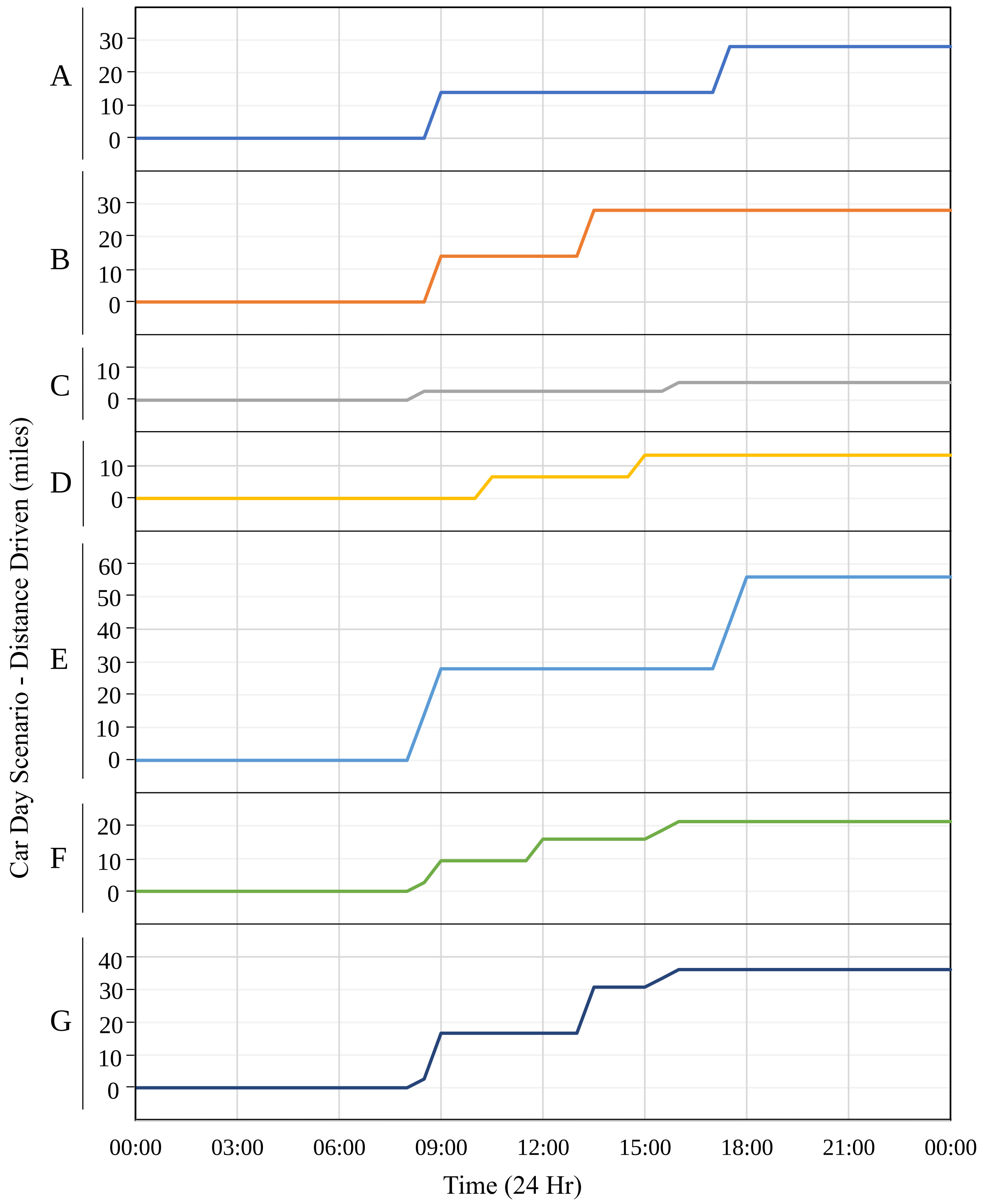


Figure 3.3: Car Day Scenarios – Miles Driven

The process employed to determine each households' Car Days, and thus enabling the determination of each households' cars activity is illustrated in figure 3.4. Temporarily, the numbers 1 to 7 were assigned to Car Day scenarios A to G, so that a random number generator could be used for this distribution. When this process was deployed, the resulting Car Day assignment to each household and its vehicles are shown in table 3.7.

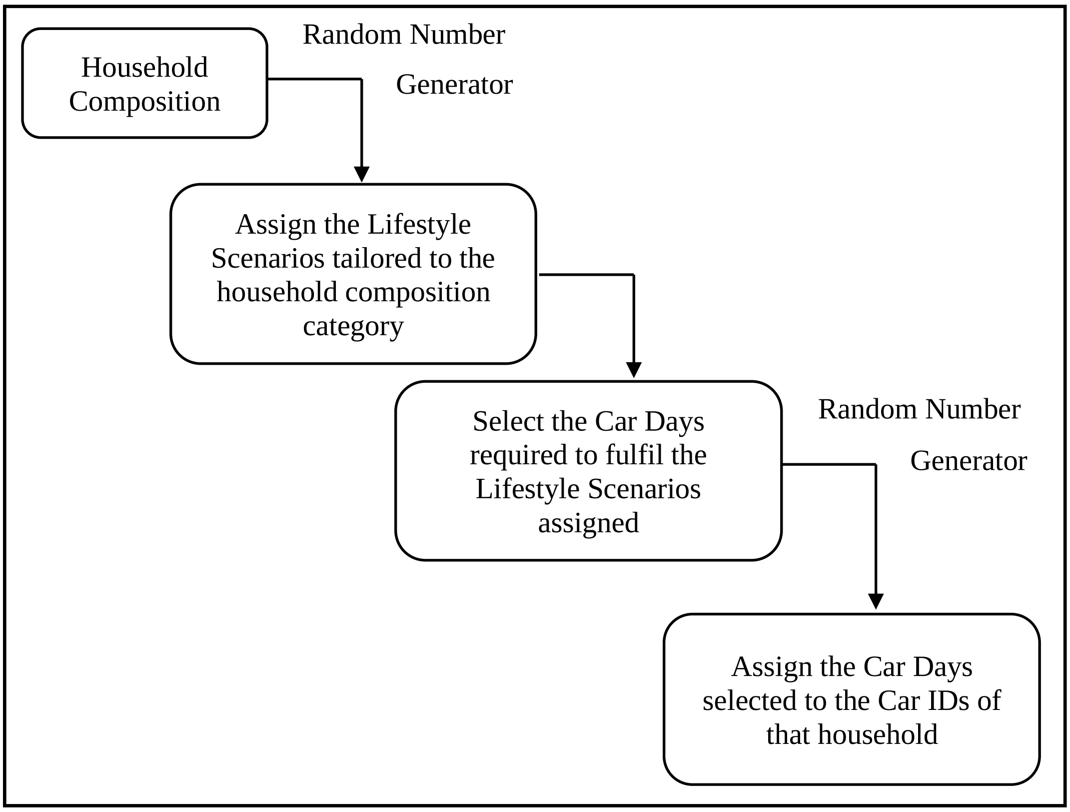


Figure 3.4: Process of lifestyle scenario and car day assignment flowchart

House ID	**Lifestyle Scenario**	**Car ID's for each Household**	**Car Day**
1	1	*N/A*	*N/A*
2	1	*N/A*	*N/A*
3	1	*N/A*	*N/A*
4	1	*N/A*	*N/A*
5	2	1	D
6	3	1	A
7	3	1	A
8	2	1	D
9	3	1	A
10	2	1	D
11	3	1	A
12	2	1	D
13	3	1	A
14	3	1	A
15	3	1	A
16	4	1	D
17	6	1	E
18	5	1	A
19	4	1	D
20	5	1	A
21	4	1	D

House ID	**Lifestyle Scenario**	**Car ID's for each Household**	**Car Day**
34	13	1	A
		2	A
35	11	1	A
		2	F
36	10	1	A
		2	D
37	13	1	A
		2	A
38	10	1	A
		2	D
39	12	1	A
		2	G
40	15	1	A
		2	A
		3	A
41	16	1	A
		2	A
		3	*N/A*
42	14	1	A
		2	A
		3	C

22	9	1	A
		2	D
23	7	1	A
		2	A
24	9	1	A
		2	D
25	7	1	A
		2	A
26	7	1	A
		2	A
27	8	1	A
		2	B
28	8	1	A
		2	B
29	7	1	A
		2	A
30	10	1	A
		2	D
31	13	1	A
		2	A
32	10	1	A
		2	D
43	17	1	A
		2	A
		3	C
44	18	1	A
		2	A
		3	*N/A*
45	18	1	A
		2	A
		3	*N/A*
46	19	1	A
		2	D
		3	C
47	20	1	A
		2	A
		3	B
48	21	1	A
		2	A
		3	A
49	22	1	A
		2	A
		3	A
		4	C

Table 3.7: Car Day Scenario Distribution

3.2.2 One Day TDM Results and Evaluation

For a population of 84 vehicles, the ‘One-Day' Travel Demand Model (TDM) predicts, collectively, a total of 1,993 miles driven per day. This equates to an average of 23.7 miles driven per car per day (including 3 vehicles which remain idle at home for the day of simulation). Scaling this to a full year (365 days), indicates the average annual mileage for each individual vehicle in Bradbourne, is 8,660 miles. The National Travel Survey reports for 2019, the average annual mileage of vehicles is 7,400 miles (DfT, 2020b). This discrepancy is most likely due to the TDM only representing one day of travel, and that one day being weekday travel. Weekday travel patterns are typically the days where the highest number of miles will be driven, compared to the amount of travelling undertaken at weekends (DfT, 2019) and thus has caused a slight overestimate in the annual miles driven.

This inability to capture the variability between weekday and weekend travel patterns, also highlights another lack of consideration, which is the variability between individuals conducting the same ‘Car Days’, i.e. starting work at different times. This heterogeneity is due to the inherent unpredictability in human behaviour over long periods of time. Without capturing this inconsistency, the results of this TDM and any further work (i.e. EV charging impacts) would also lack this real-life variability.

Upon deeper analysis of the lifestyle scenarios, multiple, valid scenarios have not been considered (i.e. Two Person Households consisting of One Adult and One Child, or Seven Person

Households consisting of Four Adults (Parents and Grandparents) and Three Children). These other lifestyle scenarios would impact the number of each Car Day witnessed in the village of Bradbourne and thus the overall mileage and times of activities. Although this model shows significant progress was achieved without the need of large external travel datasets, it does also highlight the added benefit this would bring, in particular using statistics to add much needed variability to the model.

The overarching reason for the development of the TDM, as highlighted by the literature review, is to use it as a basis for investigating EV charging requirements and by extension the impact they will have on local grid infrastructure. Briefly considering these next steps, if we assume a 100% homogenous EV car population (using the 40kWh Nissan Leaf, with a consumption rate of 26.5 kWh/100mile (Electric Vehicle Database, 2018)), the estimated total of 1993 miles being driven daily by the residents of the village of Bradbourne would correspond to a total of 528 kWh being consumed daily. Considering a simple, plausible, charging scenario whereby only one EV per household will be charged each day, for households with multiple EVs, a random number generator was used to determine which EV would be charged during the given 24hr period under investigation. It was assumed that all EVs will begin the day simulation with 100% state of charge and are only ever plugged in following the last trip of the day when the vehicle will not be leaving the household again (Kang and Recker, 2009). Based on these parameters, the recharging scenario saw only 287 kWh recharged into the vehicles. Compared to the 528 kWh required by the EV car population to maintain current travel habits, this showed a loss in the system over this simulation period, which if extrapolated to longer periods of time would become problematic.

3.3 Overview of 7-Day Travel Demand Model

Following the analysis of the One Day Model (Section 3.2), an improved extended version of the model was deemed necessary. Additionally, the RAW data for the National Travel Survey became available to the authors and thus, this dataset, as well as the data from the UK Census feature heavily in this novel 7-Day Model.

3.3.1 Lifestyle Scenarios

Following the same procedure as before, the lifestyle scenarios developed for the 'One Day Model' were used again, along with those not previously considered now being included. This resulted in a total of 27 different lifestyle scenarios for the range of Bradbourne's household compositions, compared to the previous 22 scenarios included for the 'One Day Model' (table 3.4). The new lifestyle scenarios include: 7, 8, 12, 25, 27. These 27 scenarios are detailed in Table 3.8.

Household Composition	Description	Lifestyle Scenario
One Person & No Car	One Adult - N/A to this study	1
One Person & One Car	One Adult - Retired Individual	2
	One Adult - Working Full Time	3
Two Person & One Car	Two Adults - Retired	4
	Two Adults - One Works Full Time, One Does Not	5
	Two Adults - Both Work Full Time (Car Share)	6
	One Adult, One Children (<5yrs) - One Works Full Time	7
	Two Adults - One Works Part Time, One Doesn't	8
Two Person &Two Car	Two Adults - Both Work Full Time	9
	Two Adults - One Works Full Time, One Works Part Time	10
	Two Adults - One Works Full Time, One 'Other'	11
	Two Adults – Both Retired	12
Three Person &Two Car	Two Adults & One Children (<5yrs) - One Works Full Time, One 'Other'	13
	Two Adults & One Children (5-18yrs) - One Works Full Time, One School + Other	14
	Two Adults & One Children (5-18yrs) - One Works Full Time, One School + Part Time Work	15
	Two Adults & One Children (5-18yrs) - Two Work Full Time	16
Three Person & Three Car	Two Adults & One Children (17-18yrs) - Two Work Full Time, One School	17
	Three Adults - Three Work Full Time	18
	Three Adults - Two Work Full Time, One Car sits idle	19
Four Person & Three Car	Two Adults & Two Children (5-18yrs) - Two Work Full Time, One School	20
	Two Adults & Two Children (5-18yrs) - Two Work Full Time, One Car sits idle	21
Five Person & Three Car	Two Adults & Three Children (5-18yrs) - One Works Full Time, One 'Other', One School	22

	Three Adults & Two Children (5-18yrs) - Two Work Full Time, One Works Part Time	23
Six Person & Three Car	Three Adults & Three Children (5-18yrs) - Three Work Full Time	24
	Four Adults & Two Children (5-18yrs) – Two Work Full Time, Two Don't	25
Seven Person & Four Car	Three Adults & Four Children (5-18yrs) - Two Work Full Time, One Doesn't, One School	26
	Four Adults & Three Children (5-18 yrs & <5yrs) – Two Work Full Time, One Doesn't	27

Table 3.8: Lifestyle scenarios for 7-Day TDM

These 27 lifestyle scenarios were then assigned to each of the 49 households which matched the household composition, using a random number generator. This method did result in some lifestyle scenarios not being assigned to a household and thus not incorporated into the TDM. For example, there are two possible scenarios drawn up for the Household Composition category '*Seven Person & Four Car*', however, based upon the dwelling statistics of Bradbourne, there is only one household of seven occupants in the village. Thus scenarios 26 and 27 cannot both be investigated. The lifestyle scenarios not incorporated into the TDM are as follows: 25 and 27. The results of the lifestyle scenario assignment to the households of Bradbourne can be seen in Table 3.9 below.

House ID	**Lifestyle Scenario**	**No. of Occupants**	**No. of Vehicles**
House 1	1	1	0
House 2	1	1	0
House 3	1	1	0
House 4	1	1	0
House 5	2	1	1
House 6	3	1	1
House 7	3	1	1
House 8	2	1	1
House 9	3	1	1
House 10	2	1	1
House 11	3	1	1
House 12	2	1	1

House ID	**Lifestyle Scenario**	**No. of Occupants**	**No. of Vehicles**
House 26	12	2	2
House 27	10	2	2
House 28	10	2	2
House 29	9	2	2
House 30	13	3	2
House 31	16	3	2
House 32	13	3	2
House 33	14	3	2
House 34	13	3	2
House 35	14	3	2
House 36	13	3	2
House 37	16	3	2

House 13	3	1	1
House 14	3	1	1
House 15	3	1	1
House 16	4	2	1
House 17	6	2	1
House 18	5	2	1
House 19	7	2	1
House 20	8	2	1
House 21	4	2	1
House 22	11	2	2
House 23	9	2	2
House 24	11	2	2
House 25	9	2	2
House 38	13	3	2
House 39	15	3	2
House 40	18	3	3
House 41	19	3	3
House 42	17	3	3
House 43	20	4	3
House 44	21	4	3
House 45	21	4	3
House 46	22	5	3
House 47	23	5	3
House 48	24	6	3
House 49	26	7	4

Table 3.9: Household Compositions

From these lifestyle scenarios, a combination of trip purposes that each household might reasonably undertake in order to fulfil the scenario (i.e. full time work – commuting trip purpose), was determined. However, to incorporate more variability in the travel patterns, a requirement highlighted from the previous 'One Day Model', additional trip purpose categories were devised. This will now be discussed in detail in the following section (3.3.2).

3.3.2 The National Travel Survey

With the development of this 7-day Travel Demand Model, access to the RAW data of the 2019 NTS, the latest year available at the time of writing, was achieved. The 2019 NTS dataset is available from the UK Data Service (DfT, 2020c), and with the RAW data, responses from rural households only could be extracted in order to further orient this work to support the rural focus of this project. This extensive data pre-processing stage required custom written python scripts in order to manipulate the RAW NTS data (DfT, 2022b). Considering this is a 7-day travel demand model, additional information is required, specifically, four key factors:

- The time the activity occurs
- The day the activity occurs
- The duration of the activity
- The number of times this activity occurs (across the 7 day period)

Table 3.10 details each of the NTS's defined trip purposes, and the average trip durations and distances, specifically for only rural household respondents to the survey.

Trip Purpose	Avg. Trip Duration (mins)	Avg. Trip Distance (miles)
Commuting	27	11.8
Business	38	20.7
Education	17	5.6
Escort Education	14	4.6
Shopping	19	7.4
Other Escort	19	8.2
Personal Business	20	8.6
Visiting friends at private home	29	15.1
Visiting friends elsewhere	20	8.3
Entertainment / public activity	23	9.8
Sport: participate	22	10
Holiday: base	97	59.7
Day Trip	28	13.2
Other including just walk	39	17.3

Table 3.10: Rural Only Households – NTS Trip Data

For simplicity, the number of trip purpose categories used for this model was reduced from 14, as set out by the NTS, to 5, two more than incorporated into the One Day Model. The following trip purposes: 'Business', 'Escort Education', 'Other Escort', 'Holiday: base', 'Other including just walk', were all discarded. The trip purposes: 'Personal Business', 'Visiting friends at private home', 'Visiting friends elsewhere', 'Entertainment / Public Activity', 'Sport: participate', were combined, via averaging their values, into a trip purpose henceforth referred to as 'Other'. This process and the resulting trip purpose categories, as well as their associated duration and distance are shown in Table 3.11.

Trip Purpose		Trip Purpose	Trip Duration	Trip Distance
Commuting	→	Commuting	27	11.8
Business			*Discarded*	
Education	→	Education	17	5.6
Escort Education			*Discarded*	
Shopping	→	Shopping	19	7.4
Other Escort			*Discarded*	
Personal Business				
Visiting friends at private home				
Visiting friends elsewhere	→	Other	23	10.4
Entertainment / Public Activity				
Sport: Participate				
Holiday: Base			*Discarded*	
Day Trip	→	Day Trip	28	13.2
Other including just walk			*Discarded*	

Table 3.11: Derived Trip Purposes for 7-Day TDM

Given the temporal resolution of the model output was set to 30 minutes, the decision was made to use a blanket duration of 30 minutes for all trip purposes, as opposed to the averaged values presented in table 3.11 above. No trip purpose presented in table 3.11 averaged over 30 minutes in duration, and thus using this blanket approach allowed for easier computation as each trip generated occupies a single 30 minute slot in the final output. The final trip purpose categories and their corresponding durations and distances can be seen below in table 3.12.

Trip Purpose	Avg. Trip Duration (mins)	Avg. Trip Distance (miles)
Commuting	30	11.8
Education	30	5.6
Shopping	30	7.4
Other	30	10.4
Day Trip	30	13.2

Table 3.12: Trip Purpose Inputs for 7-Day Travel Demand Model

3.3.3 Trip Purpose (TDM Inputs)

This RAW NTS dataset was then used to derive probabilities for the trip start times, for when the various trip purposes can occur, throughout the day. Additionally, the probability of which days each type of trip is most likely to occur on across the week can also be assigned a probability. Due to the large pre-processing requirements, the data for the duration and frequency of trips was not directly derived from the NTS data; instead, reasonable assumptions were made. The individual trip purposes and their input details will now be described in detail.

1. COMMUTING

Two types of employment have been considered in this model: full time and part time. Working days have been limited to Monday to Friday. Full time employment status work five days a week, Monday to Friday with the activity lasting 8hrs upon arrival at the work destination. Part time employment status on the other hand has two options; (1) works five days a week, 4 hrs per day, or (2) works three days a week (randomly selected) for 8hrs. For the households, and vis-à-vis the vehicles, which have been designated for part time working trips, a random number generator was used to determine which option would be attributed to the household, and for which days of the week. The model's determination of trip start time for commuting to work is based on the probability distribution shown in figure 3.5.

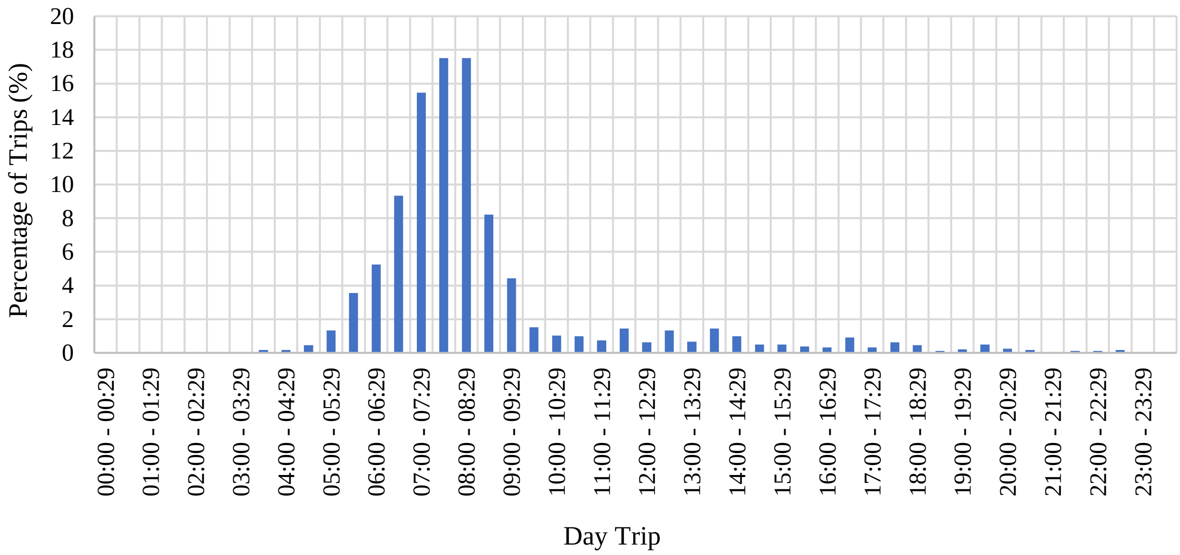


Figure 3.5: Trip start time probability distribution for 'Commuting'

2. EDUCATION

Education trip purposes are modelled in a similar way to Commuting; the occurrence is constricted to Monday to Friday and only for households for which there is an occupant of the appropriate age to be in education. An important consideration for the Education trip is if the vehicle used for an education purpose trip remains at the school for the duration of the school day or is only used for 'drop-offs' and 'pick-ups', and thus can be used for other trip purposes in the meantime. This decision process will be covered in more detail in Section 3.3.4.

Regarding the start and finish hours of the school day, and thus the trip times, the trip start time for education trips is determined by the probability distribution shown in figure 3.6. The School day is assumed to end at 15:30, and thus any return trips home or 'pick-up' trips will occur at this time. Again, the trip start time is only determined once and is repeated for each day of the activity.

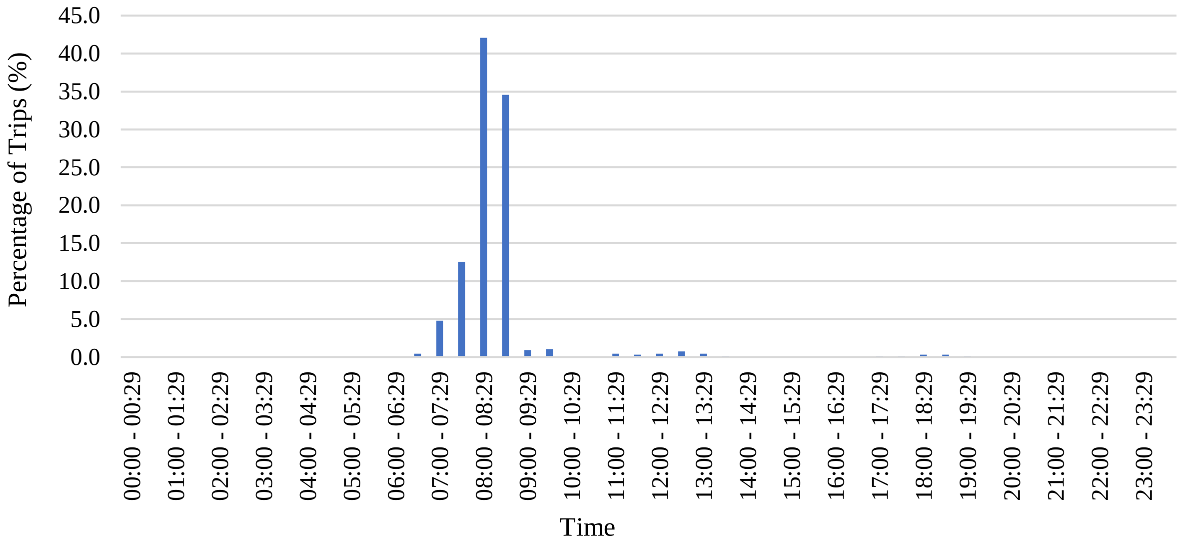


Figure 3.6: Trip start time probability distribution for 'Education'

3. DAY TRIP

The Day Trip activity has a set duration of 4hrs, which can be initiated at any start time as per the probability distribution shown in figure 3.7.

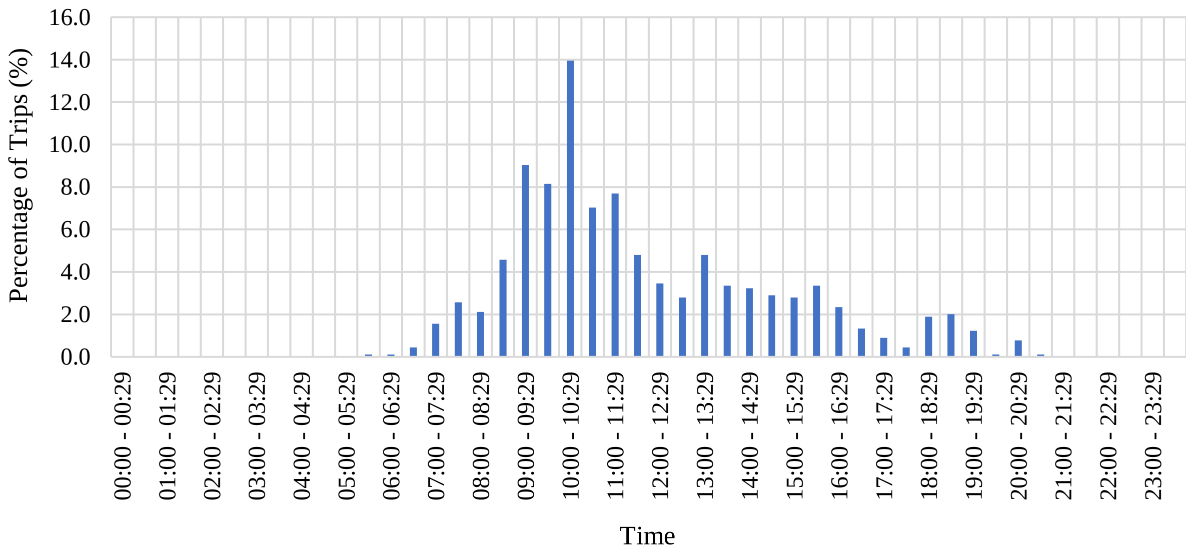
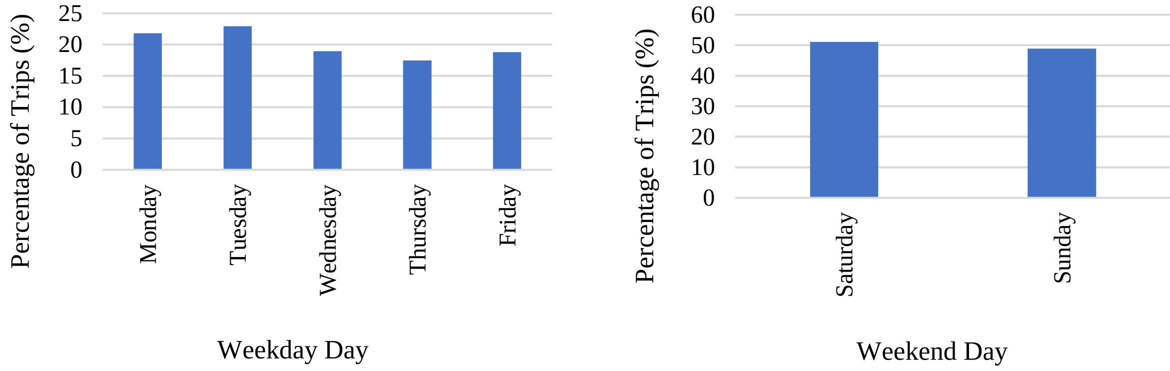


Figure 3.7: Trip start time probability distribution for 'Day Trip'

The frequency of the 'Day Trip' activity occurrence varies depending on the household's employment status. In the case of retired households, they are allocated two day trips per week, one to occur on a weekday, the other at the weekend. For employed households, only one trip is planned per week, either on a Saturday or Sunday. The decision regarding which day or days the 'Day Trip' activity takes place is determined by the probability distributions shown in figure 3.8.



(a) (b)

Figure 3.8: Day of the Week probability distribution for 'Day Trip', (a) Weekday, (b) Weekend

4. SHOPPING

The process of trip generation for 'Shopping' for each household was dependent on multiple variables. Firstly, based on NTS questionnaire responses regarding how participants carried out their shopping, only 88% of the 49 households of Bradbourne are set to conduct shopping trips across the week, the full extract data is shown in table 3.13 below. A random number generator was used to determine which households would and would not be conducting shopping trips across the simulated period.

How do you usually carry out the main food shopping?	No. of Responses (%)
Go to shops/market in person	86.1
Someone else goes to shops for me (e.g. friend, relative, carer)	2.1
Order online for home delivery	11.8
Order by phone for home delivery	0
Order by post for home delivery	0

Table 3.13: NTS Participant responses to 'How do you usually carry out the main food shopping?'

Following the determination of which households would be conducting shopping trips in the simulation, the number of trips across the 7-day period was still required. Again, the NTS dataset provided information regarding shopping activities in the form of responses to the question of how often participants travel to the shops, this data can be seen in table 3.14.

How often do you travel to the shops to buy food or drink for the home?	No. of Responses (%)
3 or more times a week	24.7
Once or twice a week	68.3
Less than once per week, but more than twice a month	3.9
Once or twice a month	2.4
Less than once a month, but more than twice a year	0.3
Once or twice a year	0.1
Less than that or never	0.4

Table 3.14: NTS Participant responses to ‘How often do you travel to the shops to buy food or drink for the home?’

Following the results shown in Table 3.14, 25% of the households which conduct shopping trips will shop ‘*3 or more times a week*’. Of these it was decided that 50% will shop three times, and the other half will shop four times per week. Another 68% of the households which conduct shopping trips will shop ‘*Once or twice a week*’. Again, 50% of these households will conduct one shopping trip over the 7 – day simulation period, and the other 50% will shop twice. The remaining 7% of shopping households, which equates to just over three households in Bradbourne, shop less than once per week. One of these households was randomly selected to conduct a shopping trip during the simulation period.

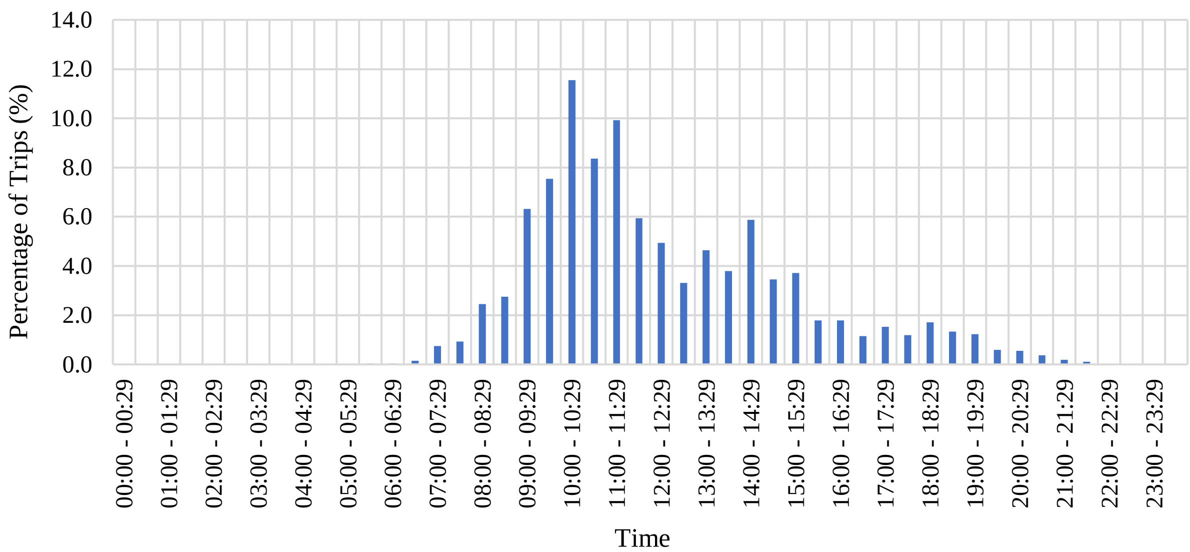


Figure 3.9: Trip start time probability distribution for ‘Shopping’

The start time probability distribution for shopping trips is shown in figure 3.9. The duration of a shopping trip was set to 2hrs and the determination of which day of the week shopping trips would occur for an individual household was controlled by the probability distribution presented in figure 3.10 below.

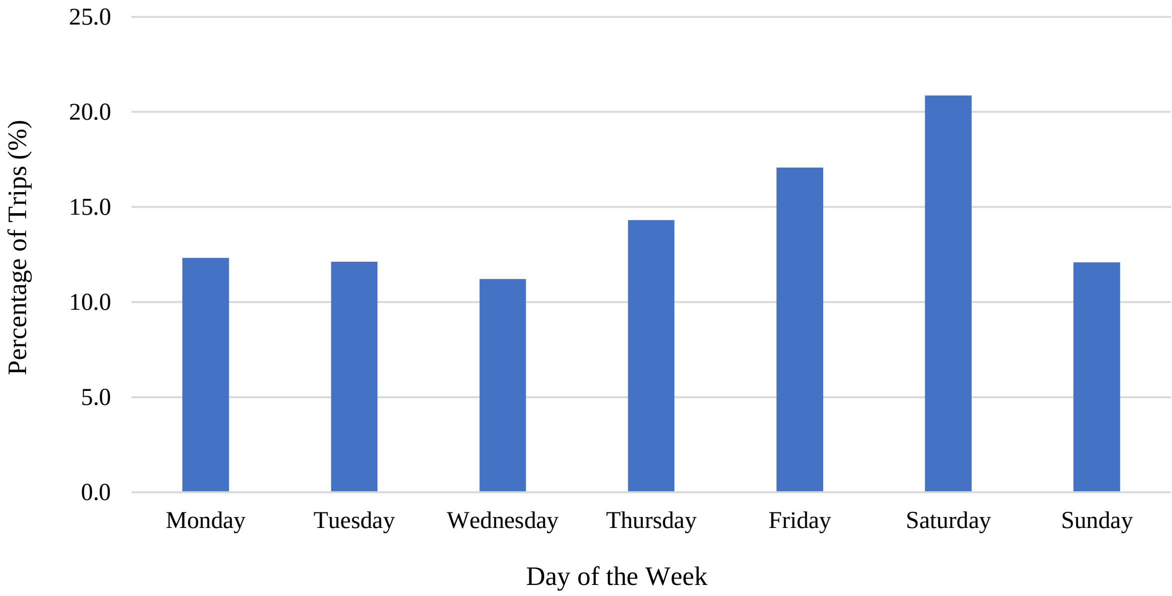


Figure 3.10: Probability distribution for ‘Shopping’ by day of the week

5. OTHER

The final trip purpose category, ‘Other’, has an activity duration of 2hrs, with a start time controlled by the probability distribution shown in figure 3.11.

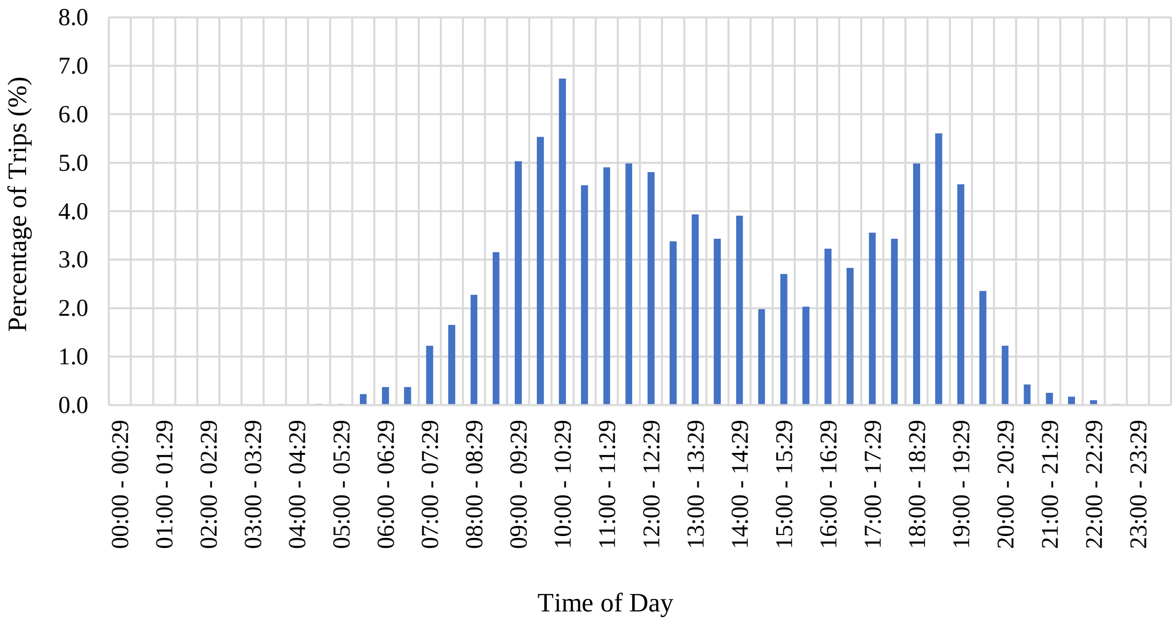


Figure 3.11: Trip start time probability distribution for ‘Other’

The NTS dataset, again, provided the probability distribution used to choose days of the week for these trips to occur, this is shown in figure 3.12. Unlike the other trip purposes, multiple ‘Other’ trips can be scheduled for the same day.

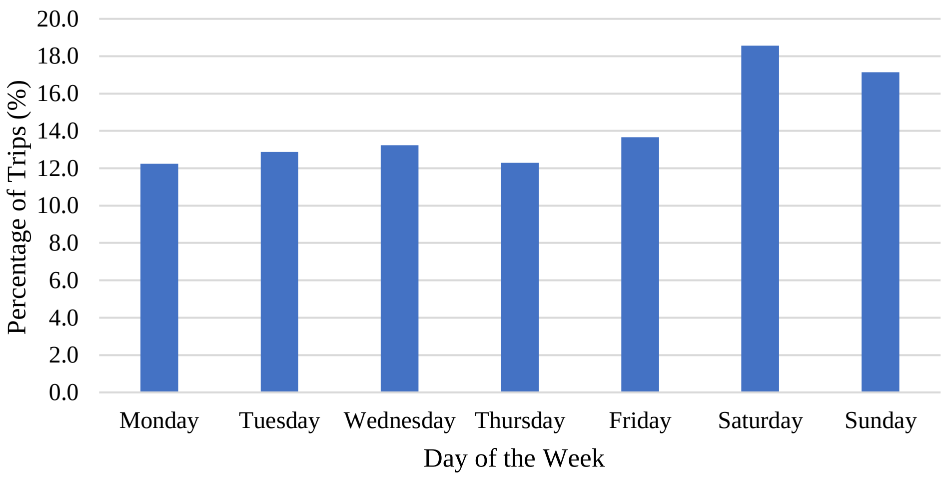


Figure 3.12: Probability distribution for ‘Other’ activities by day of the week

Regarding the number of times this activity occurs over the week of simulation, this was determined by the number of vehicles available to the household, referring back to table 3.9. Where N is the number of vehicles available to the household, the number of ‘Other’ trips that household would conduct was governed by the formula 2*N. The one exception was for the household composition category of ‘2 Person & 1 Car’ which followed the formula 3*N. This was to allow consideration for the impact of multiple adults using 1 vehicle in a household, instead of solely relating to number of vehicles. The resulting number of ‘Other’ trips for each household composition can be seen in table 3.15.

Household Composition	**No. of Other Trips**
1 Person/1 Car	2
2 Person/1 Car	3
2 Person/2 Cars	4
3 Person/2 Cars	4
3 Person/3 Cars	6
4 Person/3 Cars	6
5 Person/3 Cars	6
6 Person/3 Cars	6
7 Person/4 Cars	8

Table 3.15: Number of other trips for households based on their composition

3.3.4 Model Methodology

The model presented in this chapter utilises a logic flowchart, set by rules and decisions for generating and scheduling the various trips, detailed in the previous subsection, required by each household. The overall model process will first be presented in figure 3.13, followed by the decision flowcharts for each individual trip purpose generation, shown in figures 3.14 – 3.18. Additional parameters such as trip hierarchy and trip chaining will also be described.

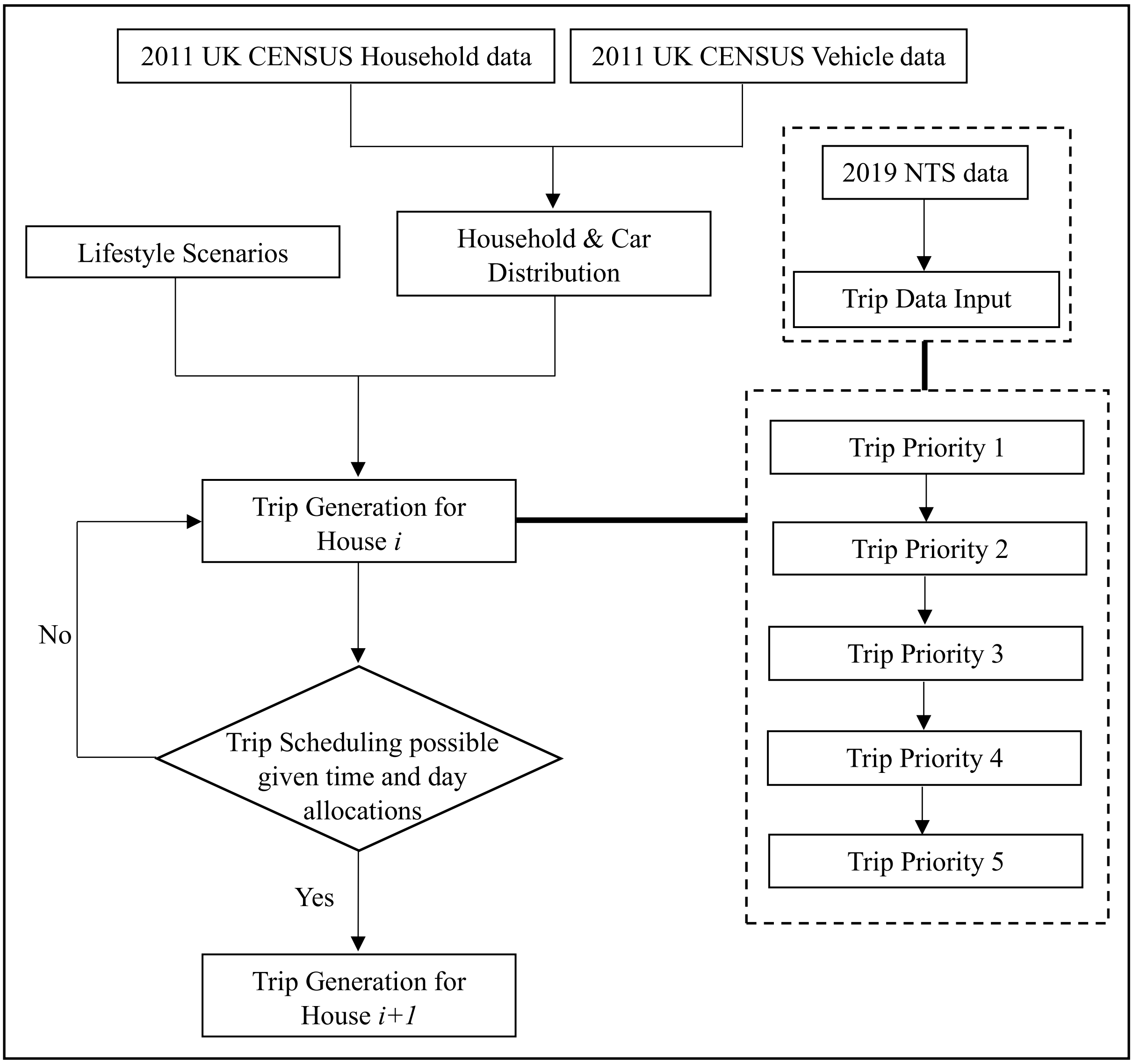


Figure 3.13: 7-Day Travel Demand Model Flowchart

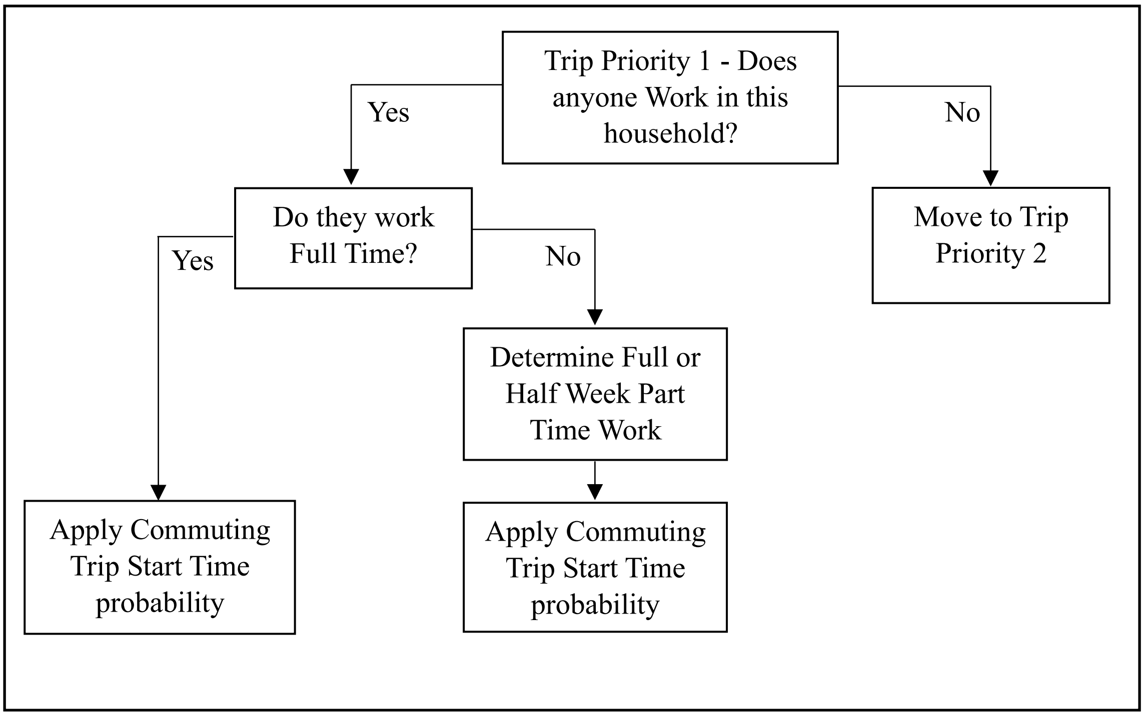


Figure 3.14: Flowchart for 'Commuting' Trip Generation

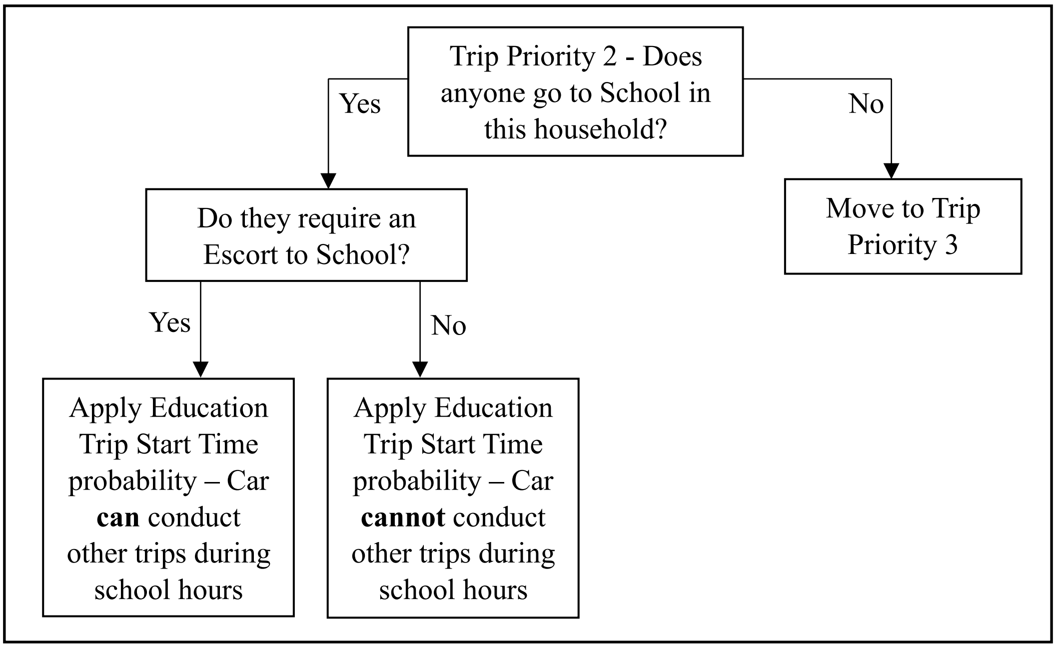


Figure 3.15: Flowchart for 'Education' Trip Generation

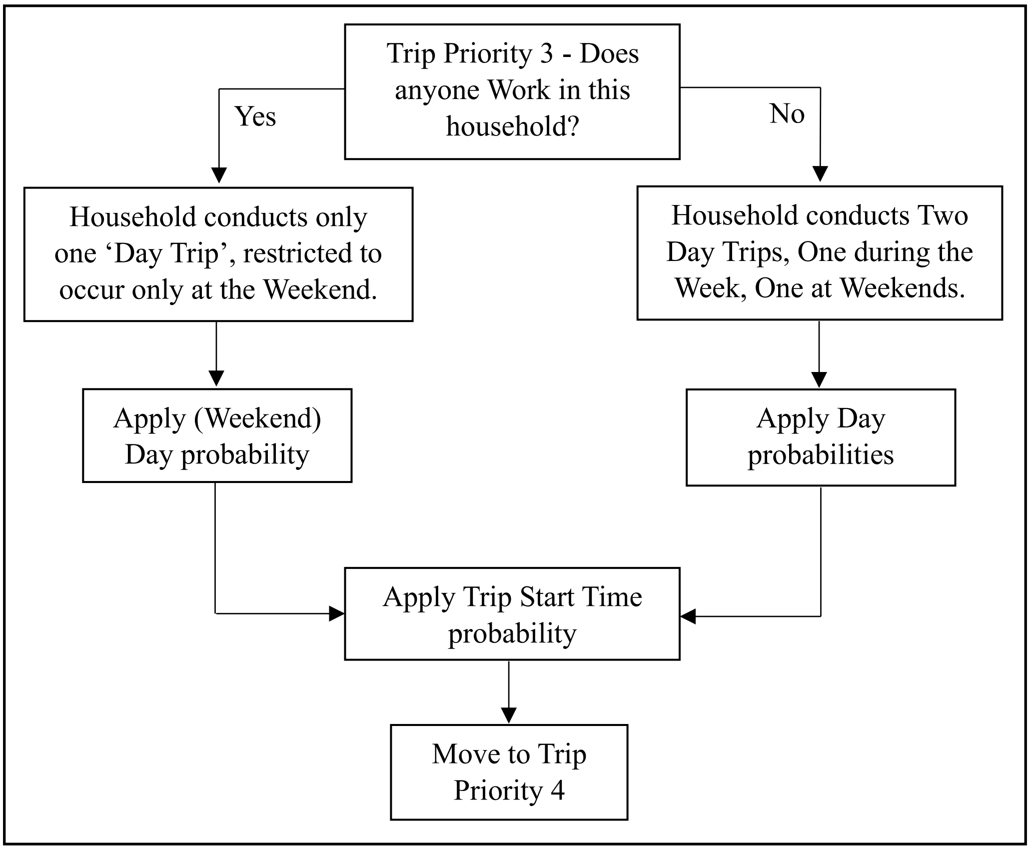


Figure 3.16: Flowchart for 'Day Trip' Trip Generation

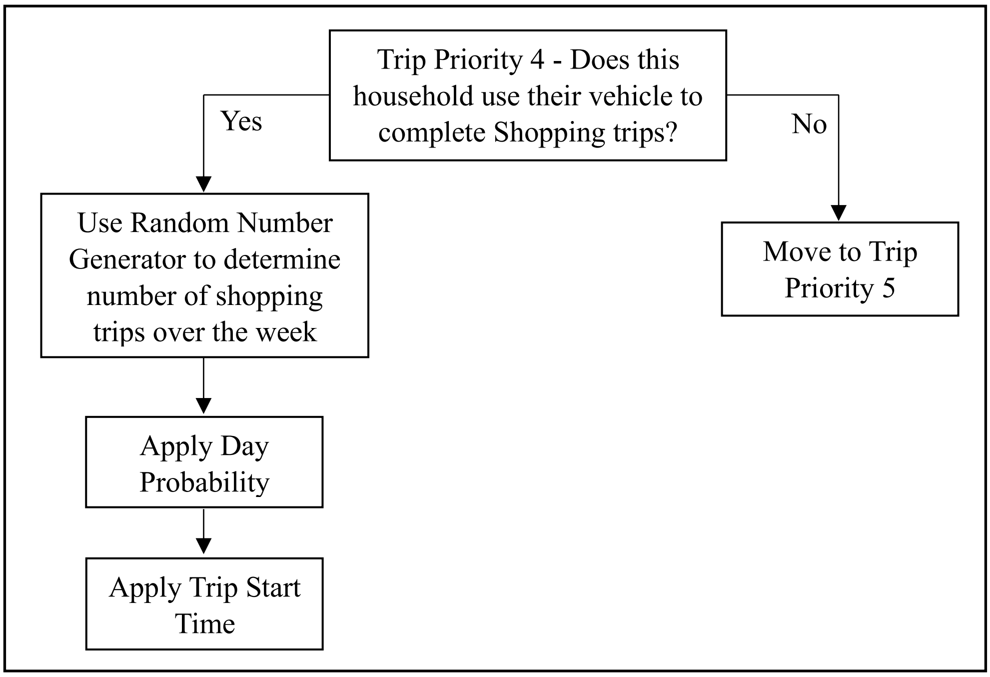


Figure 3.17: Flowchart for 'Shopping' Trip Generation

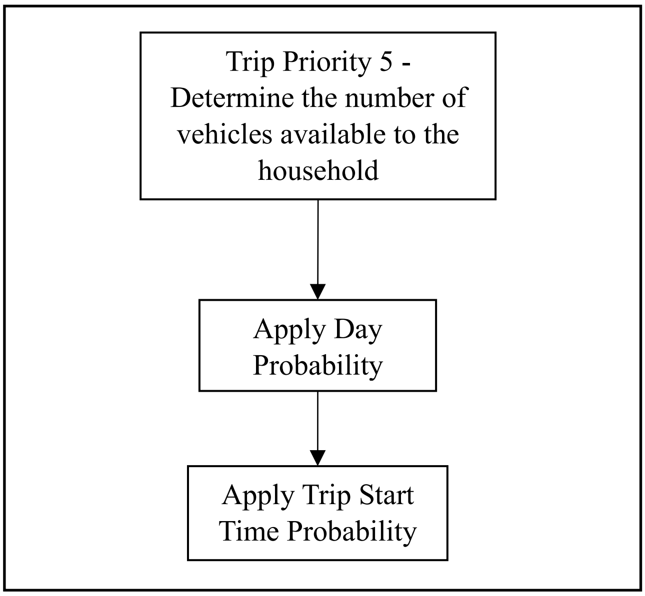


Figure 3.18: Flowchart for ‘Other’ Trip Generation

TRIP HIERARCHY

To overcome a common scheduling error occurring within the model, where two trips could be scheduled for the same time on the same day, a hierarchy order for the trip purposes was devised, shown below in figure 3.19.

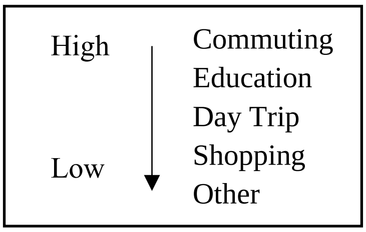


Figure 3.19: Trip Purpose Hierarchy

This hierarchy order, which can also be seen as a priority system, was devised to determined which activity takes precedent during this scheduling and generating stage of the model. Based on the research by Bowman & Ben-Akvia (2001), work is given the highest priority; thus the hierarchy order will always set this type of activity to be scheduled first. Should another trip purpose lower on the priority scale be scheduled for the same time, or during a time in which the car could not be used due to said higher priority activity, the lower priority activities start time would be recalculated until a viable solution is found.

For example, if an individual and their vehicle is scheduled to leave for work at 08:00 and the car is positioned at work from 08:30 – 16:30, but on the same day a shopping trip is scheduled for 13:00, this would not be possible. The priority system provides the solution in which the shopping trip generation process is conducted again to find a viable start time on that day.

This hierarchy order was devised based upon reasonable assumptions and the idea of '*pre-planned*' activities compared to more spontaneous activities. Work, School, and Day Trips have been viewed as trip purposes whose scheduling would be known by individuals, particularly in terms of day of the week it will occur, prior to the start of the week (the simulation period). Whereas Shopping and Other trips are regarded as more flexible or random in occurrence, and thus adjustable in their start times (Bowman & Ben-Akvia, 2001).

It is worth noting, the age of the study conducted by Bowman & Ben-Akvia (2001) – published over 20 years ago. This brings into question the validity of such as source for the trip hierarchy methodology, however, this simplistic approach was deemed suitable for the purpose of the TDM. The TDM itself is not the main aspect of this thesis, albeit a large factor, but rather an avenue of choice to determine vehicle movement which would enable inquiry into EV energy and power requirements. New methods have been developed, such as Analytic Hierarchy Process (AHP) (Zhou et al., 2015) and a Random Forest Method (Cheng et al., 2019). However, these approaches require a lot of work for implementation, resources not available and outside the scope of this thesis.

TRIP CHAINING

Early definitions of trip chaining followed the form <home-activity-home> (Holzapfel, 1986; Bowman & Ben-Akvia, 2001), which can be found still in models today (Armas et al., 2022) albeit its simpler nature and lack of ability to capture true modern travelling habits. To align with more modern travel patterns, this definition has been since modified to follow the general rule of <home-activity1-…-activityN-home> (Primerano et al., 2008). A rule still applicable with today's travel patterns (Mourtakos et al., 2024) and thus the definition for trip chaining as presented in this thesis.

In relation to the scheduling of trip chains, should the trip generation process schedule 0.5hrs or less between two activities (either before or after the end of the currently ongoing activity), these two trips will be chained together. The second trip will be pulled forward or backward to the time the previous activity ended. Trip chaining has implications for trip mileage and duration, as we are no longer using the vehicle to or from the '*home*', but rather directly from one activity to another. However, the mileage and durations presented in table 3.10 (*Section 3.3.2*) are derived values for not just trips oriented around '*home*', but every trip recorded for that purpose, i.e. including from one activity to another activity. Thus the values in table 3.11 & 3.12 have been used for all trips relating to that purpose without the need for any further data manipulation/processing.

MULTIPLE VEHICLES

For the households with multiple vehicles, attempts were made to reasonably distribute the trips between the vehicles available. Given the future uses of this model to investigate electric vehicles, the knowledge of mileages attributed to individual vehicles becomes paramount to determine the amount of energy that vehicle would use day-to-day and by extension its charging requirements. Each households' vehicles were assigned a number 1 – n, n being the total number of vehicles belonging to that household. The rules devised for trip distribution to individual vehicles were based on the different trip purposes presented earlier.

1. **Commuting** – Each employed occupant of a household conduct their commuting trips in separate vehicles (unless in the case of car-sharing - House 17). Starting with employed individual 1's commuting trips assigned to Car 1, then employed individual 2's commuting trips assigned to Car 2 and so forth.

2. **Education** – Education trips are assigned to the next available vehicle which has not been used for commuting trips. If all cars are used for commuting trips, then the last car to be assigned to an employed individual is assigned the Education trips.

3. **Day Trip** – Car 1 conducts all 'day trip' trips scheduled.

4. **Shopping** – Car 2 conducts all shopping trips regardless of the number of vehicles required for commuting or education trips.

5. **Other** – The total number of 'Other' trips for the household, as determined by Table 3.15, are split equally between the total number of vehicles available to that household.

3.3.5 Governing Equations and Parameter List

A summary of the Travel Demand Models parameters is presented in Table 3.16 below.

Model Parameter	Value
Number of Vehicles	Location specific – per census
Number of Households	Location specific – per census
Household Occupancies	Location specific – per census
Household Composition	the larger the household, the higher the number of cars that will be available
Lifestyle Scenario	1 - 27
Trip Purpose	Commuting, Education, Shopping, Other, Day Trip
Trip Duration	30 minutes
Trip Distance	See Section 3.3.3
Trip Start Time	See Section 3.3.3
Day(s) of Week for Trip	
Number of Trips (by Trip Purpose)	
Duration of Activity (Trip Purpose)	

Table 3.16: Travel Demand Model Parameter List

3.4 Results and Discussion

An example of the 7-day TDM’s output can be seen in table 3.17, which shows the simulations results of 7 days vehicle usage for House 11.

		Monday		Tuesday		Wednesday		Thursday		Friday		Saturday		Sunday	
		Location	**Miles**	**Location**	**Miles**	**Location**	**Miles**	**Location**	**Miles**	**Location**	**Miles**	**Location**	**Miles**	**Location**	**Miles**
Time	00:00	Home	0	Home	0	Home	0	Home	0	Home	0	Home	0	Home	0
	00:30	Home	0	Home	0	Home	0	Home	0	Home	0	Home	0	Home	0
	01:00	Home	0	Home	0	Home	0	Home	0	Home	0	Home	0	Home	0
	01:30	Home	0	Home	0	Home	0	Home	0	Home	0	Home	0	Home	0
	02:00	Home	0	Home	0	Home	0	Home	0	Home	0	Home	0	Home	0
	02:30	Home	0	Home	0	Home	0	Home	0	Home	0	Home	0	Home	0
	03:00	Home	0	Home	0	Home	0	Home	0	Home	0	Home	0	Home	0
	03:30	Home	0	Home	0	Home	0	Home	0	Home	0	Home	0	Home	0
	04:00	Home	0	Home	0	Home	0	Home	0	Home	0	Home	0	Home	0
	04:30	Home	0	Home	0	Home	0	Home	0	Home	0	Home	0	Home	0
	05:00	Home	0	Home	0	Home	0	Home	0	Home	0	Home	0	Home	0
	05:30	Home	0	Home	0	Home	0	Home	0	Home	0	Home	0	Home	0
	06:00	Home	0	Home	0	Home	0	Home	0	Home	0	Home	0	Home	0
	06:30	Home	0	Home	0	Home	0	Home	0	Home	0	Home	0	Home	0
	07:00	Home	0	Home	0	Home	0	Home	0	Home	0	Home	0	Home	0
	07:30	Home	0	Home	0	Home	0	Home	0	Home	0	Home	0	Home	0
	08:00	Travel	0	Travel	0	Travel	0	Travel	0	Travel	0	Home	0	Travel	0
	08:30	Work	11.8	Work	11.8	Work	11.8	Work	11.8	Work	11.8	Home	0	Other	10.4
	09:00	Work	11.8	Work	11.8	Work	11.8	Work	11.8	Work	11.8	Travel	0	Other	10.4
	09:30	Work	11.8	Work	11.8	Work	11.8	Work	11.8	Work	11.8	Day Trip	13.2	Other	10.4
	10:00	Work	11.8	Work	11.8	Work	11.8	Work	11.8	Work	11.8	Day Trip	13.2	Other	10.4
	10:30	Work	11.8	Work	11.8	Work	11.8	Work	11.8	Work	11.8	Day Trip	13.2	Travel	10.4
	11:00	Work	11.8	Work	11.8	Work	11.8	Work	11.8	Work	11.8	Day Trip	13.2	Home	20.8
	11:30	Work	11.8	Work	11.8	Work	11.8	Work	11.8	Work	11.8	Day Trip	13.2	Home	20.8
	12:00	Work	11.8	Work	11.8	Work	11.8	Work	11.8	Work	11.8	Day Trip	13.2	Home	20.8
	12:30	Work	11.8	Work	11.8	Work	11.8	Work	11.8	Work	11.8	Day Trip	13.2	Home	20.8
	13:00	Work	11.8	Work	11.8	Work	11.8	Work	11.8	Work	11.8	Day Trip	13.2	Home	20.8
	13:30	Work	11.8	Work	11.8	Work	11.8	Work	11.8	Work	11.8	Travel	13.2	Home	20.8
	14:00	Work	11.8	Work	11.8	Work	11.8	Work	11.8	Work	11.8	Shopping	20.6	Home	20.8
	14:30	Work	11.8	Work	11.8	Work	11.8	Work	11.8	Work	11.8	Shopping	20.6	Home	20.8
	15:00	Work	11.8	Work	11.8	Work	11.8	Work	11.8	Work	11.8	Shopping	20.6	Travel	20.8
	15:30	Work	11.8	Work	11.8	Work	11.8	Work	11.8	Work	11.8	Shopping	20.6	Shopping	28.2
	16:00	Work	11.8	Work	11.8	Work	11.8	Work	11.8	Work	11.8	Travel	20.6	Shopping	28.2
	16:30	Travel	11.8	Travel	11.8	Travel	11.8	Travel	11.8	Travel	11.8	Home	28	Shopping	28.2
	17:00	Home	23.6	Home	23.6	Home	23.6	Other	22.2	Home	23.6	Home	28	Shopping	28.2
	17:30	Home	23.6	Home	23.6	Home	23.6	Other	22.2	Home	23.6	Home	28	Travel	28.2
	18:00	Home	23.6	Home	23.6	Home	23.6	Other	22.2	Travel	23.6	Home	28	Home	35.6
	18:30	Home	23.6	Home	23.6	Home	23.6	Other	22.2	Shopping	31	Home	28	Home	35.6
	19:00	Home	23.6	Home	23.6	Home	23.6	Travel	22.2	Shopping	31	Home	28	Home	35.6
	19:30	Home	23.6	Travel	23.6	Home	23.6	Home	32.6	Shopping	31	Home	28	Home	35.6
	20:00	Home	23.6	Shopping	31	Home	23.6	Home	32.6	Shopping	31	Home	28	Home	35.6
	20:30	Home	23.6	Shopping	31	Home	23.6	Home	32.6	Travel	31	Home	28	Home	35.6
	21:00	Home	23.6	Shopping	31	Home	23.6	Home	32.6	Home	38.4	Home	28	Home	35.6
	21:30	Home	23.6	Shopping	31	Home	23.6	Home	32.6	Home	38.4	Home	28	Home	35.6
	22:00	Home	23.6	Travel	31	Home	23.6	Home	32.6	Home	38.4	Home	28	Home	35.6
	22:30	Home	23.6	Home	38.4	Home	23.6	Home	32.6	Home	38.4	Home	28	Home	35.6
	23:00	Home	23.6	Home	38.4	Home	23.6	Home	32.6	Home	38.4	Home	28	Home	35.6
	23:30	Home	23.6	Home	38.4	Home	23.6	Home	32.6	Home	38.4	Home	28	Home	35.6

Table 3.17: Simulation results for House 11

To provide context to Table 3.17, House 11 is a '*One person & One car*' household with one adult working full time. Consequently, this household's vehicle was designated for 'Commuting' journeys from Monday to Friday, one 'Day Trip' on the weekend, four 'Shopping' trips throughout the week, and two 'Other' trips to occur at any available remaining points during the seven day simulation period.

In total, the TDM simulated 13,520 miles during the week, distributed among the 84 vehicles of Bradbourne. This resulted from modelling 1288 trips, averaging to just under 29 trips per household per week. The probability distributions outlined in Section 3.3.3 led to substantial variations in predicted travel patterns for each individual vehicle. Vehicle travel ranged from as few as 2 trips per week to over 10, with a weekly mileage spanning from 41.6 miles to 324.8 miles. Figures 3.20 and 3.21 illustrate the vehicles that recorded the lowest and highest mileage, respectively, over the seven-day period.

House 45 – Car 3, travelled the least miles, accumulating a total of 41.6 miles during the simulated week. This vehicle was designated for only two 'Other' trips on the Thursday and Sunday. In contrast, the vehicle belonging to House 17 experienced the highest miles driven across the simulation period. House 17 has two adults both working full time and owning one car, with that car being shared by both household members for their respective commuting journeys. The vehicle also conducted a number of 'Other' trips and one 'Day Trip' over the weekend.

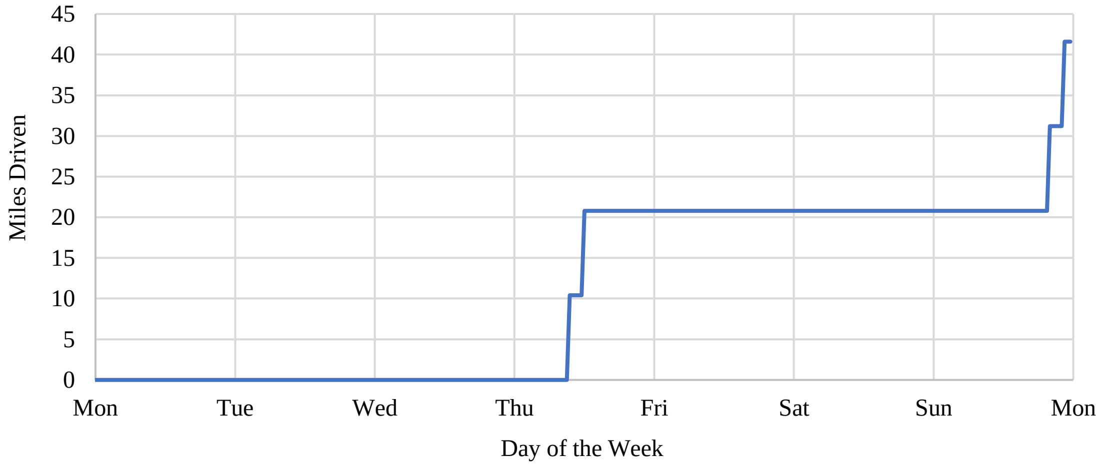


Figure 3.20: Vehicle with minimum cumulative mileage driven over the week (House 45 – Car 3)

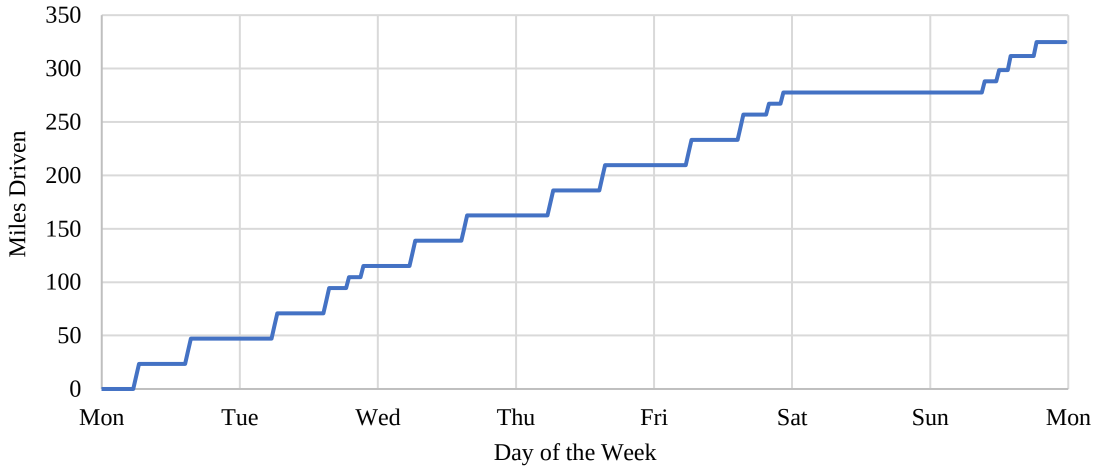


Figure 3.21: Vehicle with maximum cumulative mileage driven over the week (House 17 – Car 1)

The average vehicle travelled just under 161 miles per week, scaling up to a year, on the basis of 52 weeks, combines to a total of 8369 miles per vehicle. Table 3.18 below shows the yearly mileage by person from the 2019 NTS dataset for comparison with results from the TDM.

Rural-Urban Classification	**2019 NTS**
Urban Conurbation	5037
Urban City and Town	6772
Rural Town and Fringe	8596
Rural Village, Hamlet, and Isolated Dwelling	9756
All Areas	6515

Table 3.18: Miles per person per year from the 2019 NTS dataset categorised by rural-urban classification (NTS9907) (GOV.UK, 2022d)

As per Table 3.18, individuals residing in rural areas typically cover an annual average of 8596 to 9756 miles per year. When compared to the TDM forecast for the year, 8369 miles, this represents a 2.7% difference, leaning towards the lower end of the range. It is important to note that this variance could be attributed to the differing definitions of the values being compared. The NTS values, presented in table 3.18, are ‘Miles per Person per year’, whereas the mileages forecasted by the TDM relate to the ‘Miles per Vehicle per year’.

The distinction arises from the nature of the NTS, where participants record their travel diaries from their own point of view (POV). This approach can result in higher mileages, especially in scenarios where two individuals are in the same vehicle conducting the same journey. For example, if an adult was taking their child to school, from the perspective of the TDM presented in this thesis, a single car is used, and the mileage associated with that journey is recorded. However, when examining the NTS data, this would present itself as two individuals with their own trips, essentially doubling the mileage.

3.4.1 Trips Simulated

A trip is defined as any car journey undertaken from one destination to another, for instance the commute to and from work is classed as two separate trips. A total of 1288 trips were simulated by this travel demand model, with the distribution of each trip purpose presented below in table 3.19.

Trip Purpose	**Number of trips conducted**
Commuting	579
Education	93
Day Trip	101
Shopping	174
Other	341

Table 3.19: Total Number of Trips by Trip Purpose

This corresponded to the following mileage totals conducted by the 84 vehicle population of Bradbourne, see table 3.20.

Trip Purpose	**Miles Driven**
Commuting	6832
Education	521
Day Trip	1333
Shopping	1288
Other	3546

Table 3.20: Total Mileage of Trips by Trip Purpose

The added benefit of the high temporal resolution incorporated into the travel demand model enables the accurate determination of when vehicles are in use or not, or more importantly, when vehicles are at home or not. Understanding when vehicles are at home or not is imperative to designing recharging scenarios for the vehicles, should they be electric, when considering a solely ‘at home’ charging scenario, as does this thesis. This will be discussed further in the following chapter, Chapter 4. Figure 3.22 shows the percentage of vehicles away from home through each day of the week.

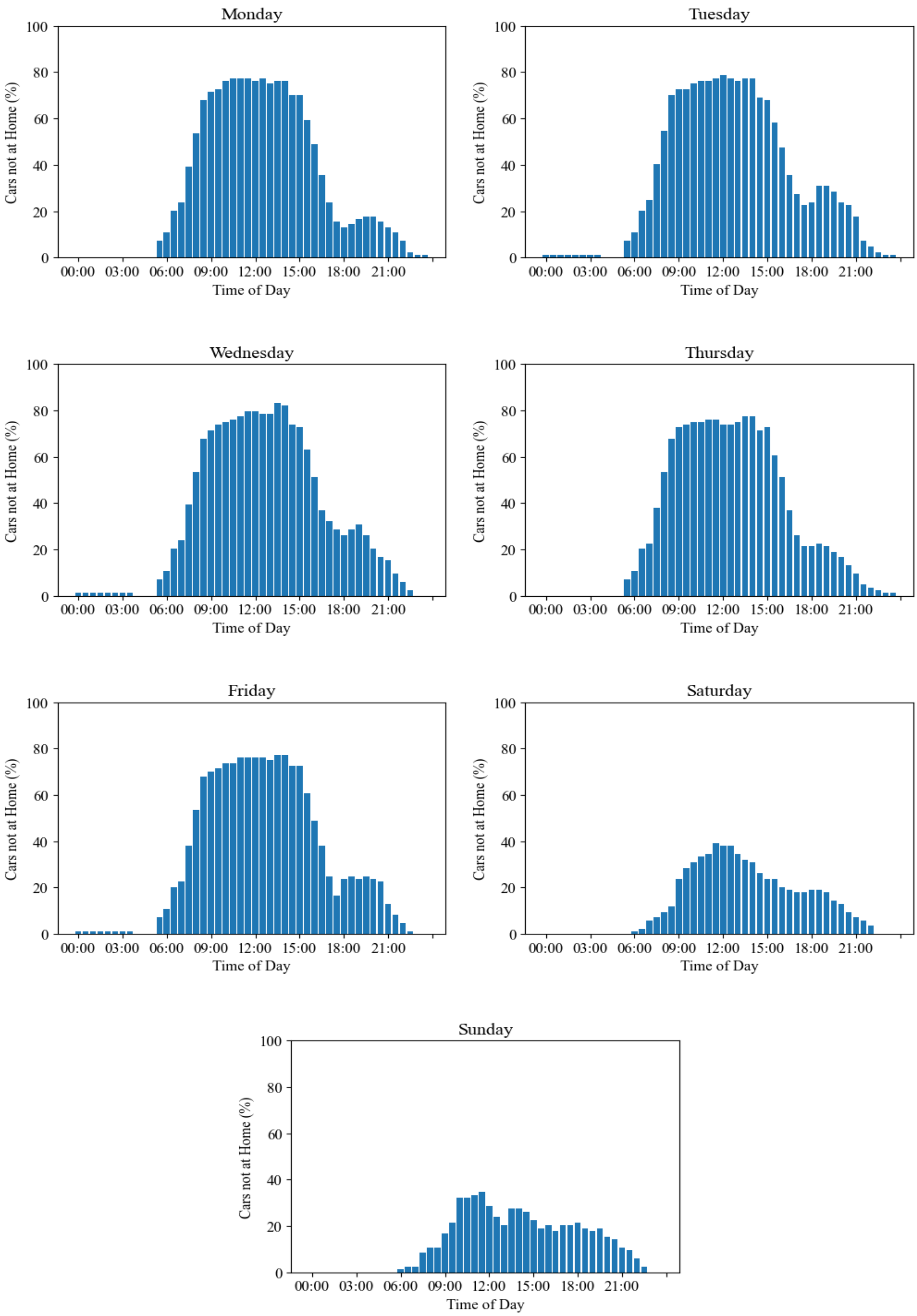


Figure 3.22: Percentage of Bradbourne vehicles not at home throughout the day for each day of the week

Two distinct overarching profiles can be seen in figure 3.22 across the seven days simulated by the TDM. These two profiles correspond to the weekdays and weekends. With regards to weekdays, there are significantly greater number of vehicles not at home throughout the day, particularly around the typical working hours of 9am to 5pm. This is followed by a second wave of increased activity in the evening as individuals conduct various post-work/school trips. The weekend however sees far fewer cars in use in general, with the majority of vehicles at home for larger periods of the day.

Figure 3.23 illustrates the six types of 'car day', referred to as Vehicle-Day Clusters (VDC), (VDC0 - VDC5) identified by Mattioli et al. (2019) through cluster analysis of the 2016 UK NTS. Although Mattioli et al. (2019) presents their results from a slightly different perspective (Mattioli et al. (2019) presents the variable "cars in use", whilst the TDM utilises a "cars not at home" perspective) to that of figure 3.22 previously, comparisons and insights can be drawn. For instance, multiple car days (VDC1, VDC2 and VDC4) illustrate two periods of high car use centred around the times of working hours (9am-5pm). Whereas Mattioli et al. (2019) report a dip between these high car use periods where the cars are no longer in use, it is highly like that the cars are still away from home during those hours. Thus, the profiles would align with the results reported in figure 3.22.

Likewise, VDC3 and VDC5 show small increases in vehicle usage later in the evening, activity that has been captured also by the TDM presented in this chapter, as discussed previously. The 'car day' VDC0, where a vehicle is not in use all day, is likely to be found for many of the vehicles over the weekend days in the TDM. Thus, resulting in the much lower vehicles away from home levels shown in figure 3.22. However, Mattioli et al. (2019) fail to sort the data by weekday/weekend to identify further car days particular to a day of the week.

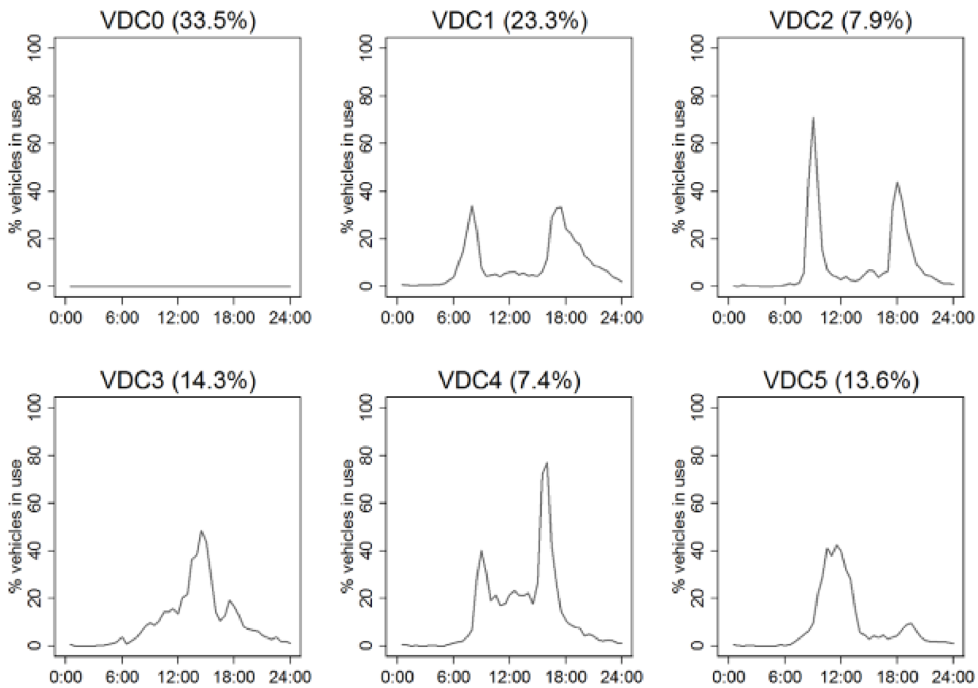


Figure 3.23: Density plots for the vehicle-day clusters identified – (Figure 1 of Mattioli et al. (2019))

The behaviours illustrated in figure 3.22 offer much to be considered. Literature suggests EV charging poses a potential issue for grid infrastructure, by the way of exacerbating peak power demand following the return from work in the evening (Mattioli et al., 2019). With research examples already now focused on mitigating this aggregated load from EV charging, through technologies such as Demand Side Management (this will be discussed further in Chapter 6) (Gottwalt et al., 2011; Mohanty et al., 2022), the results from this TDM suggest this peak power demand timing issue may be misplaced. Although many vehicles do return home from 5pm onwards, there are a considerable number of vehicles (<20%) away from home till hours much later. This may aid peak shifting efforts and minimise concern regarding grid infrastructure capabilities from a grid operators perspective. The following chapters will continue this analysis further.

3.4.2 Validation of the Travel Demand Model

As part of the NTS, each participant household completes a 7-day travel diary. As this model was built upon the 2019 dataset, the 2018 NTS dataset was used as an attempt to validate the model. The decision to use the same source for data does provide a meaningful comparator as different individuals complete the NTS survey each year - addresses for participating households are chosen at random from a public list of addresses in England (NATCEN, 2023).

A similar methodology was employed for extracting the rural households from the 2018 dataset, as was used for the 2019 dataset, where the rural households were grouped together according to number of occupants and number of vehicles. Via random selection from each group, 49 households were selected to reflect the same household and vehicle composition of the houses of Bradbourne. Whilst the 2018 NTS dataset lacked data for the '*Six Person & Three Car*' category, an alternative '*Seven Person & Three Car*' category household was selected to ensure the correct number of vehicles over number of occupants. Further, the NTS dataset had some missing trip data, which is most likely a result of incomplete participant travel diaries. For example, for some trips, start and end times were left blank. To overcome this, trips of a similar nature (same trip purpose and distance conducted by that household on other days of the week) were used to fill this void, i.e. their start and finish times were copied across.

Whilst the NTS dataset provides detailed travel data, it does not indicate the specific vehicle that undertakes the trips recorded at each household, but rather the data is captured from the occupant's point of view (POV). This hinders the determination of which precise vehicle is conducting each of the recorded journeys for households with multiple vehicles. To overcome this and extract vehicle focused trip data which could be compared with the vehicle focused model developed, it was assumed that trips recorded by individuals at the same time, belonging to the same household, would logically be conducted using the same vehicle.

Additionally, due to the participant POV of the NTS data, as opposed to the vehicular POV of the TDM, there are examples in this secondary data of recorded trips by car which are not done so by the vehicles of their household. For example, when visiting a friend's household and then a trip is conducted in the friend's vehicle. Effort was made to identify this behaviour based on the activity of the other people in the household and their car trips to ensure that only trips and the mileages associated with the cars of that participants household were extracted.

Mileage Driven over Time

Figure 3.24 is a comparison of the predicted cumulative mileage driven by the 84 vehicles of Bradbourne over the seven day simulation period (blue) and the cumulative mileage driven extracted from the 2018 NTS dataset (orange). Datapoints are plotted at 3hr intervals.

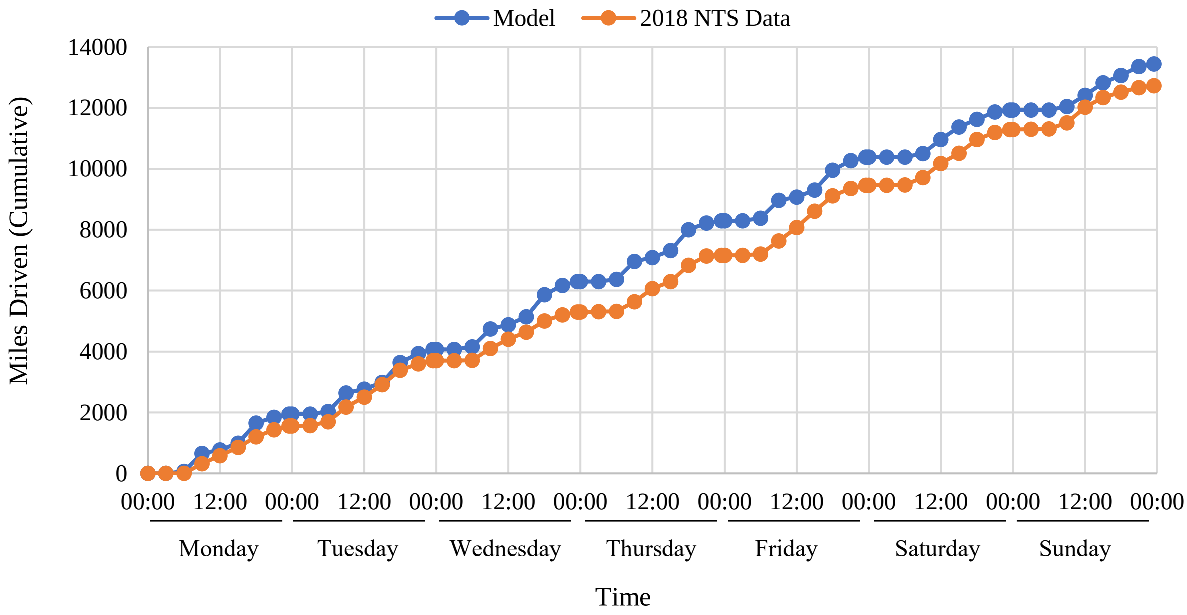


Figure 3.24: Cumulative mileage driven over the course of the simulation week

One method used for validating travel models is by determining the R-square value (Apronti and Ksaibati, 2018). Figure 3.25 plots the cumulative miles driven, as extracted from the 2018 NTS dataset against the results of the model, to which a linear trendline was overlayed which indicated an R-square value of 99.5%.

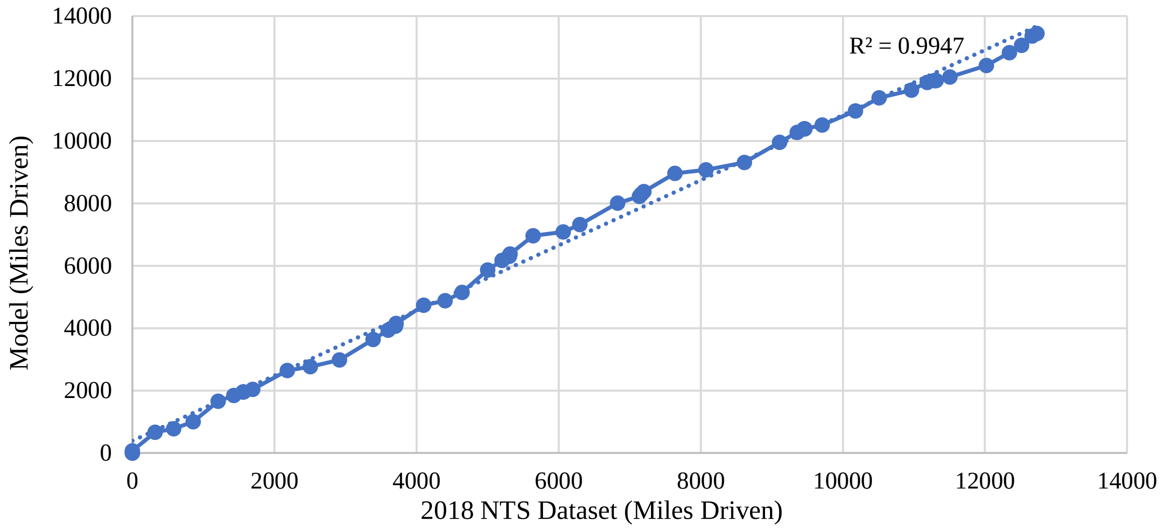


Figure 3.25: R-squared value plot

This high R-square value may be due to the relatively large 3hr interval of the above graph and would be reduced if applied to the 30 minute resolution of the models output. In comparison, Apronti and Ksaibati (2018) achieved a 74.0% R-square value for their four-step travel demand model which estimated traffic volumes for low-volume roads in Wyoming, USA.

For this act of validation, the cumulative miles driven as per my TDM act as the dependent variable, because it is the outcome measure that the model, in part, aims to predict. As detailed in Table 3.16, the list of parameters within the TDM, ‘Household Occupancies’, ‘Household Composition’, ‘Lifestyle Scenario’, ‘Trip Purpose’, ‘Number of Trips’ all serve as the independent variables to this analysis. Although ‘Number of Vehicles’ is a parameter which will influence the models output, with regards to this analysis, it is compared with the data relating to the same number of vehicles from the 2018 NTS data, as stated previously.

Additional to this, the Percent Root Mean Square Error (%RMSE) was calculated and found to be 11.8%, a large reduction compared to the 50.3% achieved by Apronti and Ksaibati (2018). Figure 3.26 shows a higher level analysis, the number of miles driven each day of the week, at the community level, and superimposed onto this is the percentage difference between the two values.

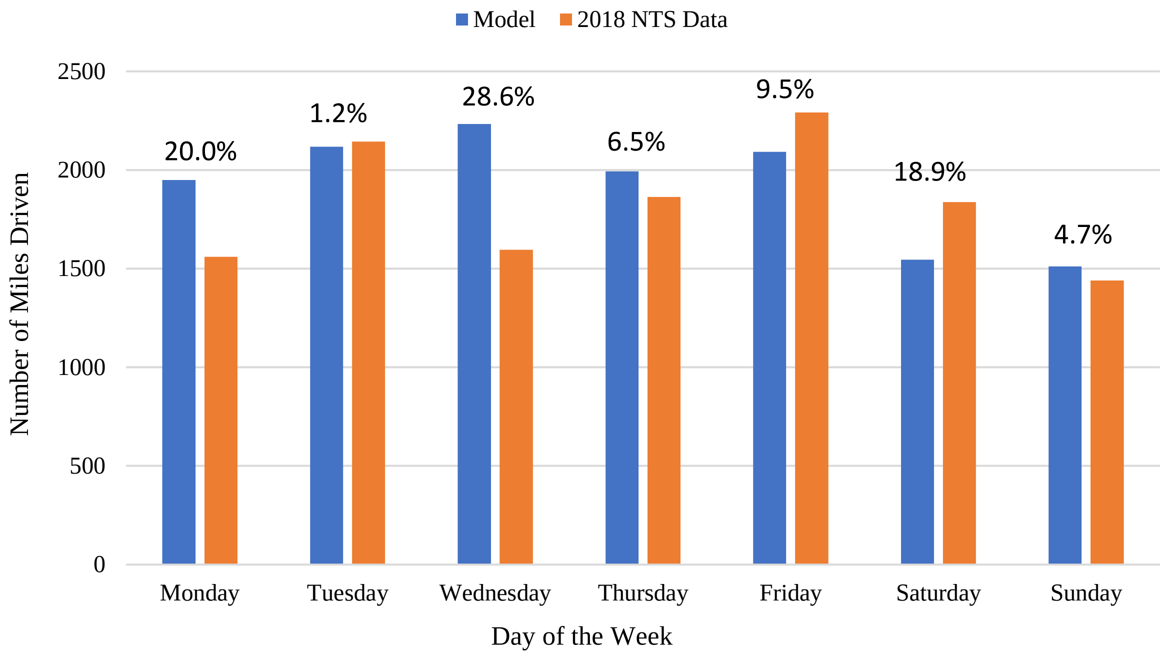


Figure 3.26: Daily mileage comparison between simulation and validation

The largest discrepancy is just over 28%, with the smallest only 1.2%. These differences will be due to the probability distribution across the days of the week for activities. An investigation into the trip purposes and their number of occurrences at the community level of Bradbourne would provide insight into what is causing the larger discrepancies.

Total Mileage over the Week

The 2018 NTS Dataset used for validation indicated a total of 12,733 miles over the course of 7 days. This is a 6% difference (787 miles) from the total mileage predicted by 7-Day TDM presented in this thesis. Considering the longer term use of this model is for assessing the impact of the EV transition in rural areas, this is an acceptable level of error for future energy calculations. This discrepancy is most likely due to the random selection process of the 49 households from the NTS dataset and would change depending on which 49 households are used. A sensitivity analysis for differing the number of other trips and/or day trips would be one possible avenue to achieving a higher level of accuracy and reducing this difference.

Household & Car Distribution

A key premise in the foundation of the travel demand model presented is the distribution of the vehicles to the households of Bradbourne. A premise of '*The larger the number of occupants, the higher the number of vehicles*' that household will have, was applied. This relationship was found to be the case within the 2019 NTS data when reviewing households up to 6 occupants and can be seen in figure 3.27 below. An arrow has been superimposed onto the figure to indicate this upwards trend between the two variables, however, bears no relation to extrapolating the data outside that plotted.

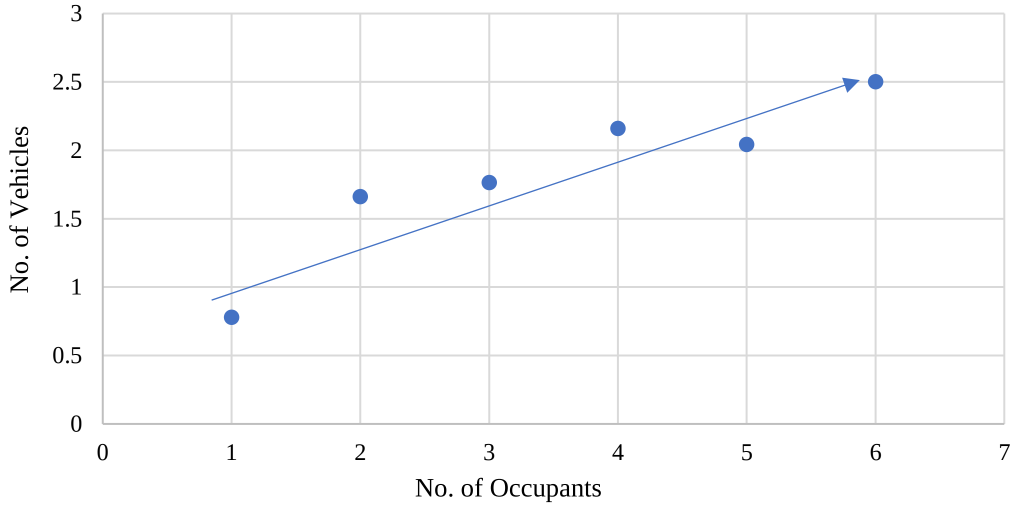


Figure 3.27: Relationship between No. of Occupants of a household and the No. of vehicles belonging to that household

3.5 Chapter Summary

This chapter has described the design and results of a 7-day travel demand model to predict the travelling patterns for a small rural village, Bradbourne, in the Peak District, UK. The process for selecting this village was initially described, which includes a detailed discussion on the implications of Bradbourne being chosen as the centre of focus for this TDM and the larger thesis. Although an applied example, case study approach has been chosen, the methodology employed to develop the Travel Demand Model is applicable to any area given the availability and fidelity of information for the models parameters. This TDM is therefore of interest to a wide range of parties, including local councils, town planners, the transportation sector in general, as well as other researchers who may benefit from utilising and adapting this model to suit other avenues of interest.

A preliminary exercise to develop a simpler ‘One Day Model’ was first presented, which provided important considerations and improvements which were then incorporated into the 7-Day TDM (Section 3.3). The key benefit highlighted by the ‘One Day Model’, or rather the energy calculations building upon it presented in section 3.3.2, is the necessity for a longer term TDM. From past literature reviewed in Chapter 2, there were little examples found for longer duration Travel Demand Models and EV Charging Models and a certain gap for this field. The development of the 7-Day model following this ‘One Day Model’ fills this research gap.

This chapter then provided a detailed overview of a novel 7-Day TDM, including the governing equations, parameters and secondary data sources used for its development. A sample output of the

Travel Demand Model was then presented, along with a validation and further discussion on the model itself. With further time resources, the methodology for the Travel Demand Model could, very easily, be expanded to even longer duration of simulations, accounting for changes which only ever occur over even longer periods of time (i.e. seasons). Validation and comparison efforts with previous models of a similar nature found and presented from the literature review also showed the high accuracy and reliability of this novel TDM.

The material discussed in this chapter accomplishes '*Objective 2a*' and will be taken forward to investigate the effects of electric vehicles completing these predicted travelling patterns, working towards the fulfilment of *Research Aim 2*.

CHAPTER 4: EV CHARGING MODEL

Having developed a suitable Travel Demand Model in Chapter 3, whereby the activities of a population of vehicles for a rural community can be predicted with a high fidelity across a 7-day period, an investigation into the feasibility of Electric Vehicles (EVs) for this community can now be examined.

This chapter will present a model which takes these travel patterns and calculates the energy consumed should the existing car population be replaced entirely by EVs. Further to this, potential charging scenarios are then simulated via a custom written python script. These processes are all encapsulated into a single novel model which will henceforth be referred to as the EV Charging Model. The parameters of the model, as well as all the input data will be discussed in Section 4.1, including the simulation process itself. A total of 8 scenarios have been developed to examine the potential impact electric vehicles will have on rural communities, the results of which will be presented and discussed in Section 4.2. The results of this model will then be compared with those from the large-scale EV trial, conducted by Western Power Distribution, in Section 4.3 as a form of validation. This chapter will conclude with a short summary, Section 4.4. Material presented in this chapter has been published previously in the following papers: McKinney et al., (2022); McKinney et al., (2023a).

4.1 Overview of the EV Charging Model

This section presents the EV Charging Model, which takes the previously calculated travel patterns for Bradbourne, and calculates not only the energy consumed should the car population be replaced by solely EVs, but also the energy demand placed on local grid infrastructure due to the recharging habits of the residents. For the purposes of continuity, the small rural village of Bradbourne remains the focus of the research for considering the various parameters and input data used for developing the EV Charging Model.

4.1.1 Model Parameters

To determine the resulting charging profiles from this travel activity, certain information is required. This includes the model and specifications of the electric vehicles themselves which shall be used to replace the current conventional petrol and diesel vehicles, the type of charge points and the battery capacities of the chosen electric vehicles. The governing equations and model parameters are also presented at the end of this subsection.

1. VEHICLE SPECIFICATION

From understanding how the vehicles of Bradbourne are used, i.e. their travelling patterns, via the Travel Demand Model presented in Chapter 3, the EV Charging Model calculates the anticipated energy impact should this travel be conducted purely with electric vehicles. As discussed in Chapter 2, BEVs are the sole focus of this thesis and thus will be the only type of EV considered in this investigation. Additionally, to ease simulation computation a 100% homogenous EV car population has been assumed.

The 40kWh Nissan Leaf was chosen as the authors have access to this car, thus enabling the possibility of future real-world data collection and analysis should that prove beneficial. It also proved to be most popular amongst researchers, as highlighted by the literature review in Chapter 2, for use in simulations and understanding an EV fleet (For example, Jones et al., 2020; Adderly et al., 2018; My Electric Avenue, 2015). The consumption rate of the car is therefore set to 26.5 kWh/100mile (Electric Vehicle Database, 2018). Although for the benefit of this thesis, the EV has been assumed to be a Nissan Leaf, as the EV Charging Models only input which reflects this is the consumption rate, the EV in question could in fact be any electric vehicle. This method improves the adaptability of the model, as any consumption rate could be used as an input to reflect a population of any vehicle, or a non-homogenous vehicle population with an average consumption rate. Additionally, with further work, the model could be adapted more so to enable multiple consumption rates and specific numbers of vehicles associated with those rates to be incorporated.

With this in mind, attention must be drawn here to multi-vehicle households. For the purposes of this thesis, each vehicle at a households will be assumed and presented to be a Nissan Leaf. However, as discussed previously, this could be any EV make and model, or even an average consumption for the vehicles at a household. In this regards, the findings presented in this thesis will have a much wider scope of relevance than if the model was to be strictly locked in to solely the Nissan Leaf via additional parameters.

2. CHARGE POINTS

The Nissan leaf comes standard with a 6.6 kW AC port, with options for a fast 46 kW DC port should the buyer wish. Only home charging has been considered by this thesis, i.e. no charging will occur at public places, so all energy lost due to EV usage will have to be recharged at home. The importance of home charging and its expected high frequency of usage was highlighted by Hardmen et al. (2018) and discussed in detail in Section 2.4 of Chapter 2. Therefore, given the constraints of home charging only and household electrical wiring, as well as efforts to reduce the computational complexity of the model, all Nissan Leaf’s within the simulations of the EV Charging model will only have the standard 6.6 kW onboard charge port.

Given the selection of the Nissan Leaf vehicle and the 6.6 kW charging port, Pod Point's 7 kW Chargers, a preferred charge point brand by Nissan (Nissan, 2021), will be incorporated into the model. Thus 7 kW Pod Point charge points will be used to support the standard 6.6 kW AC charging port on the Nissan Leaf. The efficiency of the charger and the battery input have been assumed to be 100%, and at this stage of investigation, the efficiency of this factor is negligible. However, future adaptations of this model, discussed in Chapter 8, would incorporate more realistic charging efficiencies.

Each vehicle is assumed to have its own independent charge point, i.e. the number of vehicles belonging to a household dictates the number of chargepoints at that household. For example, a 3 vehicle household will have 3 chargers. In addition, only home charging will be considered. Hardman et al. (2018) indicated the meaningfulness of investigating a 100% home charging scenario during their study on EV charging behaviour, and as previously discussed will be the sole focus the work presented in this thesis.

3. BATTERY CAPACITY

As stated above, the EV chosen for this simulation is the 40 kWh Nissan Leaf, so named for its 40 kWh maximum battery capacity. For battery life improvement measures, vehicle manufacturers restrict the accessible range of a consumer in relation to their EVs battery capacity. This is so as to not fully deplete or overcharge the battery, acting like a buffer. In the case of the Nissan Leaf, this limitation amounts to 37 kWh (Electric Vehicle Database, 2018). In the simulation model, it was assumed that this 3 kWh difference would be evenly distributed between empty and fully charged states, resulting in the battery fluctuating between a state of charge of 3.75% and 96.25%.

Additionally, as part of an effort to further enhance the EVs battery life and adopt a more realistic battery use scenario, the model has been configured to maintain any EVs battery SOC within the range of 20-80% (from the consumers perspective, i.e. 20-80% of 37 kWh). These various battery capacity limits are illustrated in Figure 4.1. This gives an accessible battery capacity of 22.2kWh of energy for the vehicle operation in the travel demand model scenarios, and therefore gives the vehicle an 84 mile range with the energy consumption figures quoted previously. Imposed on the model is a 0% limit, whereby an EVs battery will remain at 0% until the next charging event is scheduled. Any travel conducted in this period will still be allowed to continue so for the vehicle to return home for the charging event to occur. This is to ensure, most importantly, that total charging times remain accurate.

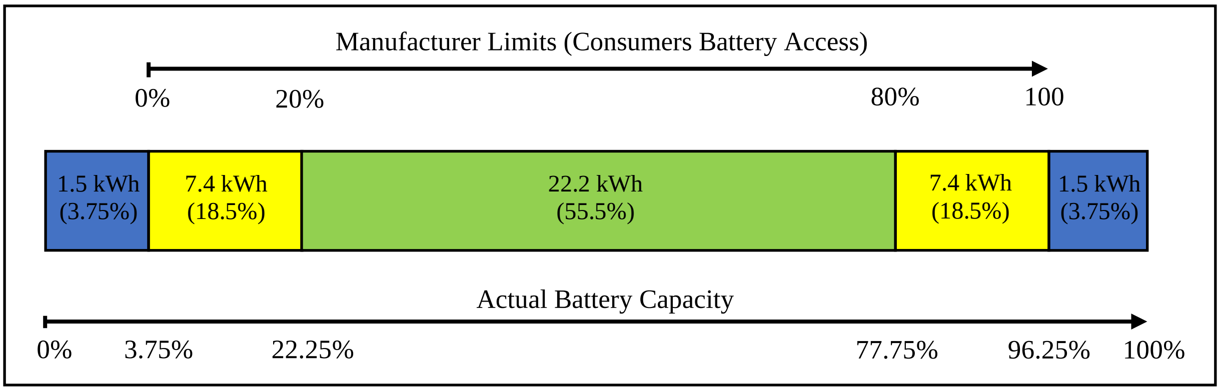


Figure 4.1: Battery Capacity (*Not to Scale)

4.1.2 Electricity Tariffs

Electricity tariffs are how energy providers charge their customers for the electricity they consume. There are two main types, fixed rate (Standard) and variable (Economy), representing different pricing structures for which consumers can opt for. High correlations have been found between charging schedules and the electricity price rate structure households are contracted to (Kim, 2019). Thus electricity tariffs are an important factor which largely influence charging behaviour, specifically the time of charging.

The type of electricity meter installed in a household determines the electricity tariff that applies. While various electricity meter types exist in the UK, the EV Charging model only focuses on standard and economy meters due to their prevalence in UK households. Each of these meter types corresponds to a specific electricity meter tariff presumed for each household.

Households equipped with a standard meter will be assumed to be on a Standard electricity tariff, while those with an economy meter are assumed to be on an Economy 7 tariff. In the case of households on a standard electricity tariff, the EV charging process commences immediately upon the vehicle plugging into a charge point, as there is no financial timing consideration (electricity costs remain constant throughout the day).

In contrast, households on an Economy 7 tariff initiate EV charging only at midnight (00:00), coinciding with the commencement of the cheaper, off-peak hours of the tariff. These off-peak hours for the Economy 7 tariff are presumed to fall between 00:00 and 07:00. It is important to note that for households served by an Economy 7 tariff, if a recharging event does not fully recharge (80% capacity) within this time period then no more charging will occur until the next day regardless of the SOC of the vehicle. Within these limitations, four scenarios for electricity tariff popularity have been analysed:

1. 100% Economy tariffs

In this scenario, all households will be set to have Economy 7 meters and electricity tariffs in the EV Charging Model. These Time-Of-Use (TOU) tariff plans are predicted to become ever more common place through the transition to EVs, with EV specific tariff plans already taking advantage of the cheaper night-time (off-peak) price rates they can offer (Hardman et al., 2018).

2. 100% Standard tariffs

In contrast to the 100% Economy tariffs scenario, in this one, now every household will be assumed to have a Standard electricity meter and tariff plan. As opposed to the 100% Economy tariff scenario, which causes the electricity tariff to determine charging start times, with the Standard electricity tariff it is the time of day the vehicle returns home which governs when vehicle charging begins. Thus the charging events for each household in this scenario modelling will be largely determined by the travelling patterns.

3. A 50:50 split of the two tariff types

In this scenario, a random number generator was used to assign half of the Bradbourne households with Economy 7 tariffs and half with Standard tariffs. The distribution of electricity tariffs to households can be seen in Table 4.1 below. This mixture scenario is aimed at understanding the possible demand-side management solutions that tariff options could provide from a grid impact perspective.

House ID	Electricity Tariff	House ID	Electricity Tariff
House 1	Standard	House 26	Economy
House 2	Standard	House 27	Economy
House 3	Economy	House 28	Standard
House 4	Economy	House 29	Standard
House 5	Economy	House 30	Standard
House 6	Standard	House 31	Economy
House 7	Economy	House 32	Standard
House 8	Economy	House 33	Economy
House 9	Standard	House 34	Economy
House 10	Economy	House 35	Standard
House 11	Standard	House 36	Economy
House 12	Economy	House 37	Economy
House 13	Economy	House 38	Standard
House 14	Standard	House 39	Standard
House 15	Standard	House 40	Economy
House 16	Economy	House 41	Standard
House 17	Standard	House 42	Economy
House 18	Standard	House 43	Economy
House 19	Standard	House 44	Economy
House 20	Economy	House 45	Economy

House 21	Standard	House 46	Economy
House 22	Standard	House 47	Standard
House 23	Standard	House 48	Economy
House 24	Standard	House 49	Standard
House 25	Standard		

Table 4.1: Electricity Tariff Distribution for 50:50 split scenarios

4. 37.5% Standard, 62.5% Economy split of the two tariff types

This scenario split was determined using real-world data (BEIS, 2022) for the village of Bradbourne, with the aim of providing the most realistic representation for the village in its current state. The 'split' was determined by postcode level electricity data released by the UK Government every year which includes the number of meters and type of meters (BEIS, 2022). Bradbourne is comprised of 6 postcodes (ONS, 2021) and the number of electric meters, and their types for each postcode is shown in Table 4.2.

Postcode	2013	2015	2016		2017		2018	
	Standard	Standard	Standard	Economy	Standard	Economy	Standard	Economy
DE6 1NP	-	-	-	-	-	-	-	-
DE6 1PA	19	19	6	10	6	10	-	10
DE6 1PB	20	15	-	14	-	13	-	13
DE6 1PD	-	-	-	-	-	-	-	-
DE6 1QY	-	-	-	-	-	-	-	-
DE6 1RG	-	-	-	-	-	-	-	-

Table 4.2: Postcode Level Electricity Meter Data for the postcodes of Bradbourne

As shown in Table 4.2, this postcode level electricity meter data lacks continuity across the years and completeness. Due to the sampling methodology, any postcodes which serve a small number of households (<10), which is a common occurrence for rural areas, does not get recorded and has resulted in a lot of missing data. Taking all of this into account, only data from 2016 & 2017 (BEIS, 2022) for the postcode DE6 1PA was used to derive a 'real-life' ratio for the two electricity meter types, as these years and postcode provide the most continuity in readings. The results are shown in Table 4.3, as well as the percentage split which this scenario will use.

Standard Electricity Meters	Economy 7 Meters
6	10
37.5%	62.5%

Table 4.3: Electricity Tariff Split for realistic scenario

This percentage split was then extrapolated to all 49 households of Bradbourne, and a random number generator was used to assign each house one of the two electricity meter types. Table 4.4 shows each household and its assigned Electricity Tariff for this scenario.

House ID	Electricity Tariff	House ID	Electricity Tariff
1	Economy 7	26	Standard
2	Standard	27	Standard
3	Economy 7	28	Economy 7
4	Standard	29	Economy 7
5	Economy 7	30	Standard
6	Economy 7	31	Economy 7
7	Economy 7	32	Economy 7
8	Standard	33	Economy 7
9	Standard	34	Economy 7
10	Economy 7	35	Standard
11	Economy 7	36	Economy 7
12	Economy 7	37	Standard
13	Standard	38	Economy 7
14	Economy 7	39	Economy 7
15	Standard	40	Economy 7
16	Standard	41	Economy 7
17	Economy 7	42	Economy 7
18	Economy 7	43	Economy 7
19	Standard	44	Economy 7
20	Standard	45	Standard
21	Standard	46	Economy 7
22	Standard	47	Economy 7
23	Economy 7	48	Economy 7
24	Economy 7	49	Economy 7
25	Standard		

Table 4.4: Electricity Tariff Distribution for 37.5:62.5 split scenarios

4.1.3 Charging Scenarios

The EV Charging model was employed to simulate a total of 8 scenarios, which are detailed in Table 4.5 below. These scenarios represent two distinct charging behaviours, encompassing the range of electricity tariff combinations mentioned in section 4.1.2.

The first charging behaviour emulates a practice where individuals allow their EVs battery to deplete to the 20% capacity limit before initiating a recharging event. This behaviour closely resembles the refuelling process observed in the current ICE regime (Berkeley et al., 2018).

In contrast, the second charging behaviour involves plugging the EV in for charging every night, irrespective of the travelling undertaken that day, provided the battery capacity is below 80%. This approach draws inspiration by the charging behaviour consumers commonly employ for other household electronic devices, such as mobile phones and laptops. To implement this behaviour in the model, the lower threshold for initiating charging was set to 80%, meaning that any usage of the EV that day will trigger a charging event when the vehicle returns following its last journey of the day.

These two charging behaviours are designed to capture the extreme ends of the spectrum, reflecting the highly variable nature of EV charging, a phenomenon driven by the inherently variable nature of human behaviour (Fotouhi et al., 2019).

No. of Chargers	**Electricity tariff**	**Scenario**	Charging initiates once EV falls to below 20% SOC
1 per car	0% Standard : 100% Economy	1	
	37.5% Standard : 62.5% Economy	2	
	50% Standard : 50% Economy	3	
	100% Standard : 0% Economy	4	

No. of Chargers	**Electricity tariff**	**Scenario**	Charging initiates every night
1 per car	0% Standard : 100% Economy	5	
	37.5% Standard : 62.5% Economy	6	
	50% Standard : 50% Economy	7	
	100% Standard : 0% Economy	8	

Table 4.5: Details of the 8 charging scenarios to be investigated

4.1.4 The Simulation Process

The simulation is executed by a custom written Python script. This script adheres to a structured design reminiscent of a flowchart, comprising a series of rules and decision points, similar to the methodology presented for the TDM in Chapter 3. These rules and decisions generate the energy consumption profiles for each individual vehicle and dictate when charging events occur within the simulation time period. Extensive pre-processing was required to manipulate the resulting output table from the Travel Demand Model, this was also carried out by a custom written python script. The overall model process is presented below in Figure 4.2.

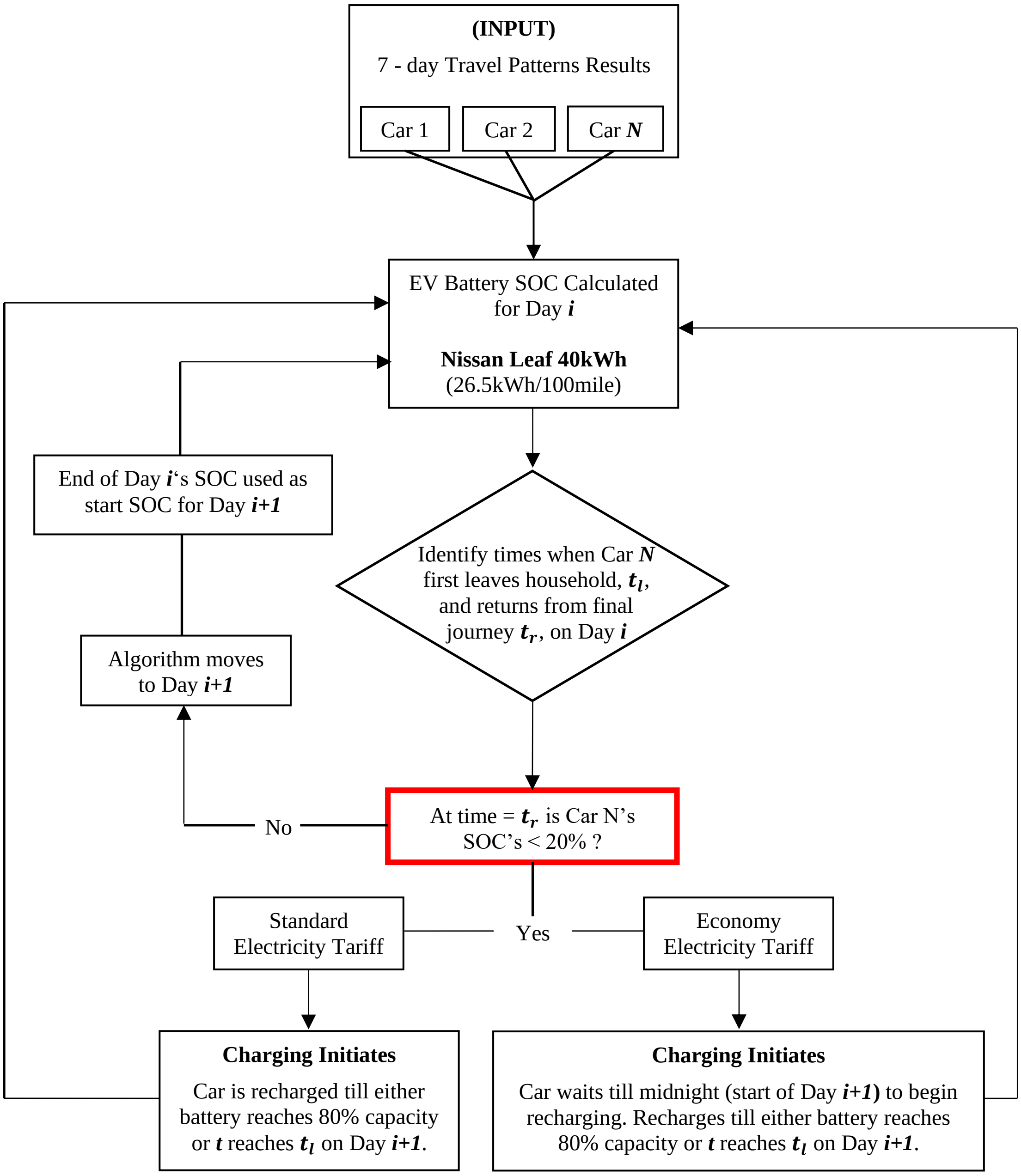


Figure 4.2: Flowchart representing the Simulation Process

As illustrated in figure 4.2, the predicted 7-day travel patterns for all 84 vehicles located in Bradbourne serve as the initial input for the EV Charging model. The simulation can be configured to run for any desired number of weeks, with the TDM results replicated to match the specified duration. Furthermore, as discussed in the Chapter 2 (Section 2.4) the travel patterns for the first Monday are duplicated and added to the start of the simulation, to act as a 'Day 0' (Pareschi et al., 2020).

On Day 0, all vehicles start with 100% battery capacity before conducting the forecasted days travel. This results in a range of State of Charges (SOCs) for each individual vehicle to begin with on the first Monday of the simulation, i.e. Day 1. Using the Nissan Leaf's consumption rate of 26.5

kWh/100mile and the mileages driven forecasted by the predicted travel patterns, the battery depletion through the day can be calculated.

Figure 4.2 details the simulation process specifically for scenarios 1, 2, 3 & 4, where charging is initiated when an EVs battery capacity falls below the 20% threshold. If, after the vehicle's last journey of the day, the battery capacity reaches this lower threshold, it triggers a charging event for that specific vehicle (Kang and Recker, 2009). The timing of this charging event is contingent upon the household to which the vehicle belongs, specifically the electricity tariff serving that household. As described in Section 4.1.3, in cases where the household is served by a standard tariff, charging begins immediately upon the vehicle's return home following the last journey of the day. Conversely, if the household is on an Economy 7 tariff, the vehicle commences charging at midnight (when the cheaper electricity rates begin).

The vehicle is then charged until it reaches a predefined upper threshold limit (as depicted in Figure 4.2, set at 80%) or until the vehicle is scheduled to depart from the household. , whichever comes first. This entire process repeats for each day of the week and continues for the specified number of weeks for which the simulation has been configured.

For scenarios 5, 6, 7, & 8, whereby the charging behaviour occurs every night regardless of battery capacity levels, so long as it is below 80%, the simulation process is exactly the same as described above except for this change in initiation, which begins as soon as the vehicle returns home. This was achieved through changing the lower 20% threshold in the model (highlighted in the bold red box) to 80% (i.e. any SOC less than the 80% capacity limit would initiate a charging event).

GOVERNING EQUATIONS AND PARAMETER LIST

As a summation of the above simulation process, all parameters and the governing equations of the EV Charging Model will now be presented (see Table 4.6).

Model Parameter	**Value**
Consumption Rate	26.5 kWh/100mile
Fleet Composition	100% homogenous
Charge Points	100% homogenous: 7kW PodPoint (6.6kW onboard)
Total Battery Capacity	40 kWh
Accessible Battery Capacity	37 kWh
Consumer Battery Capacity	22.2 kWh (20-80%)
Electricity Tariffs	Standard/Economy
Charging Behaviour	Every night/20% threshold
Number of Charge Points	One charge point per vehicle

Table 4.6: EV Charging Model Parameter List

Governing this simulation process, as described previously are numerous calculations for each half-hour time interval of each day. Each of these time intervals are denoted a number, i, ranging from

0 – 47. This is to represent each half-hour of a day. The governing equations for these calculations are then as follows:

EV Energy Consumption:

$$Energy, E_i = miles_i * consumption\ rate \qquad (1)$$

The energy consumed by the EVs, as the simulation progresses through the output of the TDM (see Table 3.16 of the previous chapter), is calculated by the cumulative miles driven each day, at every half-hour interval (t_i), multiplied by the consumption rate (see Equation 1). The consumption rate is converted to 0.265 kWh/mile for simplification.

EV Battery Capacity:

$$Battery\ Capacity_i = Battery\ Capacity_0 - Energy, E_i \qquad (2)$$

For each day, at any one time interval (t), the battery capacity from the end of the previous is taken and the cumulative energy requirement (as per Equation 1) is subtracted from this initial battery capacity – see Equation 2.

Charging Power:

If a charging event is triggered, as per the simulation process described previously, for each time interval, i, power is drawn by the PodPoint charger (3.3 kW) – limited by the 6.6kW Nissan Leaf onboard charger.

Charging Energy:

$$Charging\ Energy, CE_i = Charging\ Power_i * T \qquad (3)$$

Following the inserting of the Charging Power, the Charging Energy is calculated as per Equation 3 above, where T is equal to the length of time of the interval, i, 0.5 hour (30 minutes).

EV State of Charge:

The State of Charge (SOC) for the vehicle at each time interval, i, is calculated via Equation 4 below.

$$SOC = \left(\frac{Battery\ Capacity_i}{Total\ Battery\ Capacity}\right) * 100 \qquad (4)$$

4.2 Results and Discussion

Simulations ran for a duration of 4 weeks. This was to ensure the resulting system governed by the EV Charging Model reached a steady state and no divergences occurred in the longer term, i.e. the scenario would not end up losing energy over time – as seen from the 1-Day TDM results (see Section 3.2.2). To ensure this energy balance, from the resulting 4 weeks, a time period was selected from which to investigate deeper. The criteria for this time period selection was as follows:

- The sum of all EV battery capacities must be the same at both the start and end points of the time period selected, or as close as possible given the half-hour resolution of the model. This is to ensure the 1st law of thermodynamics is adhered to and thus upholding the sustainability of the system for future projections.
- In conjunction with the first criteria, for both the start and end points selected, the total charge across all EV batteries for each of the four different electricity tariff scenarios must also be the same, or as close to. This ensured that the electricity tariff options for each of the two behaviour scenarios could be compared.

Given that the simulations spanned a total of 4 weeks, a system utilising weekdays and week numbers was adopted to distinguish between the weeks. Across these four weeks, the days were labelled from 'Mon1' to 'Sun4', where each day of the week is followed by its respective week number. First looking at Scenarios 1, 2, 3 and 4, the results of running the EV charging model over a 4 week period are presented in Figure 4.3, with the selected time period superimposed.

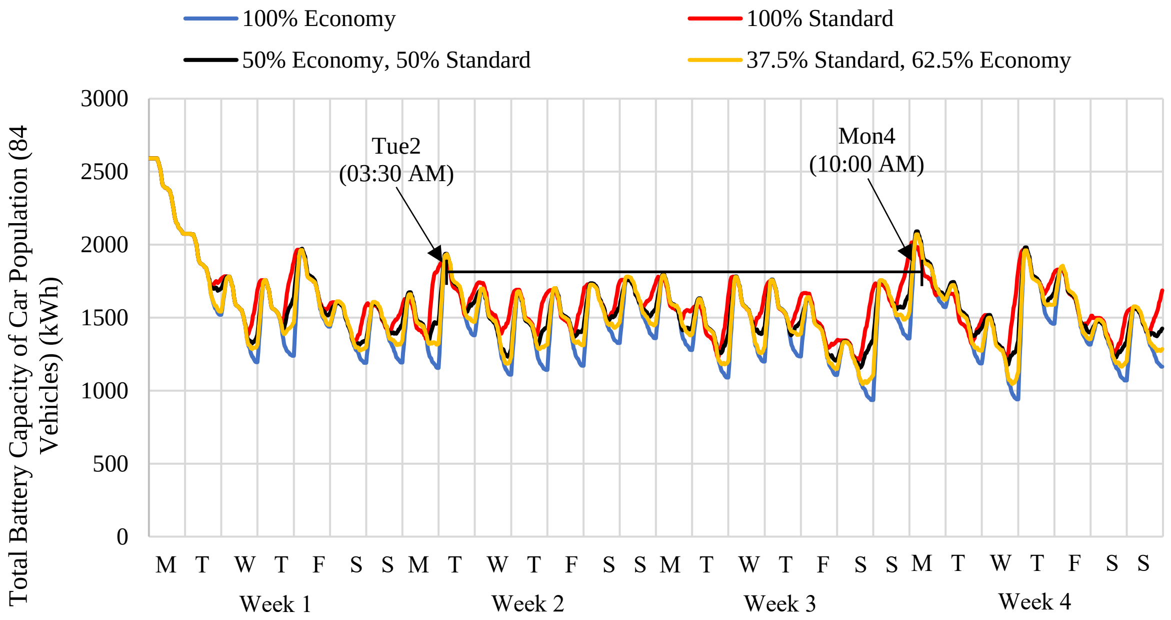


Figure 4.3: Total charge across all EV batteries of the vehicle population of Bradbourne (Scenarios 1, 2, 3 and 4)

For scenarios 1, 2, 3 and 4, the time period from 'Week 2 Tuesday' to 'Week 4 Monday' was selected, 03:30 and 10:00 respectively. This 13 day period was chosen to ensure an energy equilibrium within the system when investigating charging energy and power, as well as to facilitate comparisons across the four electricity tariff options.

From Figure 4.3, the first scheduled charging events do not occur until Tuesday of Week 1. Considering a population of 84 Nissan Leaf vehicles, each with a 40kWh capacity, of which only 37 kWh is available to the consumers, the maximum collective capacity within the system at any given time is 3108 kWh. The simulation starts on Monday, Week 1, with an initial capacity of approximately 2600 kWh. This variation is attributed to the 'Day 0' SOC initialisation, meaning the 84 vehicles do not all start with fully charged batteries but rather a range of pre-depleted batteries. The start and end SOC's for each vehicle will be presented later in this chapter, in section 4.2.1, for only the selected time period of the scenarios.

To reiterate, scenarios 1, 2, 3 and 4 follow the charging behaviour of vehicles not commencing charging until their battery level reaches the lower threshold of 20%. With this behaviour in mind, its notable that Bradbourne's EV population maintains an average of roughly 1500 kWh of charge collectively across its 84 vehicles, that equates to an average battery charge of 18kWh (48%) at any given moment.

Turning the focus to the selected time period of Scenarios 5, 6, 7 and 8, the results of these simulations can be seen in Figure 4.4 below.

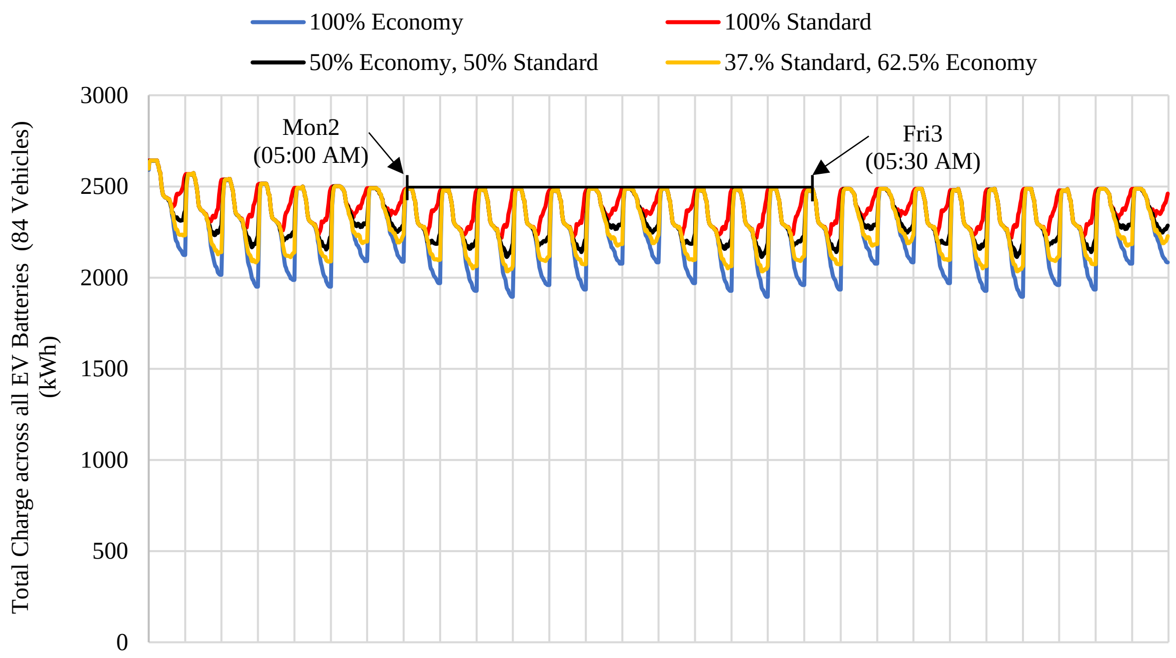


Figure 4.4: Total charge across all EV batteries of the vehicle population of Bradbourne (Scenarios 5, 6, 7 and 8)

Scenarios 5, 6, 7 and 8 focused on the charging behaviour centred around charging nightly irrespective of a vehicles SOC. Compared to the previous set of scenarios (scenarios 1, 2, 3 & 4), this behaviour yields a much higher amount of energy stored in the vehicles at any one time. The average energy within the system increased to 2250 kWh due to the significantly higher frequency of charging events.

With the higher charge threshold set at 80%, the maximum energy capacity in the system at any one time, i.e. all 84 EVs holding 80% battery capacity, is 2486.4 kWh. This threshold is consistently achieved by the population of EVs in scenarios 5, 6, 7 & 8. Furthermore, in contrast to the other modelled charging behaviour (of scenarios 1, 2, 3 & 4), this charging pattern exhibits a higher degree of day-to-day predictability, which proves advantageous for grid demand management solutions. The time period selected for scenarios 5, 6, 7 & 8 is from ‘Monday Week 2’ to ‘Friday Week 3’, following the criteria previously discussed. The specifics of these selected time periods can be found in the Table 4.7 below.

No. of Chargers	**Electricity tariff**	**Scenario**		**Time Period (Tue2 03:30 – Mon4 10:00) (kWh)**	**Delta (kWh)**
1 per car	0% Standard : 100% Economy	1	Charging initiates once EV falls to below 20% SOC	1872.16 – 1896.987	+24.827
	37.5% Standard : 62.5% Economy	2		1875.787 – 1877.915	+2.128
	50% Standard : 50% Economy	3		1898.89 – 1896.987	-1.903
	100% Standard : 0% Economy	4		1884.796 – 1790.598	-94.198

No. of Chargers	Electricity tariff	Scenario		Time Period (Mon2 05:00 – Fri3 05:30) (kWh)	Delta (kWh)
1 per car	0% Standard : 100% Economy	5	Charging initiates every night	2486.4 – 2484.534	-1.866
	37.5% Standard : 62.5% Economy	6			
	50% Standard : 50% Economy	7			
	100% Standard : 0% Economy	8			

Table 4.7: Selected Time Periods for the 8 scenarios investigated

When evaluating the two selected time periods, most notably was the increased difficulty in selecting a suitable time period for Scenarios 1, 2, 3 & 4 compared those of Scenarios 5, 6, 7 & 8. This is solely due to the charging behaviour implemented, or rather the difference in charging frequency and routineness the two behaviours invoke. For scenarios 1, 2, 3 & 4, as charging is much less frequent but also more sporadic, identifying a period of time where start and end energies are the same was not possible and so large deltas can be seen compared to that of scenarios 5, 6, 7 & 8. However, across the four scenarios (Scenarios 1, 2, 3 & 4), combined, there is only a delta of -70 kWh. Smaller deltas may be possible, but at the cost of reducing the duration of the selected time period.

In contrast, for Scenarios 5, 6, 7 & 8, due to the higher frequency of charging events (almost nightly for all vehicles in use), a very small delta was achieved (<2 kWh). Thus, the time period selected for further investigation enables any conclusions drawn to withstand tests over larger time scales as no energy is lost from the system. Nevertheless, Figure 4.3 also shows any conclusions drawn from scenarios 1, 2, 3 & 4 can also withstand extrapolations over larger time scales, regardless of the larger delta for the selected time period, as the energy in the system is still replenished.

The time periods detailed in Table 4.7 will be the period of time for which the in-depth analysis of the EV charging model results will be focused on. These results will be presented and discussed in the following two subsections (4.2.1 & 4.2.2).

4.2.1 Scenarios 1, 2, 3 and 4

Figure 4.5 below shows the predicted energy consumption profile during the selected time periods for scenarios 1, 2, 3 and 4 given the population of 84 electric vehicles in Bradbourne. The consistently highest peak energy demands are observed in the 100% Economy tariff scenario due to the amalgamation of multiple charging events occurring simultaneously during the few hours charging events can be scheduled (00:00 – 07:00). As the number of households served by a standard electricity tariff increases (scenarios 2, 3, & 4), the energy consumption (or rather demand from the grid) is spread out over a longer period of time. This is expected as the charging events for standard tariff households can begin at any time and are thus only dictated by the travel patterns of the vehicle itself.

When considering the higher proportion of Economy tariff scenarios, the charging events are predominantly initiated at midnight, resulting in the higher peaks at that specific hour. The difference between peak energy demands of the opposing tariff scenarios (100% Economy vs. 100% Standard) is substantial, exceeding 100kWh in comparison to roughly 50kWh, respectively. This indicates that the choice of electricity tariffs within this community can result in an 100% increase in peak energy demands.

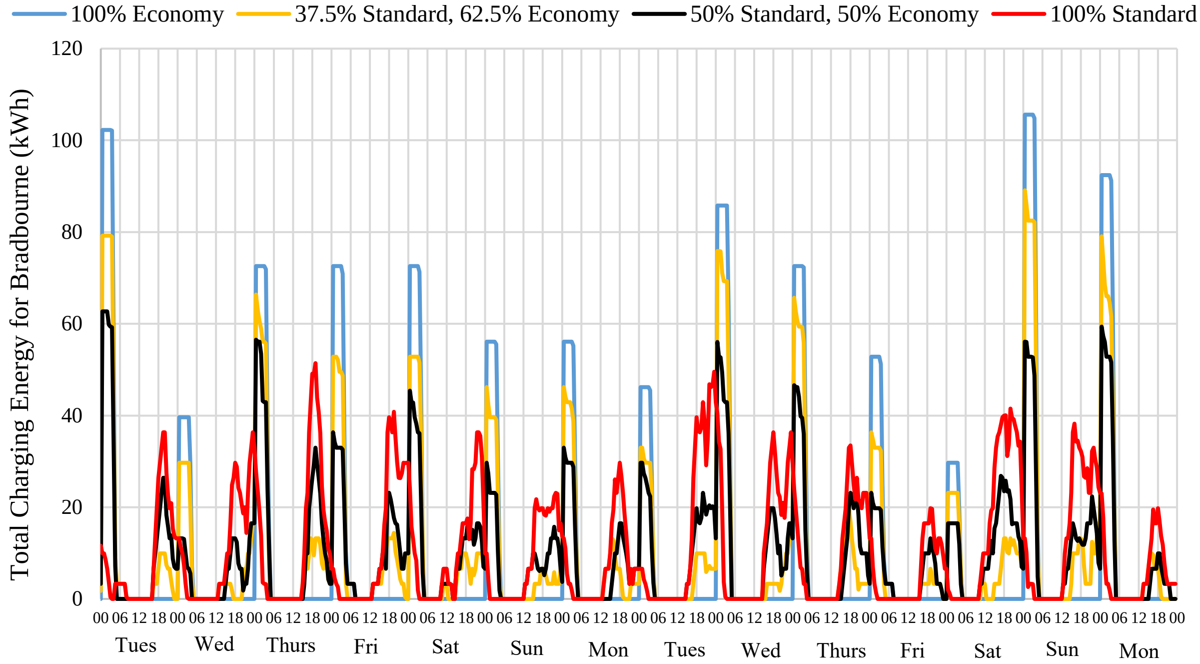


Figure 4.5: Charging Energy for scenarios 1, 2, 3 and 4

The power demand due to the 84 chargers is presented in Figure 4.6. As expected, the power profile is roughly twice the values of the energy demand, due to the half-hour resolution of the models. Likewise with the energy demand, the power perspective also shows that the most regular scenario is the 100% standard tariff (scenario 4). This scenario provides the largest balance of delivering the required power and energy over the longest period of time, thus not creating large demand spikes which could be cause for concern for grid infrastructure/operators. Directly opposing current trends and pressures which push for electric vehicle owners to adopt the more economy style tariffs via EV specific tariffs available on the market.

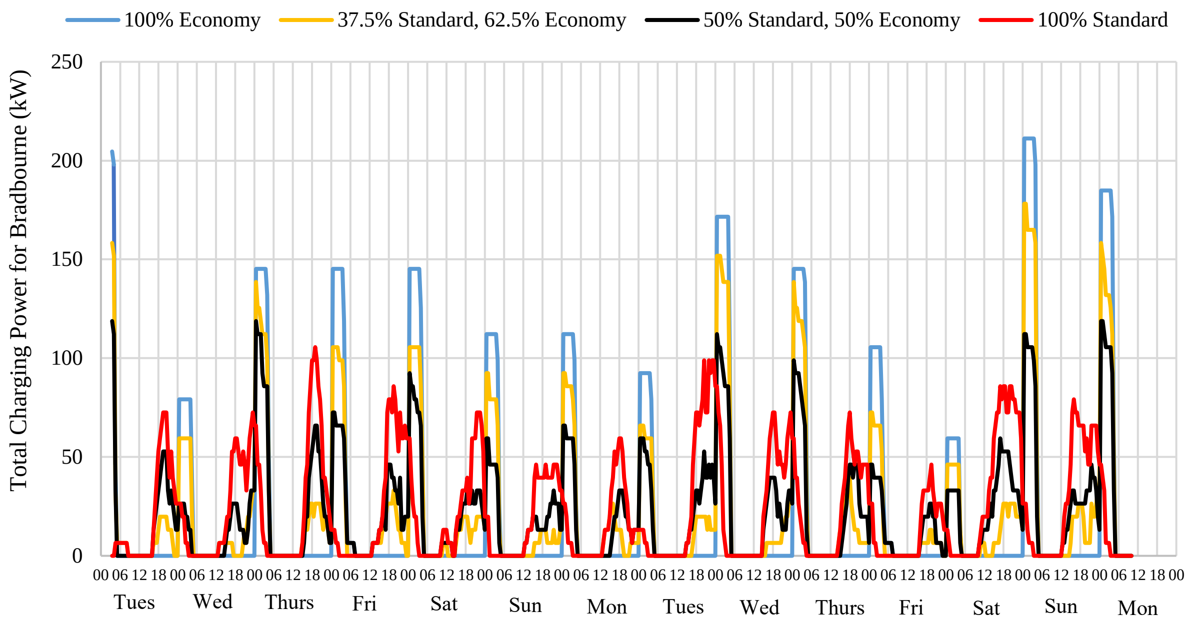


Figure 4.6: Charging Power for scenarios 1, 2, 3 and 4

Looking at the SOC of the vehicles in the model, in particular the start and finish SOC's, Figure 4.7 and Figure 4.8 show that great variability in these parameters was achieved through this model. Figure 4.7 presents just the 100% Economy tariff, with the start and end SOC for each vehicle, as well as the direction of the SOC change over the course of the selected time period for scenario 1 (Tue2 03:30 – Mon4 10:00). Whereas, to show this same variability across the other tariff scenarios, a subplot has been created for all three, see Figure 4.8.

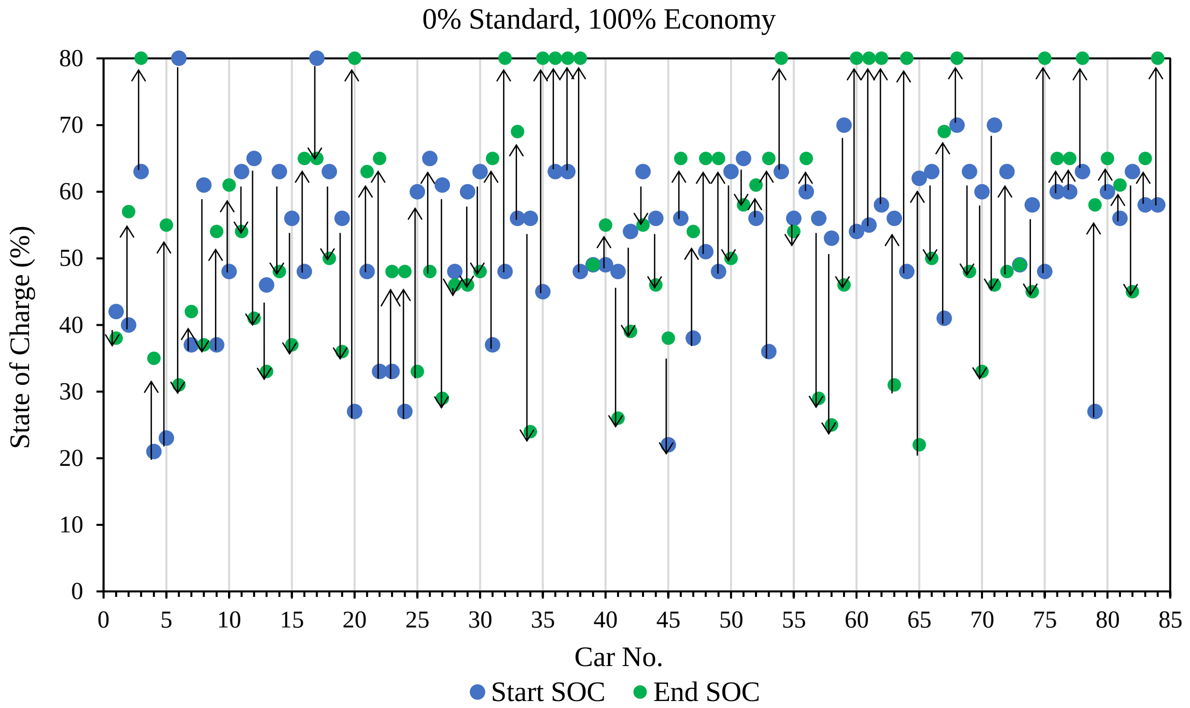


Figure 4.7: Start and End SOC’s for scenario 1 (100% Economy tariffs)

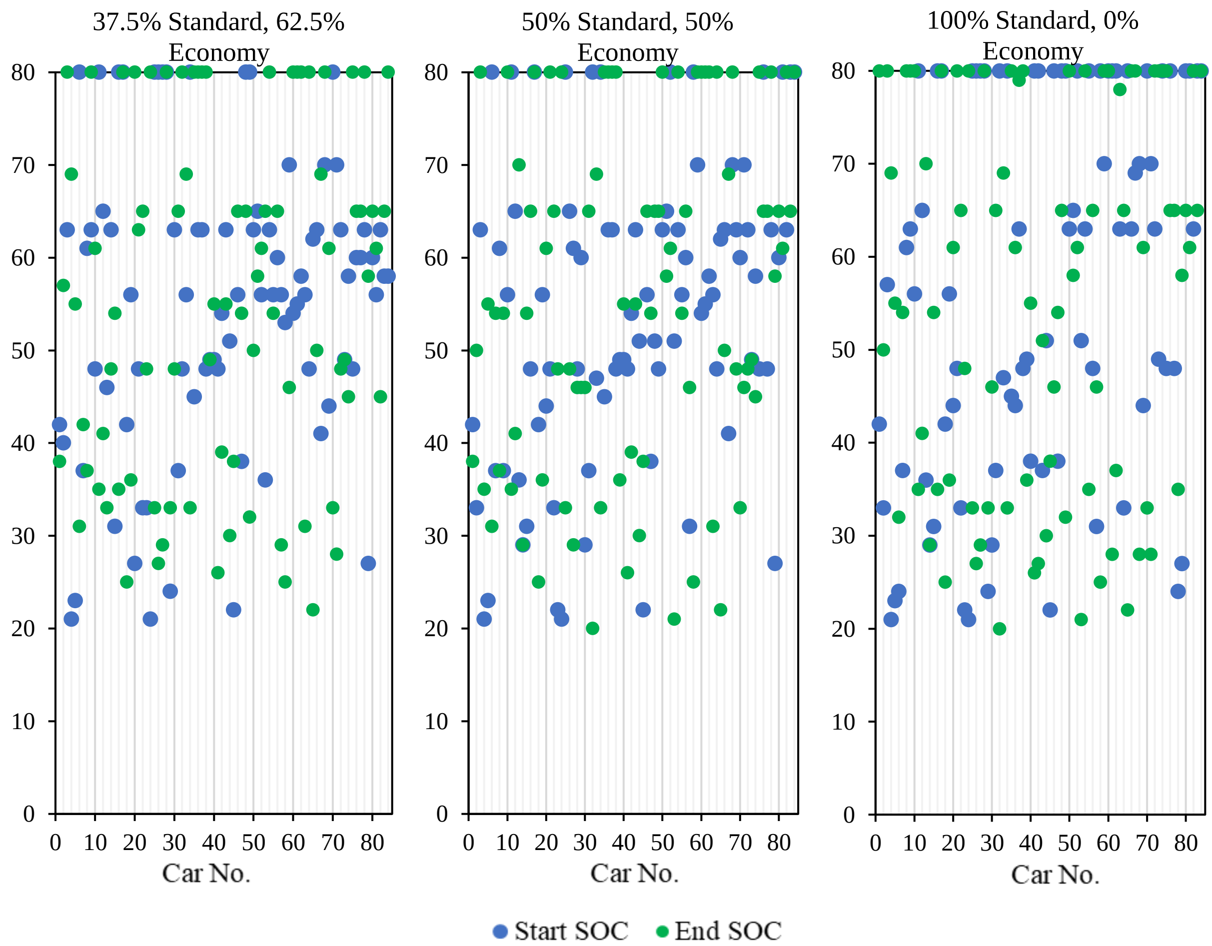


Figure 4.8: Start and End SOC’s for scenarios 2, 3 and 4

It should be noted that in Scenario 1, 2, 3 and 4, as a consequence of the simulation methodology, a total of 9 vehicles experienced circumstances where the vehicles battery depleted to 0% capacity. Due to the nature of charging events only occurring once the 20% threshold has been reached, if a vehicle reaches a low state of charge, for example 22% after the last journey of the day, a charging event for this vehicle will not be triggered that night and thus this vehicle is required to complete the travel activities of the following day with only 22% capacity. Should this day's activity require more than 22% capacity of the battery, this results in the vehicle modelled to reach 0%. A more realistic approach could be to add a 'foresight' aspect to the custom written python algorithm which considers the next day's travel activity in its decision to initiate a charging event, a behaviour likely to be shown by a real-life EV consumer. This can also be averted by raising the lower charging threshold, as will be shown by scenarios 5, 6, 7 and 8, in Section 4.2.2.

Figures 4.9, 4.10, 4.11 and 4.12 below show SOC profiles over the course of the selected time period, Tue2 03:30AM till Mon4 10:00AM, for the average and both max and min vehicles, from each of the four scenarios, scenario 1, 2, 3 and 4 respectively. The 'Min Profile' is defined as the SOC profile which reaches the lowest SOC during the course of the simulation, out of all 84 vehicles. The 'Max Profile' on the other hand represents the SOC profile which decreases the least and finally the 'Average SOC Profile', the average of all 84 vehicles SOC profiles.

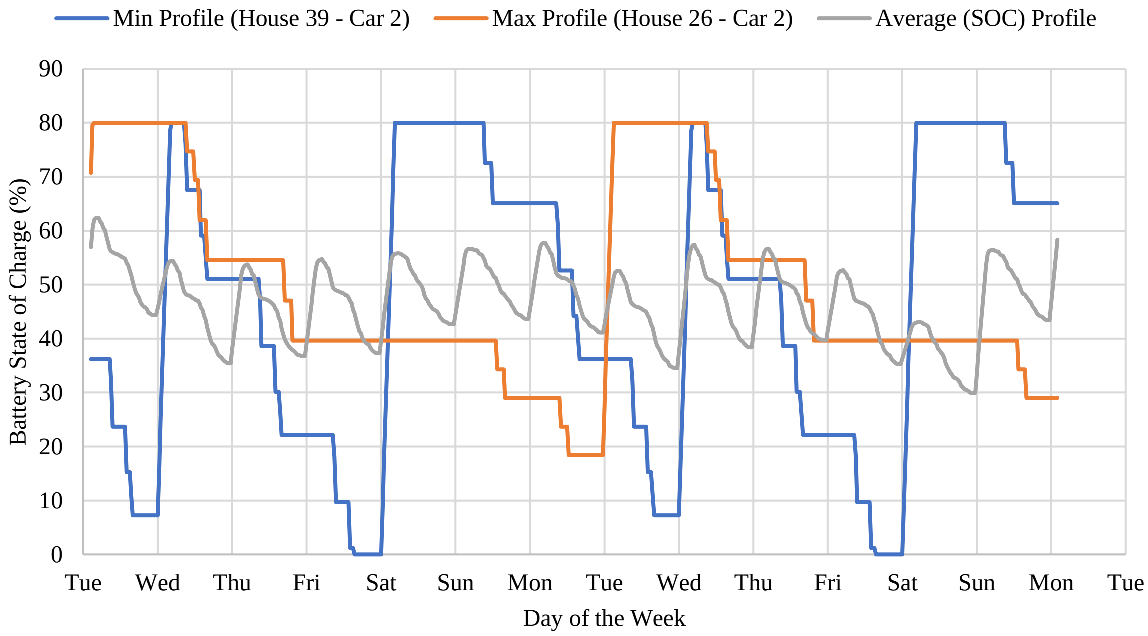


Figure 4.9: The maximum, minimum and average SOC profiles for Scenario 1 (100% Economy)

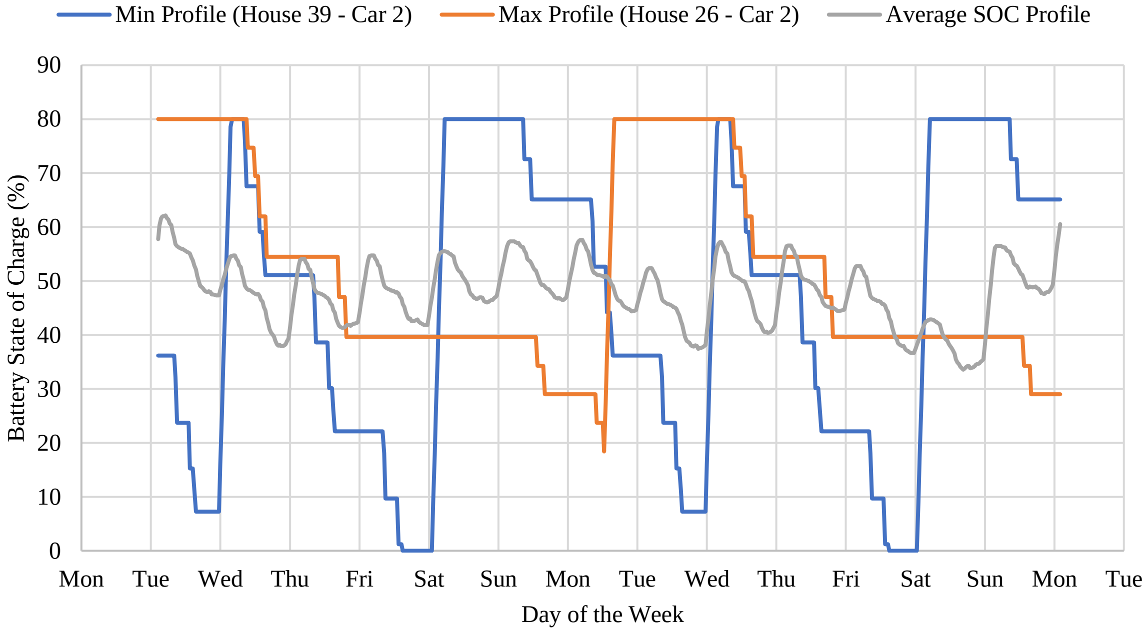


Figure 4.10: The maximum, minimum and average SOC profiles for Scenario 2 (37.5% Stand, 62.5% Econ)

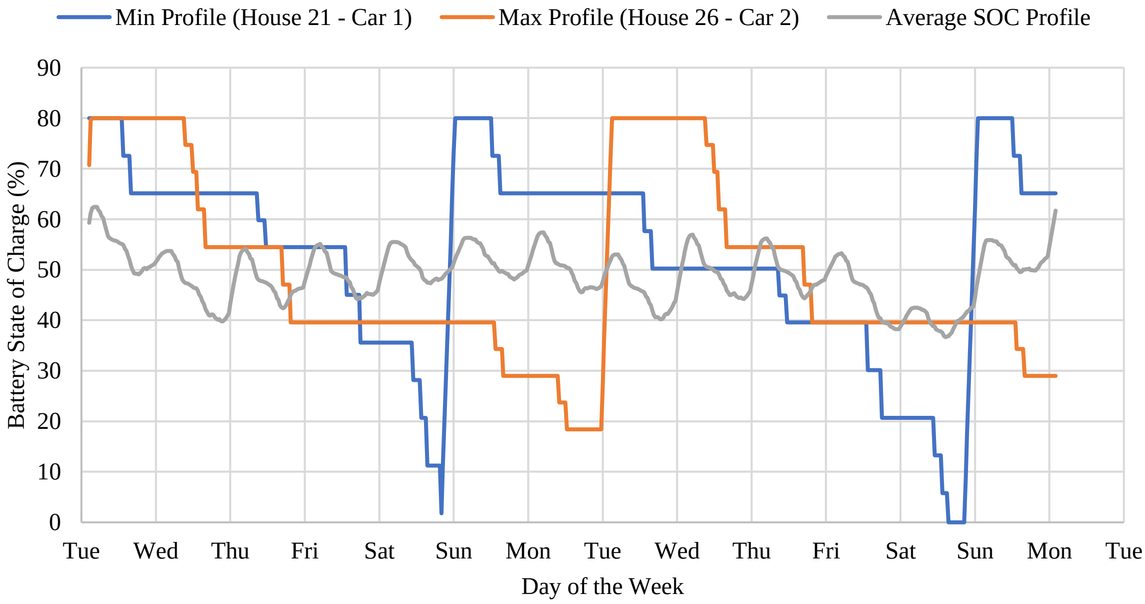


Figure 4.11: The maximum, minimum and average SOC profiles for Scenario 3 (50% Stand, 50% Econ)

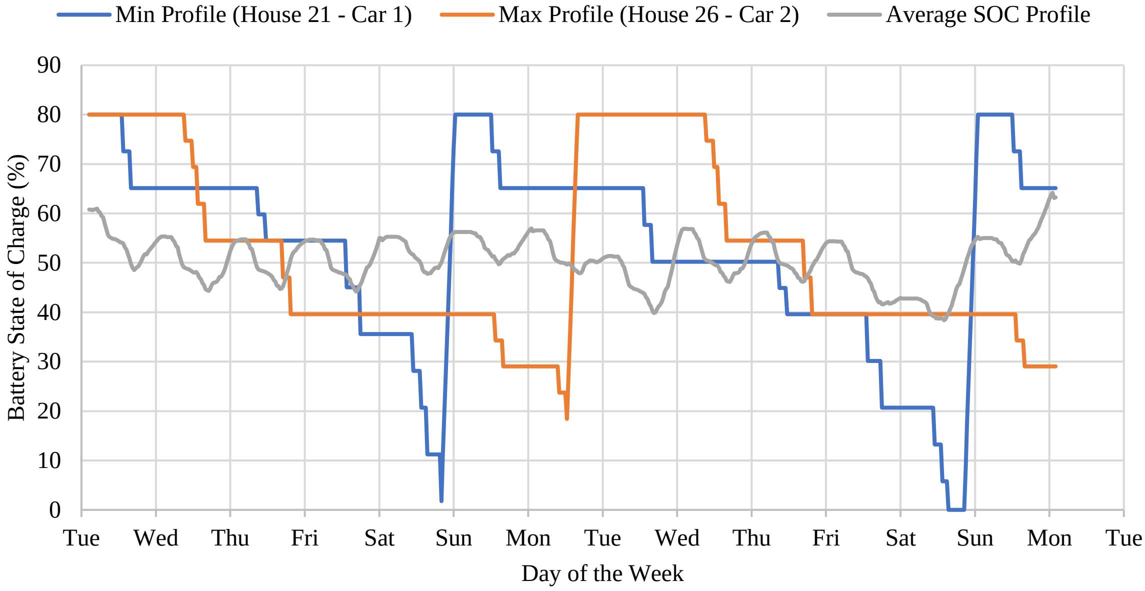


Figure 4.12: The maximum, minimum and average SOC profiles for Scenario 4 (100% Standard)

As highlighted by Figures 4.9 – 4.12, the model set up for these scenarios (Scenarios 1, 2, 3 & 4) did result in some vehicles reaching 0% battery capacities. A result indicating that should EVs be recharged in a manner similar to the refuelling schedule of ICE vehicles, EVs will not be able to complete the same travel requirements from drivers. The largest offending vehicle was 'House 39 – Car 2', which saw the vehicle sit at 0% battery charge for over 9hrs. In order for the vehicle to have completed the journeys that day, a further 8 kWh (over 21% battery capacity) would have been needed.

This is inherently due to the limitations imposed on the EV Charging Model, namely that charging cannot begin until less than 20% battery capacity has been achieved. Without the foresight of the following trips, the simulated vehicles can enter a day's travelling patterns with anything more than 21% charge. Such cases arrive whereby this is not sufficient charge to complete the planned travel activity before the next charging opportunity, which will follow the last trip of the day. This pattern can be seen in Figure 4.13 which illustrates the details for the vehicle in question, House 39 – Car 2, around this particular phenomenon.

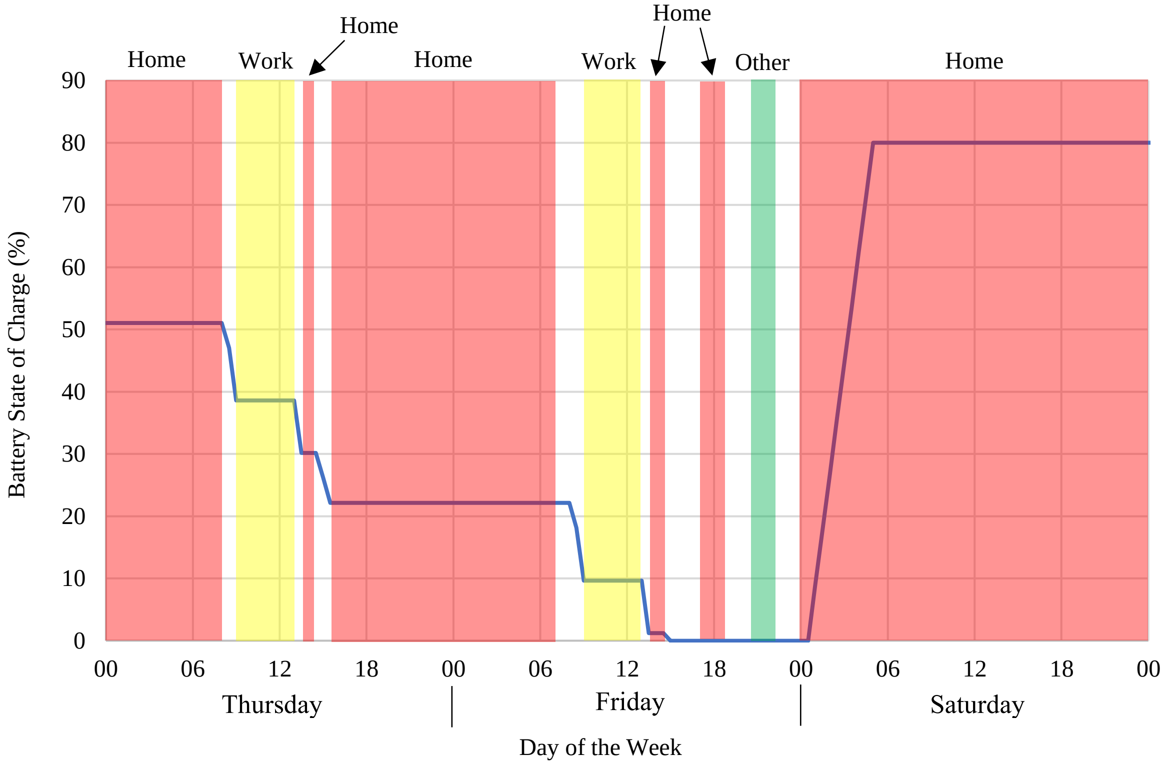


Figure 4.13: Travel Pattern and State of Charge for House 39 – Car 2 (Thurs2 till Sun3) (Scenario 1)

'House 39 – Car 2' begins Thurs2 at Home (indicated by the area highlighted in red), before taking children to school and then onto a work (Part-time). Any travelling period is defined by the white area of the graph. The vehicle then returns home shortly from work (shown by the area highlighted in yellow) before picking up said children from school and remaining at home for the rest of the night. This travel reduces the vehicles SOC to 22% by the end of Thurs2, and thus the charging of this vehicle is not yet triggered. This travel pattern repeats on Fri2; however, an additional 'Other' trip is planned on the Friday evening (highlighted in green) which results in the further decline of the EVs battery to 0%. As House 39 in this scenario, Scenario 1, is on an Economy tariff, the recharge of this vehicle does not begin until the start of Sat2. Through the early hours of Saturday, during the reduced price hours of the Economy tariff, the vehicles is recharged back to 80%. No travel occurs on the Sat2 and so this SOC continues through to the Sun2.

Figures 4.09 – 4.12 do show that the 'Min Profile' is affected by electricity tariff. As discussed, whilst House 39 – Car 2 is the worst performing when all households are placed on an Economy tariff, House 21 – Car 1 supersedes this for the case of Standard tariffs. The analysis of results shown in Figures 4.10 and 4.11, particularly focusing on the Min profiles for the split tariff option scenarios (Scenarios 2 and 3), allow us to ascertain the appropriate electricity tariffs for these Min Profile households, which would be Economy and Standard, respectively.

4.2.2 Scenarios 5, 6, 7 and 8

Scenarios 5, 6, 7 and 8 focused on the charging behaviour whereby each vehicle charged nightly, irrespective of its daily travel activities. These scenarios encompassed a range of electricity tariff combinations for the various households of Bradbourne, as detailed in section 4.1.2. Figure 4.14 below shows the energy demand for each of these four scenarios during the selected time period.

A noteworthy observation when comparing these four scenarios (scenarios 5, 6, 7 and 8) to the initial four (scenario 1, 2, 3 and 4) is the significantly higher magnitude of both energy and power demand for the high Economy tariff scenarios, which has almost doubled. This phenomenon is a consequence of the higher number of chargers in simultaneous use, stemming from the more frequent charging events seen in these scenarios. This also results in higher peak demand but existing for a much shorter amount of time, as seen in scenario 1. Conversely, when comparing the higher standard tariff scenarios of both charging behaviours (scenarios 3 and 4 against scenarios 7 and 8), the energy demand at any given moment decreases for the latter charging behaviour (charging every night). This reduction can be attributed to the higher frequency of charging events in these latter scenarios. If this is coupled with the high standard tariff distributions (such as scenario 7 and 8) which allows charging events to occur over an extended period of time, due to the less restrictions on timings of charge events, and thus reducing the larger instantaneous demands observed in scenarios 3 and 4.

Overall, scenarios 5, 6, 7 and 8 exhibit reduced charging times compared to scenarios 1, 2, 3, and 4. These trends are also evident in the power demand profiles for scenarios 5, 6, 7 and 8, shown in Figure 4.15. When considering the impact on the grid, the significantly higher power demand, not only compared to the previous four scenarios (scenarios 1, 2, 3 and 4), but particularly in the context of the higher Economy split tariff options (scenarios 5 and 6), raises concerns. This will be discussed further in the following chapter, chapter 5.

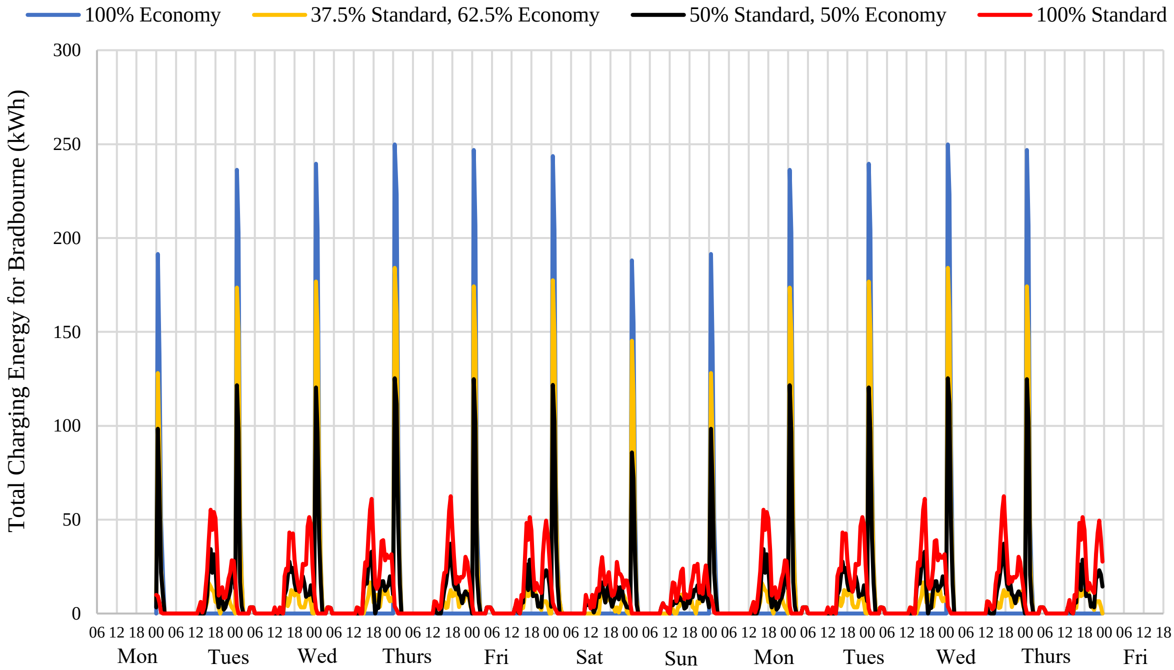


Figure 4.14: Charging Energy for scenarios 5, 6, 7 and 8

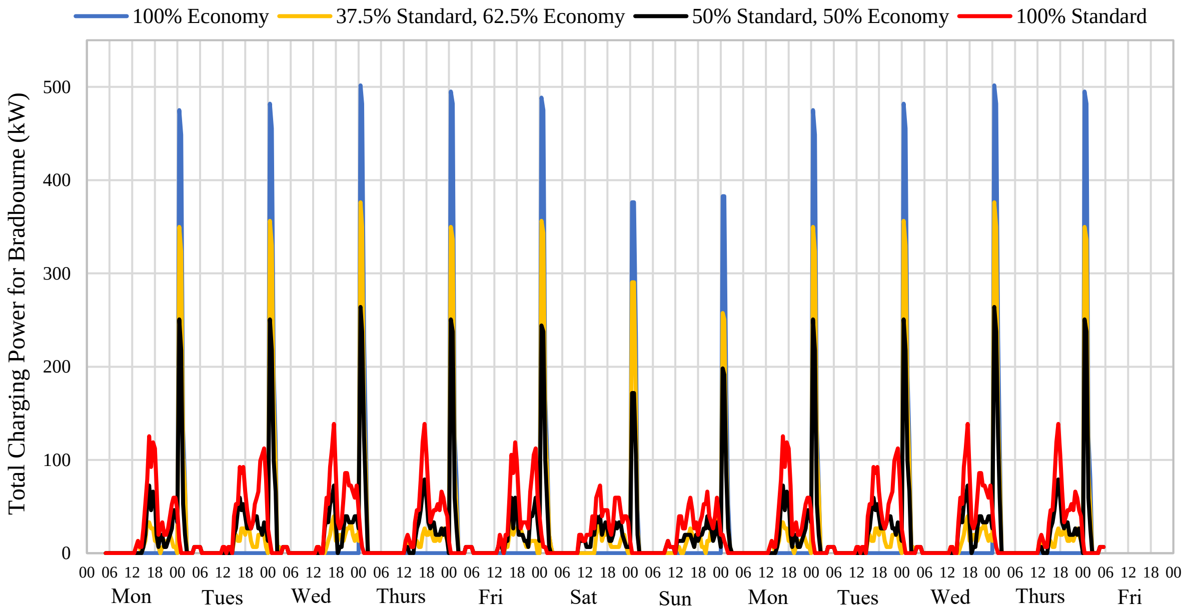


Figure 4.15: Charging Power for scenarios 5, 6, 7 and 8

Examining the vehicles' SOC in scenarios 5, 6, 7 and 8, we observe that the 100% Standard (Scenario 8) is depicted independently in Figure 4.16. The other 3 tariff split options are displayed together in Figure 4.17. As indicated initially by Figure 4.4, during the course of these scenarios the majority of EVs are recharged every night. Thus, the start and end SOC's for the selected time period (Mon2 5:00 – Fri3 05:30), especially given that the start and end time are the early hours of the day, for the majority of vehicles will be 80%. This causes a lot of the points in Figure 4.16 to overlay one another, resulting in primarily the End SOC's being in view.

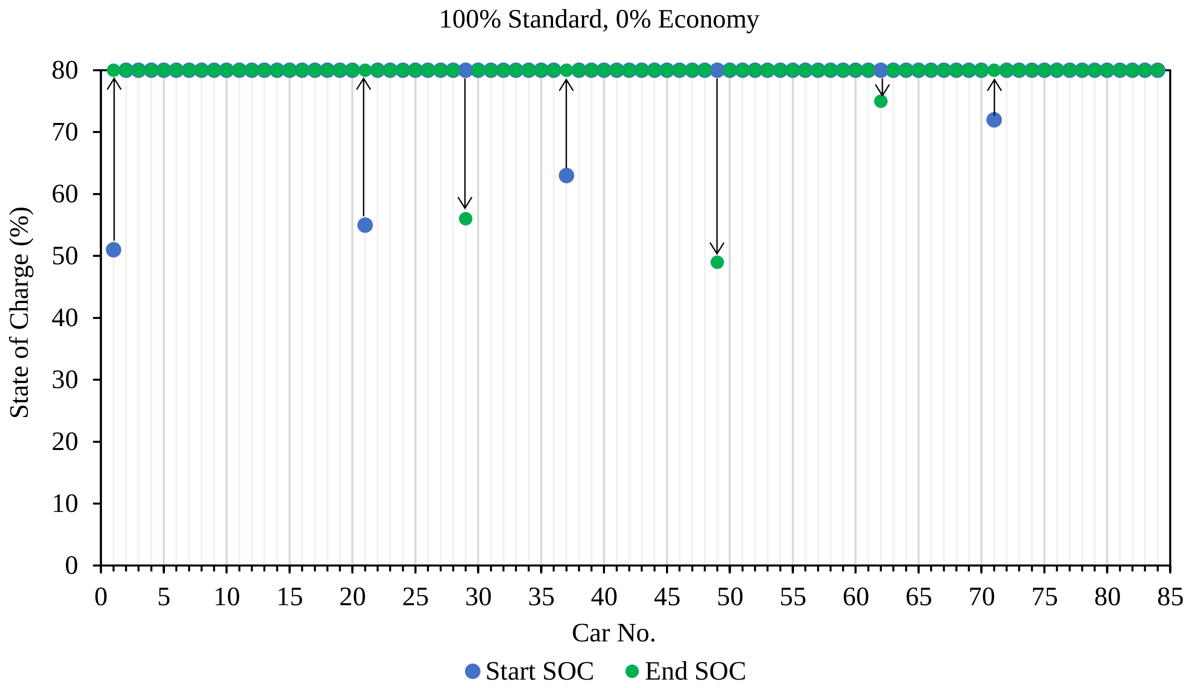


Figure 4.16: Start and End SOC’s for scenario 8 (100% Standard tariffs)

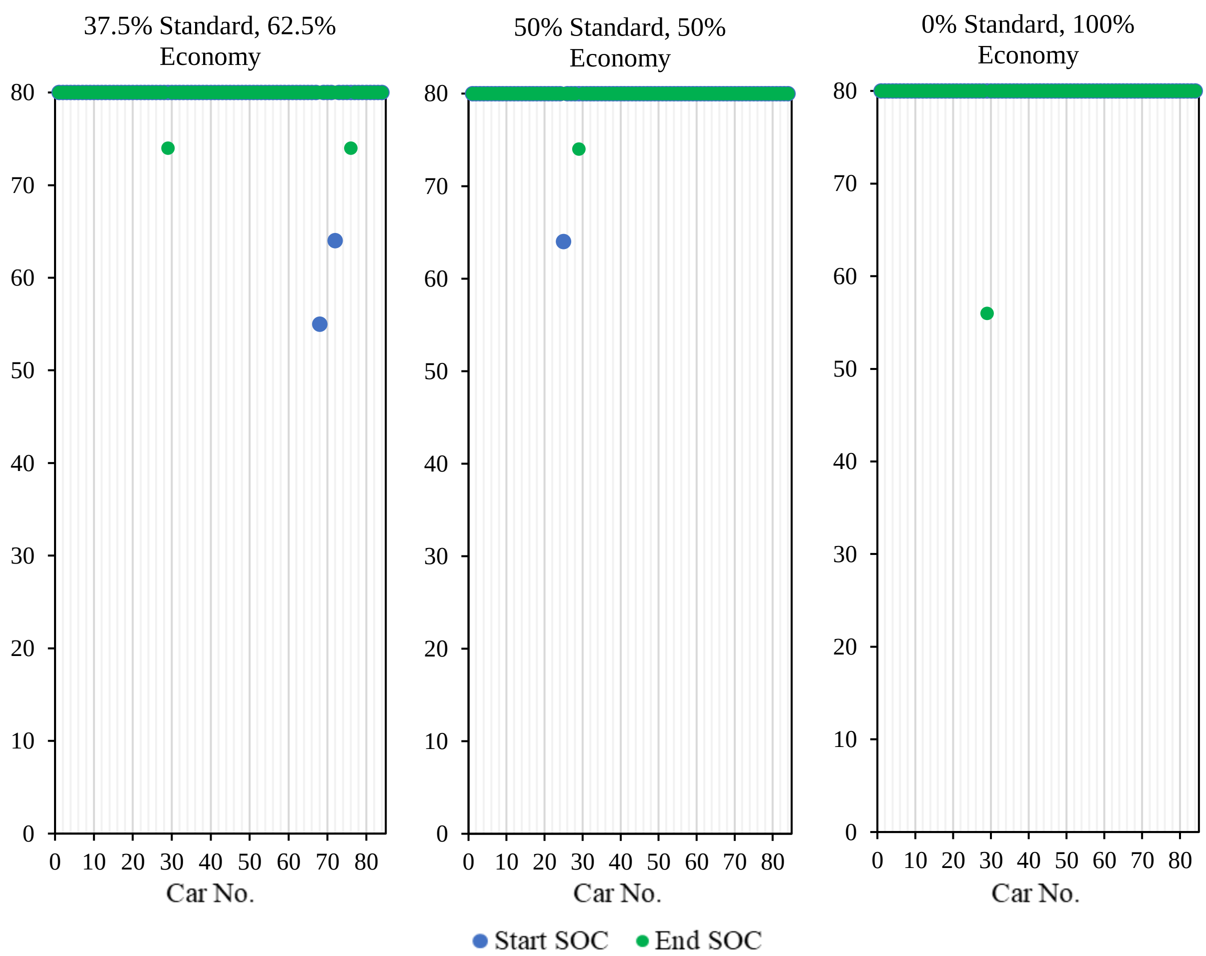


Figure 4.17: Start and End SOC’s for scenarios 5, 6 and 7

As shown by Figure 4.16 and Figure 4.17, only a few vehicles end up with less than 80% SOC at the end of the selected time period. For these four scenarios where every car is recharged back to 80% every night, this would seem to highlight an error at first glance. However, some vehicle's travel patterns can belong to individuals simulated to have overnight work patterns, i.e. they don't return till the morning of the following day and given the end time of the selected time period being 05:30AM, these few vehicles have either not yet returned home to charge, or the days travel pattern begins before 05:30AM.

When focusing solely on the EV chargers themselves, without considering their impact on the current grid demand, these findings suggest that a shift towards standard electricity tariffs becoming the predominant option for household electricity pricing would be the more favourable approach for grid stability. This challenges the common belief that EV charging should be pushed to the early hours for demand management purposes – a principle upon which many energy companies base their EV specific tariffs (offering cheaper rates overnight). However, investigations into the integration of these energy and power demands with existing grid readings is necessary to arrive at a definitive conclusion. This will be explored in the following chapter, Chapter 5.

A crucial aspect of this model that warrants further attention is the assumption of one charger per vehicle. In reality this may not practical, particularly for households with multiple vehicles, where household electrical wiring constraints could limit the simultaneous use of numerous chargers. Whilst the possibility of 84 chargers in use simultaneously from a grids perspective is grounded, scenarios exploring various numbers of charge points per household should be investigated.

Figures 4.18, 4.19, 4.20 and 4.21 below show SOC profiles over the course of the selected time period for scenarios 5, 6, 7 and 8 (Mon2 05:00AM till Fri3 05:30AM), respectively. Again, each figure plots the 'Min Profile', 'Max Profile', and 'Average SOC Profile'.

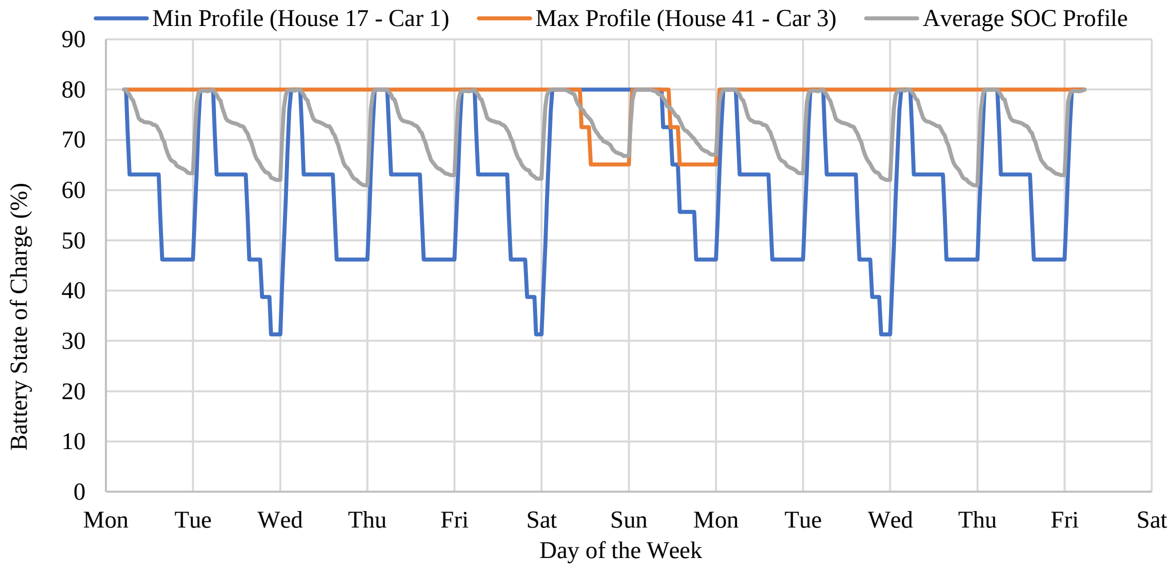


Figure 4.18: The maximum, minimum and average SOC profiles for Scenario 5 (100% Economy)

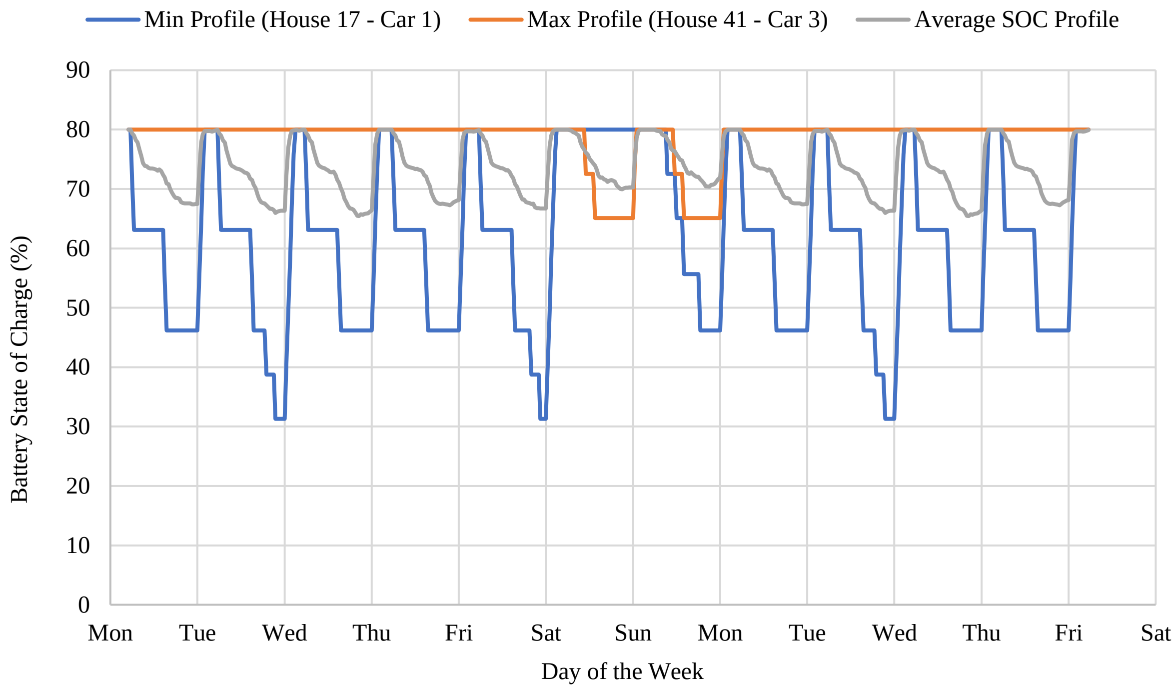


Figure 4.19: The maximum, minimum and average SOC profiles for Scenario 6 (37.5% Stand, 62.5% Econ)

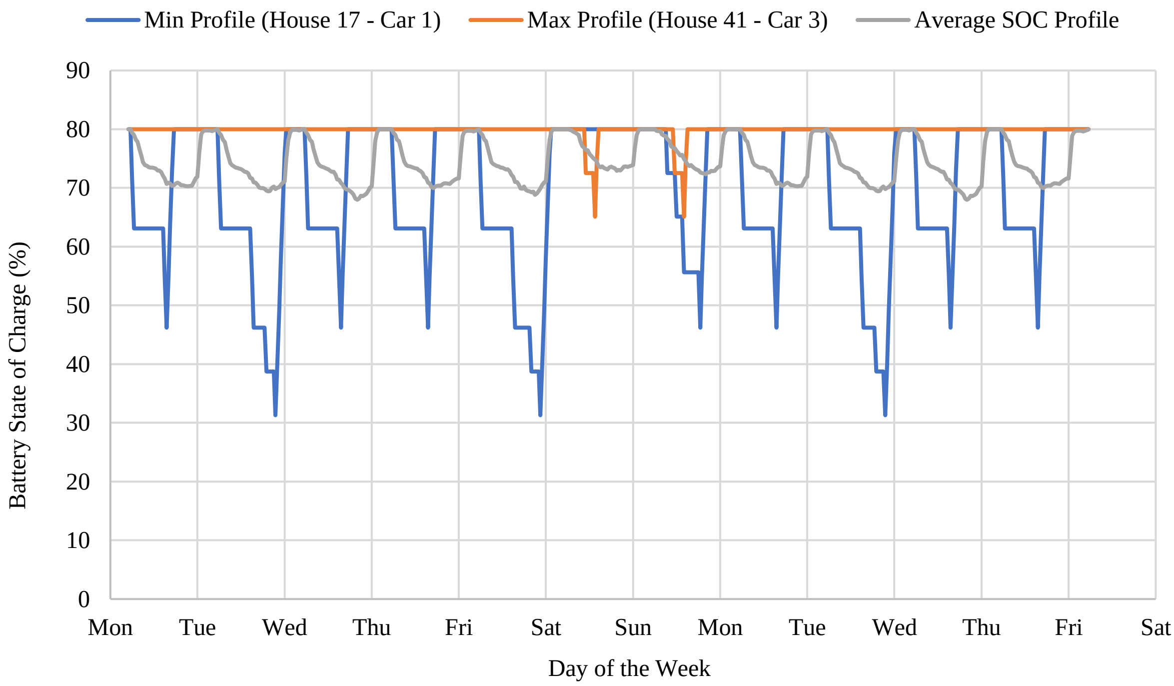


Figure 4.20: The maximum, minimum and average SOC profiles for Scenario 7 (50% Stand, 50% Econ)

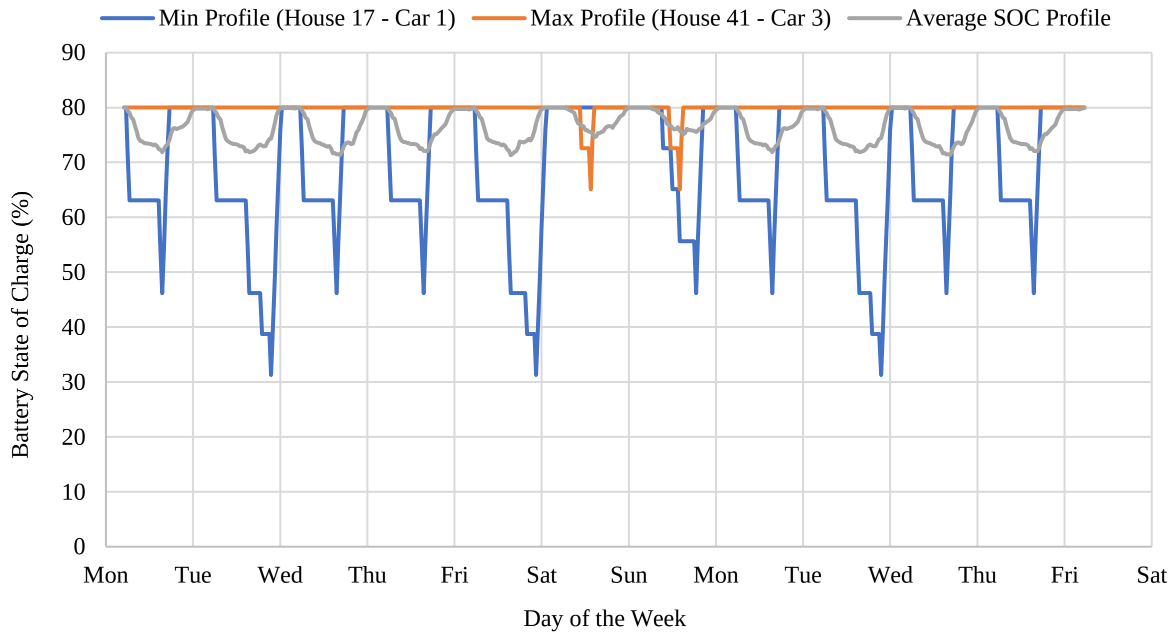


Figure 4.21: The maximum, minimum and average SOC profiles for Scenario 8 (100% Standard)

4.3 Validation of the EV Charging Model

Effort was made to perform some validation on the results of the EV Charging Model against the data collected by Western Power Distributions as part of their Electric Nation Project (Western Power Distribution, 2019). Between April 2016 and October 2019, the electricity distribution network for the Midlands, Southwest, and Wales; Western Power Distribution, conducted a large scale project to investigate EVs and their impact on grid infrastructure – The Electric Nation Project (Western Power Distribution, 2019). For 18 months, nearly 700 EV owners and their charge points were monitored and so offers a comprehensive source for comparison and validation.

4.3.1 Time When Charging Began

As highlighted previously, the electric vehicle transition is expected to change current load profiles witnessed by the electricity grid. The most likely scenario being increased local peaks in consumption (Ridder et al., 2014). Particular to this are the timings and understanding of EV charging events and thus these have been selected as the focus for the validation of the EV Charging Model. Figure 4.22 has been extracted from the 'Customer Trial Final Report' of the Electric Nation Project, available from Electric Nation (2019).

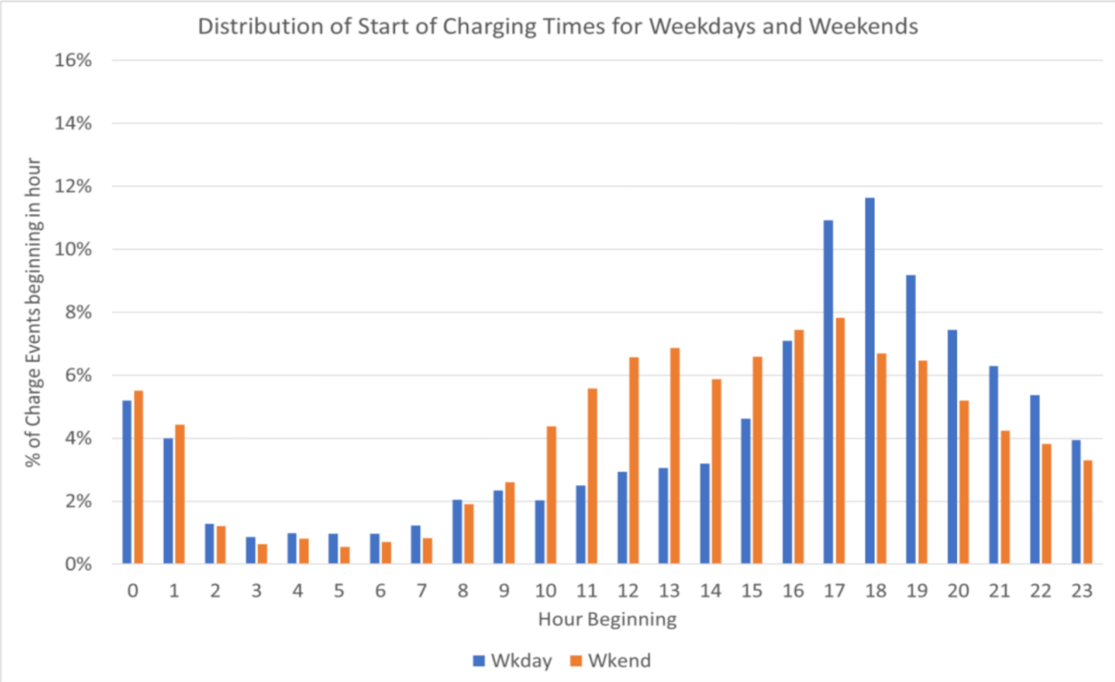


Figure 4.22: Distribution of Start Charge Time – Weekday and Weekend (Figure 8-3, p.141, Electric Nation, 2019)

The comparable information from all 8 charging scenarios has been extracted and presented in Figure 4.23 below. The timing of charge events across the various scenarios simulated via the EV Charging Model are the largest impacted factor, given the two core variables manipulated: Electricity Tariffs, and Charging Behaviour. Figure 4.23 is presented as follows to ease comparison: each column represents the scenarios adopting the two different charging behaviours. Scenarios 1-4 (LHS) being that of EV owners waiting for their vehicle to reach the lower 20% battery capacity threshold, whereas Scenarios 5-8 (RHS) seeing EV owners charge their vehicle every night. Each row of graphs in Figure 4.14 represents a different electricity tariff split, starting from 100% Economy (Scenarios 1 and 5) at the top, ranging to 100% Standard (Scenarios 4 and 8) at the bottom.

There is much variation between Figure 4.22 and Figure 4.23, most apparent is the lack of captured charging events occurring in the early hours. This will be due to the combination of constraints placed in the electricity tariff pricing hours and the lack of consideration for night-time journeys. Also very apparent is the accordance of Scenarios 4 and 8 with the real-life charging events captured by the Western Power trial compared to the other scenarios (shown in Figure 4.24). However, to confirm such similarities, information regarding the electricity tariffs of the Electric Nation participants would need to be known.

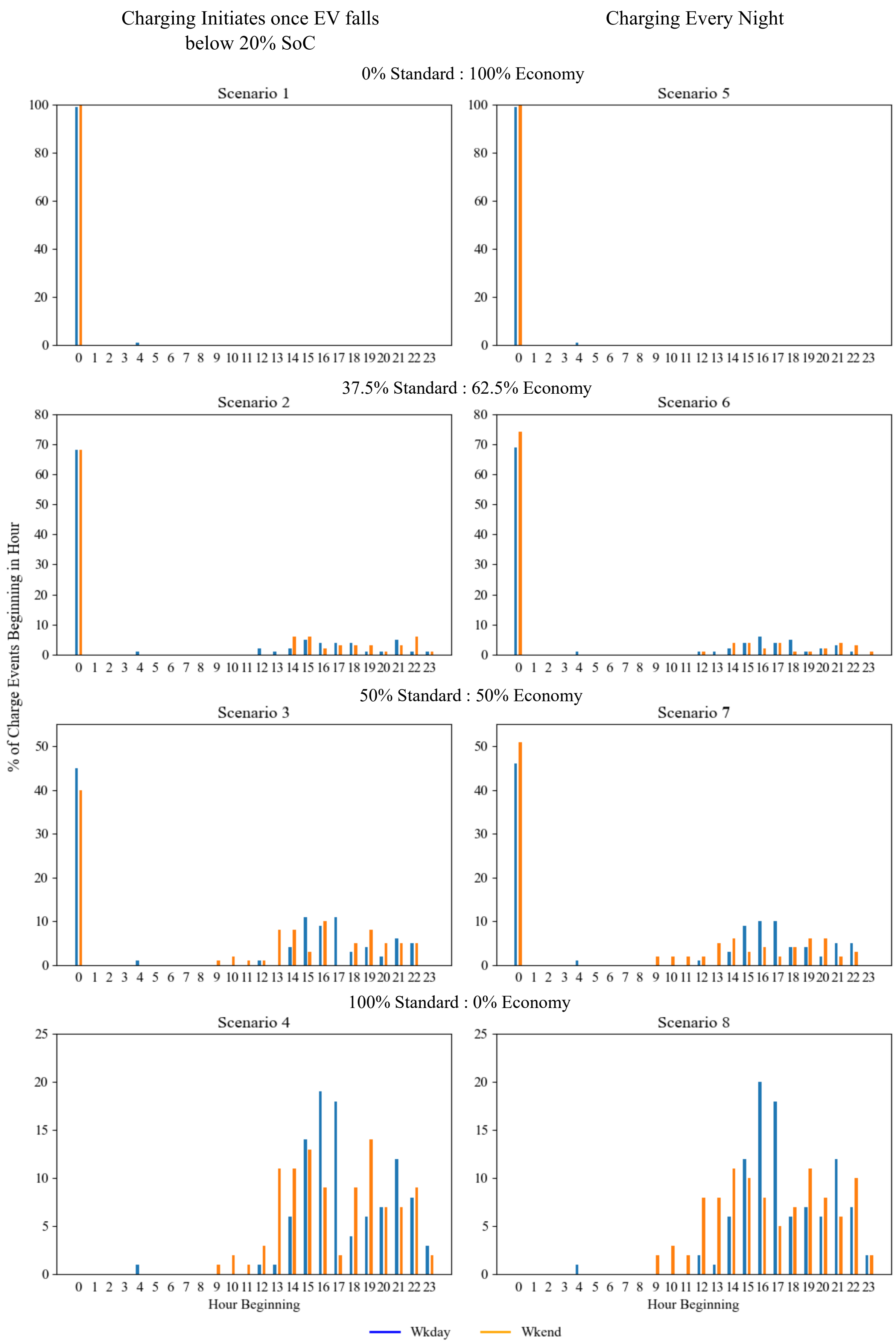


Figure 4.23: Distribution of Start Charge Time – Weekday and Weekend

Although the spread of charge start times in scenarios 4 and 8 most closely reflect the real life recordings as seen by Western Powers' Electric Nation study (Figure 4.22), there is still some considerable difference. A comparison of these two scenarios and the results from Western Powers' study is presented. The weekday distribution can be seen in Figure 4.24 and the distribution for Weekend charging start times shown in Figure 4.25.

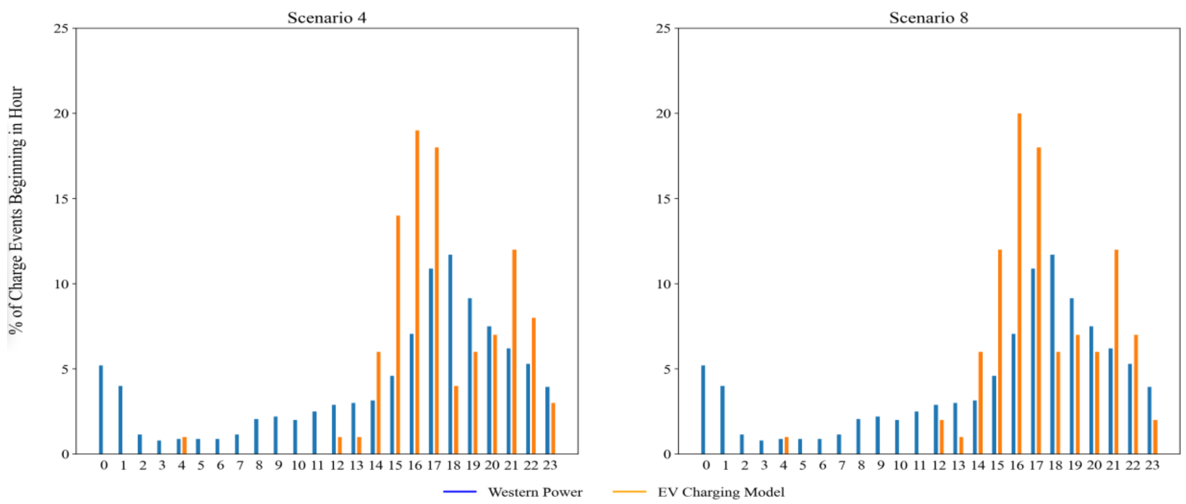


Figure 4.24: Comparing Distributions of Start Charge Times between Western Powers' and Scenario 4 & 8 – Weekday Only

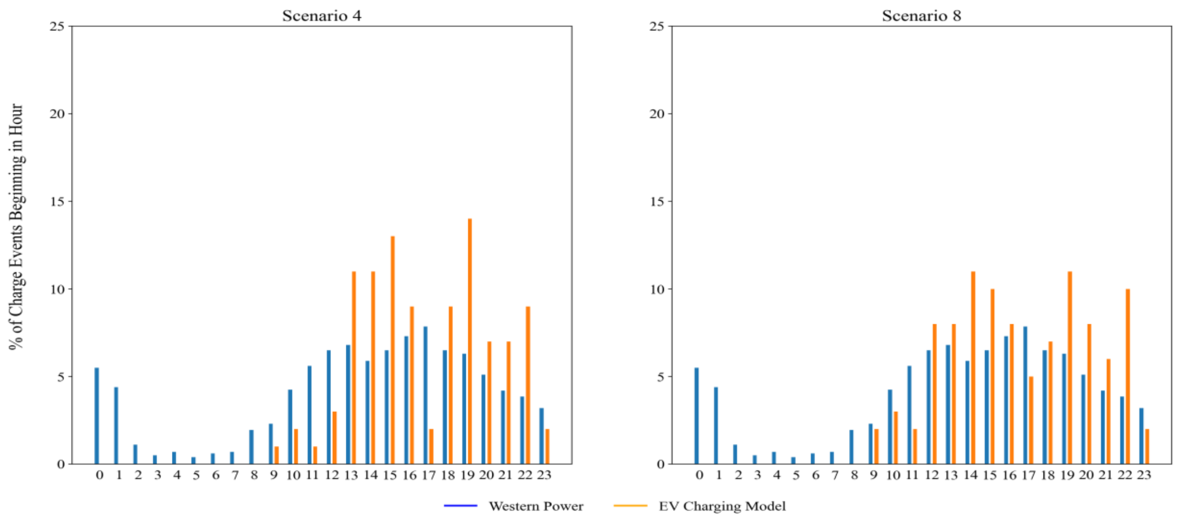


Figure 4.25: Comparing Distributions of Start Charge Times between Western Powers' and Scenario 4 & 8 – Weekend Only

This is most likely due to multiple reasons; however, most prevalent would be the amount of data captured. The Electric Nation study ran for 18 months, whereas the results presented for the EV Charging Model are only for a period of 4 weeks. The larger duration of the Electric Nation Study also captures the variability experienced by individuals themselves, i.e. the variability due to holidays, school terms and weather impacts. For instance, the travel patterns over 4 weeks may look different should those 4 weeks be captured during school term time or not for households with school children. This heterogeneity is not captured by the TDM used in this work and thus may lead to the higher concentration of results in these scenarios occurring over a shorter time period of the day. Additionally, the EV Charging model simulates a total of 84 vehicles only, compared to the larger sample size of the Electric Nation study, nearly 700 individuals. The smaller sample size simulated fails to capture this larger variance in the results.

This effect can be seen more so when comparing the results of Weekday profiles to Weekend profiles. During the weekend, car usage occurs in a shorter period of the day, with journeys beginning later and final journeys ending sooner (as shown in Figure 3.20 in Chapter 3). This exhibited behaviour manifests itself in charging events again by occurring during a shorter window of the day. As shown by Figure 4.25, the results from the EV Charging Model for Scenarios 4 & 8 on weekends exhibit smaller differences to the Western Power Electric Nation Data compared to the weekdays, Figure 4.24.

4.4 Chapter Summary

This chapter presented a novel EV Charging Model, developed to capture the energy and power requirements to sustain the travel patterns of the 84 vehicles belonging to Bradbourne, as simulated by the Travel Demand Model discussed in Chapter 3. A total of 8 scenarios were simulated, varying two main parameters of the model – Electricity Tariffs and Charging Behaviours. The simulations ran for a period of 4 weeks, from which a specified time period was selected to ensure all results presented are in accordance with the 1st Law of Thermodynamics. This necessity being highlighted by the preliminary work conducted in Chapter 3.

The results presented were for 4 variations of household electricity tariff options (combinations of Economy and Standard tariffs) and 2 behavioural options (charging upon the battery reaching a lower threshold and charging every night regardless of SOC) to create the 8 scenarios investigated. Key findings from the results of the EV Charging Model saw an expected pattern emerge between energy and power demand for the EV population. Power was essentially double that of energy, due to the half hour nature of the EV Charging Model and the underlying TDM. Interestingly, for scenarios 1-4, results indicated no discernible relationship between the day of the week and energy/power demand, whereas with relation to scenarios 5-8, higher demand was seen generally over the weekdays, with less at weekends. This pattern is expected when considering current travel patterns, and the underlying TDM. Scenarios 5-8 also saw vehicles have a generally higher SOC at any one time which will provide some comfort to rural residents with one of the primary concerns for EVs in rural areas being range anxiety (Tiwari et al., 2020; Carley et al., 2013).

Following further discussions of the results, a comparison, to act as a sort of validation for the EV Charging Model, with Western Power Distribution’s Electric Nation study was conducted.

The adaptability and scalability of this novel EV Charging Model should not be overlooked. Although not investigated in the scenarios presented in this thesis; due to resource constraints, this EV Charging Model is capable of handling a variety of scenarios, including differing fleet compositions, fleet sizes and charge point availabilities. These features will prove to be useful to policy makers and electrical grid planners who will be fully able to understand the requirements of an EV population and how consumers of an area may attempt to recharge them. For consumers themselves, specifically rural communities, the work presented in this Chapter should serve as antidote for any concerns regarding range and usability of EVs in rural settings. This will be further discussed in Chapter 8. With the work presented in this chapter and the previous, *Research Aim 2* has been achieved.

The findings from this chapter will be used to investigate the impact these energy and power simulations have on the local grid infrastructure as well as providing a basis for financial analysis to further aid the facilitation of electric vehicles in rural areas.

CHAPTER 5: IMPACT ON GRID SUPPLY DEMAND DUE TO EV UPTAKE IN RURAL AREAS

The previous chapter concluded with the presentation of energy and power requirements due to the charging of 84 electric vehicles which could be located in the village of Bradbourne. Multiple scenarios were discussed that highlight the large variability in the population's energy and charging requirements, and most importantly, the potential for sudden spikes in power demand due to multiple simultaneous charging events. The effects of which will be the main focus of this chapter.

This chapter begins by examining the local grid infrastructure surrounding Bradbourne (Section 5.1), including a largescale dataset acquired from Western Power Distribution (WPD). At the time of writing, WPD is now known as National Grid (National Grid, 2023), however hereafter, this network operator shall still be referred to as Western Power Distribution (WPD). This is followed by Section 5.2, which looks at the combination of this dataset with the results of the EV Charging Model presented in Chapter 4. Here examples are given to show the unreliable nature of instantaneous power readings depending on the resolution of time used and the standard which will be taken forward for further analysis. A look into grid failures is presented in Section 5.3, and the cause for concern that integrating this large EV fleet on local grid infrastructure will have. Lastly, a forecast model for determining when these levels of EV integration are likely to occur has been developed and presented in Section 5.4. The chapter concludes with Section 5.5. Material presented in this chapter has been published previously in the following papers: McKinney et al., (2023a, f).

5.1 Local Grid Infrastructure

As highlighted in the previous chapter, arguably the more concerning aspect of the EV transition is the power demand, compared to the energy demand. This chapter's focus will be to take the results and conclusions drawn from Chapter 4 and investigate their real-world impact.

Energy demand can always be met through increasing production capabilities (i.e. building more sources of generation). However, the power drawn is limited by the physical infrastructure that comprises the grid (i.e. the size and ratings of the transformers). This constraint is only exacerbated in rural areas which typically consist of less robust grid infrastructure in general (i.e. smaller substations, or transformers, attached to wooden poles) (Western Power Distribution, 2022a).

As described in Chapter 3, the area of interest and focus of the simulation is the rural village of Bradbourne, located in the Peak District. To keep this work in line with previous, the work in this chapter continues to focus on this same area. Bradbourne is served by the network operator Western Power Distribution (WPD). Typical grid infrastructure pathways are illustrated in Figure 5.1 below.

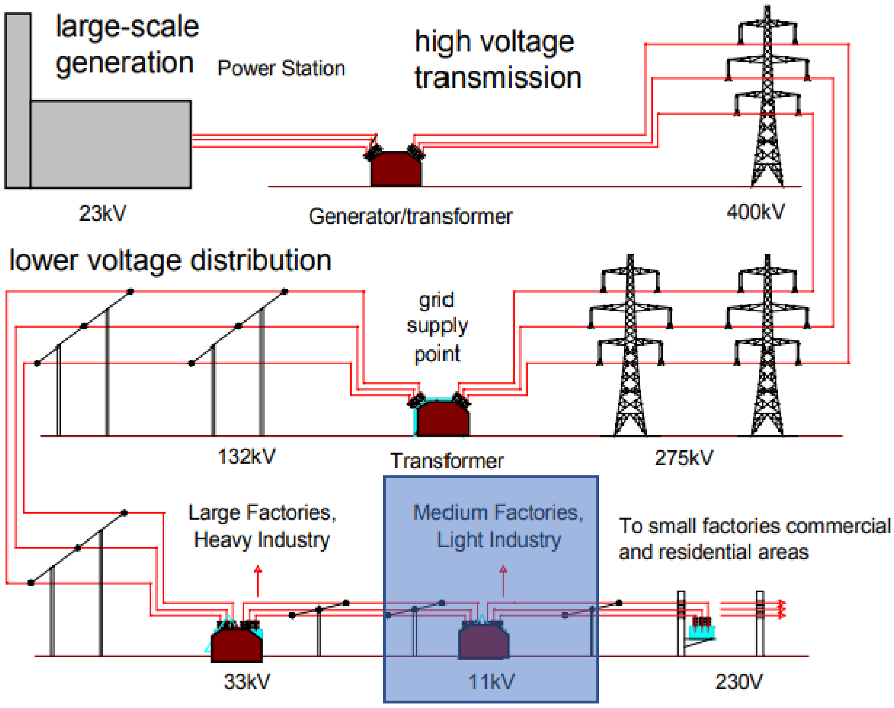


Figure 5.1: Electricity Network Diagram (Parliamentary Office of Science and Technology, 2001)

Within Bradbourne itself, there is only one local road-side transformer, transformer 890416 (IVY COTTAGES BRADBOURNE). This is the lowest level of grid infrastructure within Bradbourne that is publicly listed via WPDs Electric Vehicle Map (Electric Vehicle Map, 2023). However, as this information is sourced from the EV Capacity Map Application, no details regarding the specifications of this transformer are provided. To assess the grid impact of the results from the EV Charging model presented in the Chapter 4, aspects such as demand headroom need to be determined. To acquire this information, the choice was made to move upstream, in terms of the electricity network, to a higher substation level (diagrammatically highlighted in the blue box in Figure 5.1).

Figure 5.2, taken from WPD's Network Capacity Map, shows the area of coverage of primary substation 890067 (Longcliffe 33 11kv S Stn) which serves Bradbourne and the surrounding areas.

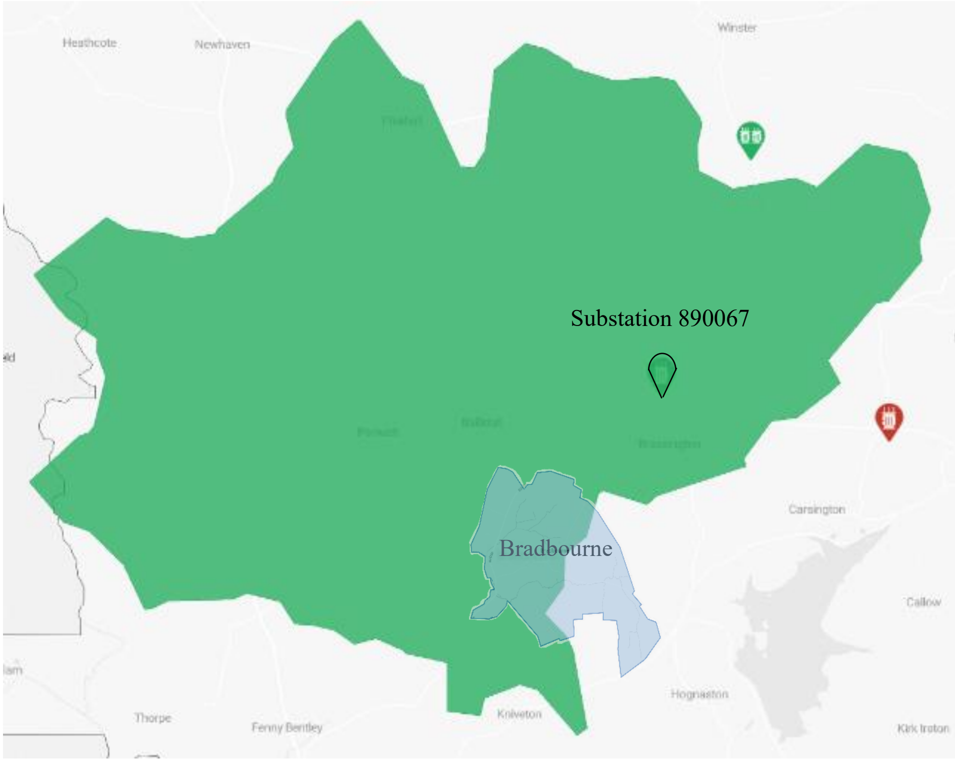


Figure 5.2: Network Capacity Map – Primary Substation 890067 (Network Capacity Map, 2023)

5.1.1 Western Power Distribution Dataset

Western Power Distribution (WPD), the network operator responsible for supply to this area, was approached to support this research project via the supply of data on the local grid infrastructure to Bradbourne, vis-à-vis energy or power measurements. WPD was able to provide recordings of power drawn every half-hour for Transformers 1 & 2 at the Longcliffe Primary Substation 890067. Following some pre-processing steps to clean the dataset, as some datapoints were either missing or mis-reads, this was replaced with their nearest other half-hour values, the values for T1 & T2 were combined. Assuming a Power Factor Correction (PFC) value of 0.95 (Network Capacity Map, 2023), this allowed for the conversion of this transformer data from Apparent Power (VA) into True Power (W), which enabled greater synergy between this dataset and the results from the EV Charging Model. The dataset provided by WPD, following these pre-processing steps, can be seen below in Figure 5.3.

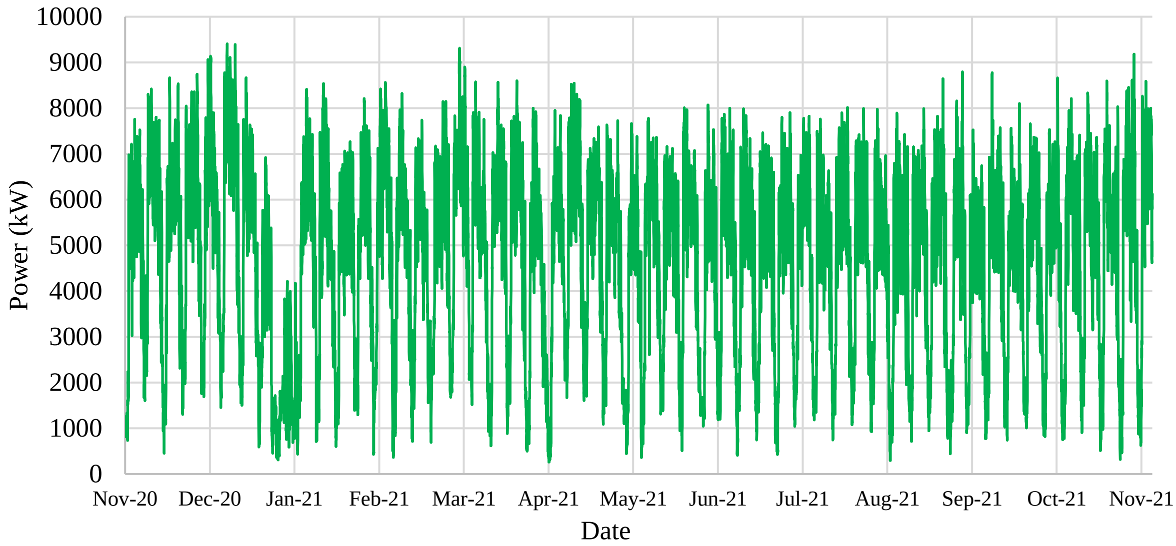


Figure 5.3: WPD Dataset – Power readings for Substation 890067

Over a year (376 days) of power data was supplied by WPD, with a date range of 01/11/2020 till 12/11/2021. Noting this timeframe was largely disrupted by COVID-19 and thus there will be a large impact on the power demand compared to 'normal' use. From speaking with WPD during the stages of acquiring this dataset, continual monitoring of substations and the recording of their usage is not common practice for substations where there are no concerns. Only when it is required for analysis of various kinds is data collection carried out on their part. This resulted in an inability to filter for an 'ideal' dataset (ideal being a pre or post-COVID date range when usage would reflect regular behaviours), however fortunately the substation in question which serves Bradbourne, and the larger area (Figure 5.2) had been monitored recently.

An in-depth analysis of this substation dataset has not been carried out, as the requirement here is to use the data in combination with the results of the EV Charging Model to investigate the impacts of EV integration in this area. Nevertheless, Figure 5.3 shows the expected cyclical nature of power demand at a substation across days, where we see reduced demand during the early hours and across weeks, with reduced demand on Saturday and Sundays easily seen as compared to weekdays. Additionally, there is a large drop in power demand for a few weeks during the Christmas and New Years period, which is most likely due to the closing of businesses and thus the remaining demand is due solely to the residential sector.

5.2 Impact on Grid Supply Demand

WPD was only able to provide power readings from the substation, most likely due to power being the main concern for a grid operator, as opposed to energy. Similarly, with the integration of EVs, power requirements are of greater concern than the energy requirements these vehicles demand. Therefore, the focus of the grid impact study on Bradbourne's local grid infrastructure will be concentrated on the increased power demand from EVs.

Due to the size differences between the area covered by the dataset provided by WPD, and the area of Bradbourne, the decision was made to extrapolate the results of the EV Charging Model to a comparable area as covered by the WPD data, the results of which were validated. This validation comprised of comparing 'household occupancy' and 'cars per household' for the two respective areas: Bradbourne and the larger total area covered by the WPD data. This required the composition of the land area covered by primary substation 890067, which was determined via the combination of the various census output areas which make up this area, see figure 5.4. Unfortunately, as can be seen from the figure, it is never possible to get a clear and complete overlap of data from more than one source.

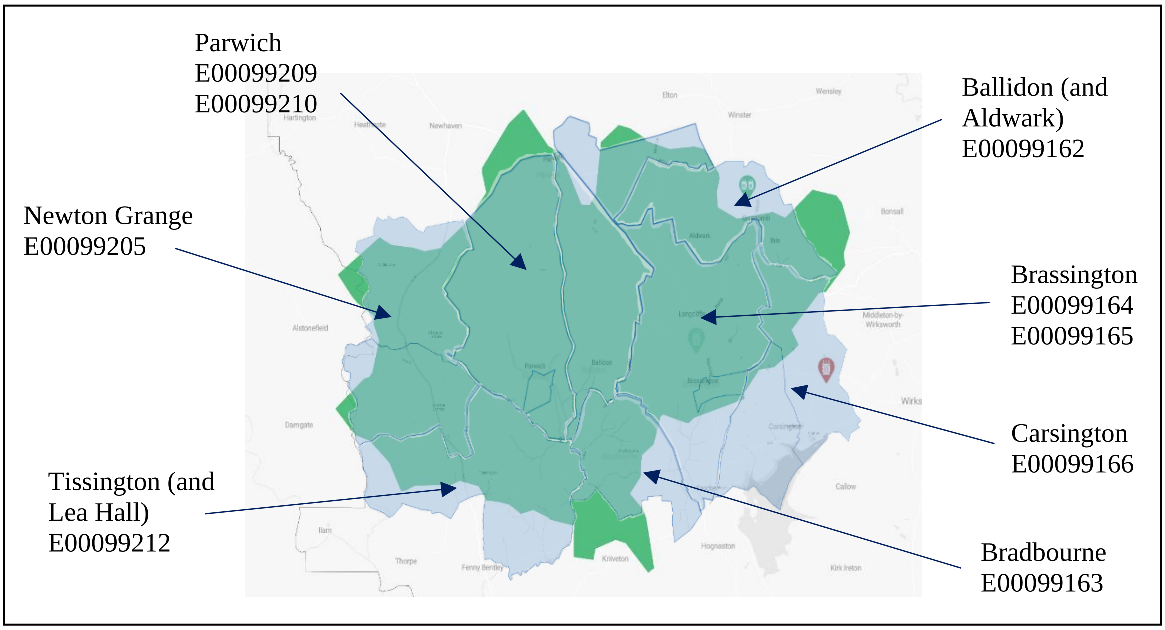


Figure 5.4: Primary Substation 890067 coverage area with census output areas (COA's) overlaid

For each of these seven census output areas, the household composition and vehicle availability of each household was retrieved from the UK Census (Nomis, 2013a; Nomis, 2013b) – following the same process described in Chapter 3, Section 3.1. The results of this can be seen below in Figures 5.5 & 5.6, which compare the occupancy and vehicle distributions of Bradbourne to the other areas, respectively.

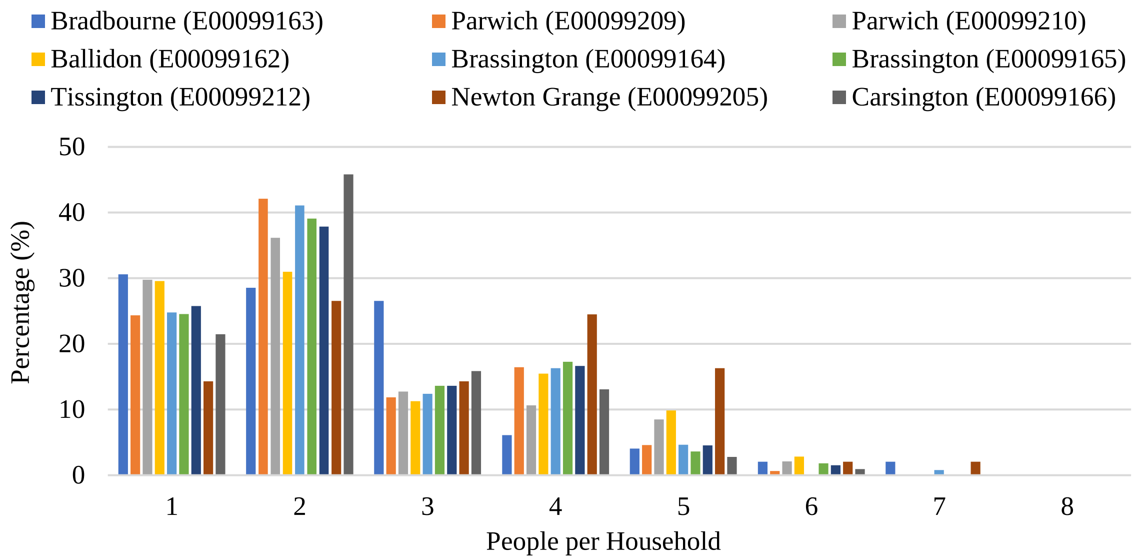


Figure 5.5: Occupancy

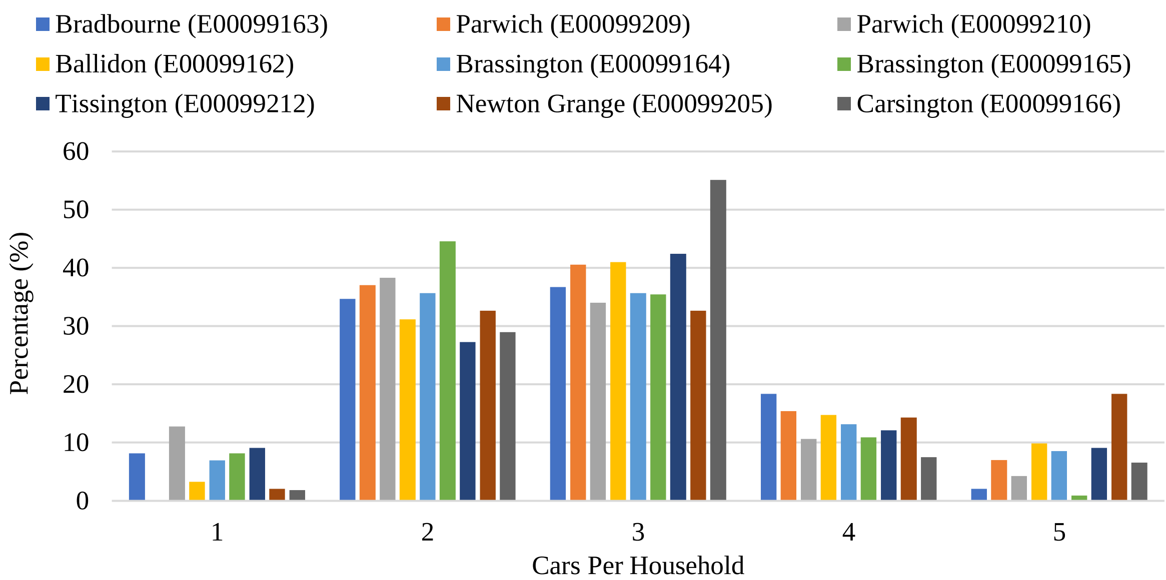


Figure 5.6: Vehicle availability

Figures 5.5 & 5.6 show that the composition(s) of Bradbourne (used to develop parameters for the TDM in Chapter 3, and the EV Charging Model in Chapter 4), are representative of the larger area within which Bradbourne lies. Therefore, the results of the EV charging model have been scaled to assume a more accurate grid demand against the larger area constituting the WPD dataset.

Scaling was achieved through determining the factor between the 84 vehicles of Bradbourne and the total number of registered vehicles across the seven census output areas covered by primary substation 890067. Across all these census output areas (Figure 5.4), a total of 1380 vehicles belonging to 780 households exist (a breakdown of these numbers is in Appendix B) and have been scaled by a factor of 16.43. This scaling factor was applied to the results of the EV charging model and the results can be seen in Figures 5.7 and 5.8 for each electricity tariff scenario 1-8. As mentioned previously, only power data was supplied for the grid demand by WPD and so only the power results from the EV Charging Model will be taken forward for further analysis.

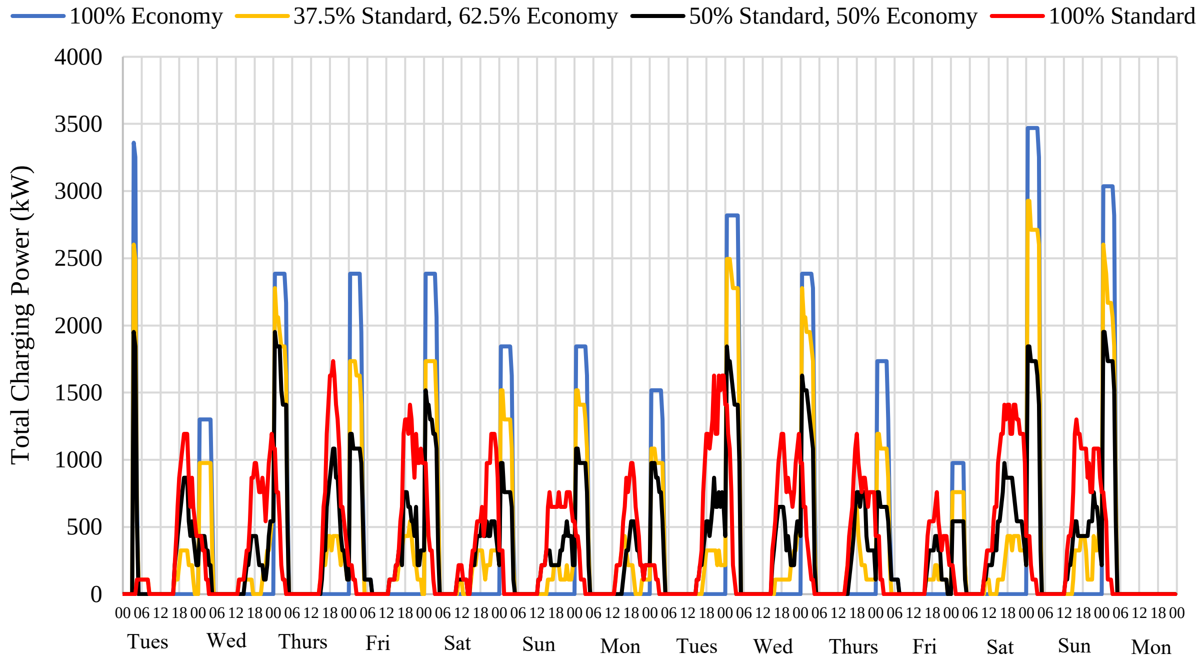


Figure 5.7: Power demand from EV Charging Model scaled - Scenarios 1, 2, 3 and 4

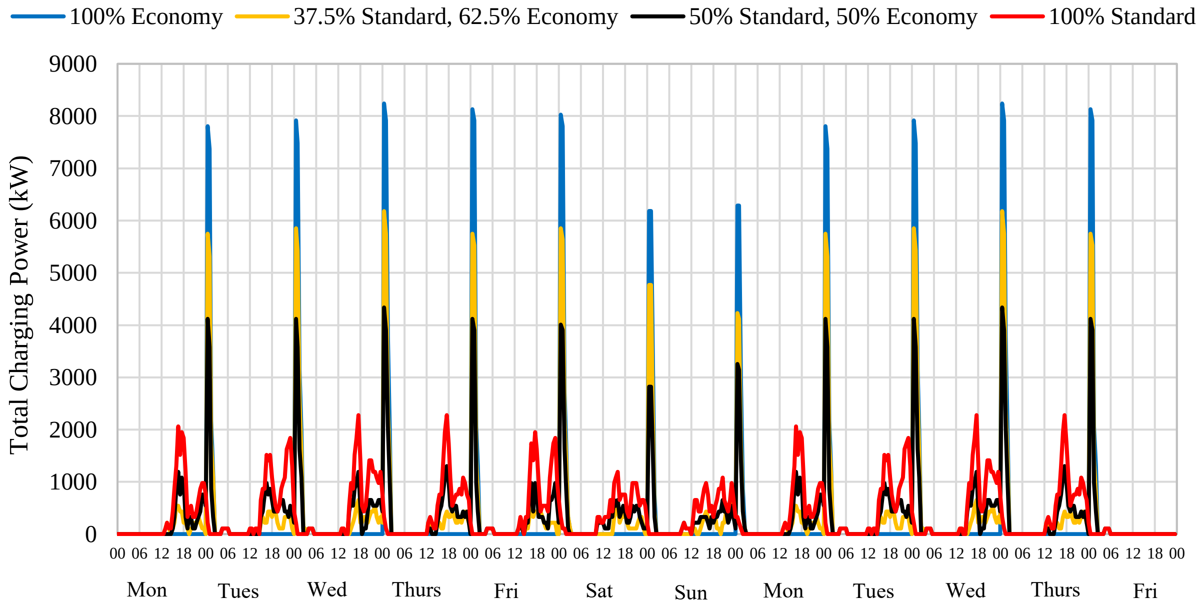


Figure 5.8: Power demand from EV Charging Model scaled - Scenarios 5, 6, 7 and 8

Combining these extrapolated EV Charging results with the WPD dataset can be done in various ways, each yielding differing results. Three methods have been explored with the aim of selecting the best to take forward for further analysis. The three methods are:

- Daily Average
- Highest Peak
- Average Week

After having examined selected time periods discussed in Chapter 4 (Table 4.6), the simulation was found to not diverge over a longer time duration. Thus, to allow for easier visualisations of the data, a period of one week was chosen to showcase the combination of EV Charging and pre-existing grid loads. The three different approaches presented illustrate the importance of temporal resolution and averaging, particularly when it comes to power, and how these can manipulate results and the conclusions drawn.

With regards to the three approaches, this required the averaging for all half-hours of the day across each of the 376 days of data provided by the WPD, separated by the days of the week. For example, each half-hour timestep for 00:00-00:30 for every Monday within the dataset was averaged to provide a 'typical' Monday 00:00-00:30 value. This was repeated half-hourly for every day of the week to generate the data for the 'Average Week' method. These were then averaged again to obtain the 'Daily Average' data across all 48 half-hour values of each day. For the 'Highest Peak' method, the largest half-hour instantaneous power demand value recorded across the years' worth of data was identified, and the week surrounding this value taken forward. To generate the same values for the EV fleet, the same processes were undertaken on the scaled results from the EV Charging Model (Table 4.6).

5.2.1 Daily Average

This method took the WPD dataset and reduced it down to an average single value for each day of the week. The same was applied to the results of the scaled EV Charging Model results. This combination, for scenarios 1-4 and 5-8 are presented in Figure 5.9 and 5.10 respectively.

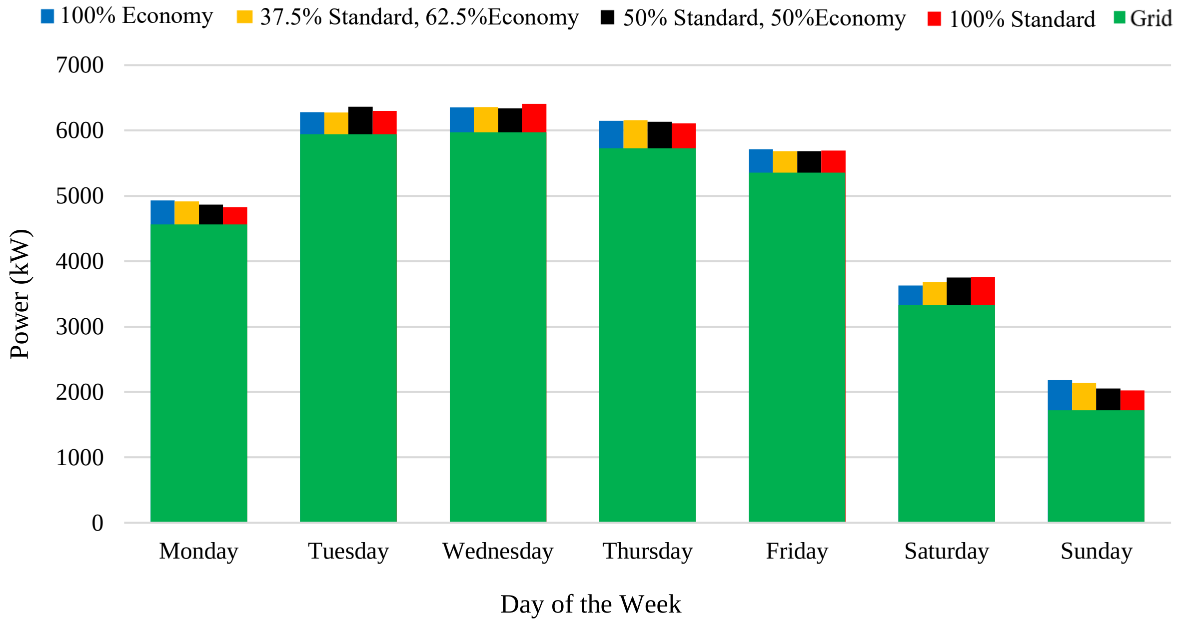


Figure 5.9: Scenarios 1, 2, 3 & 4

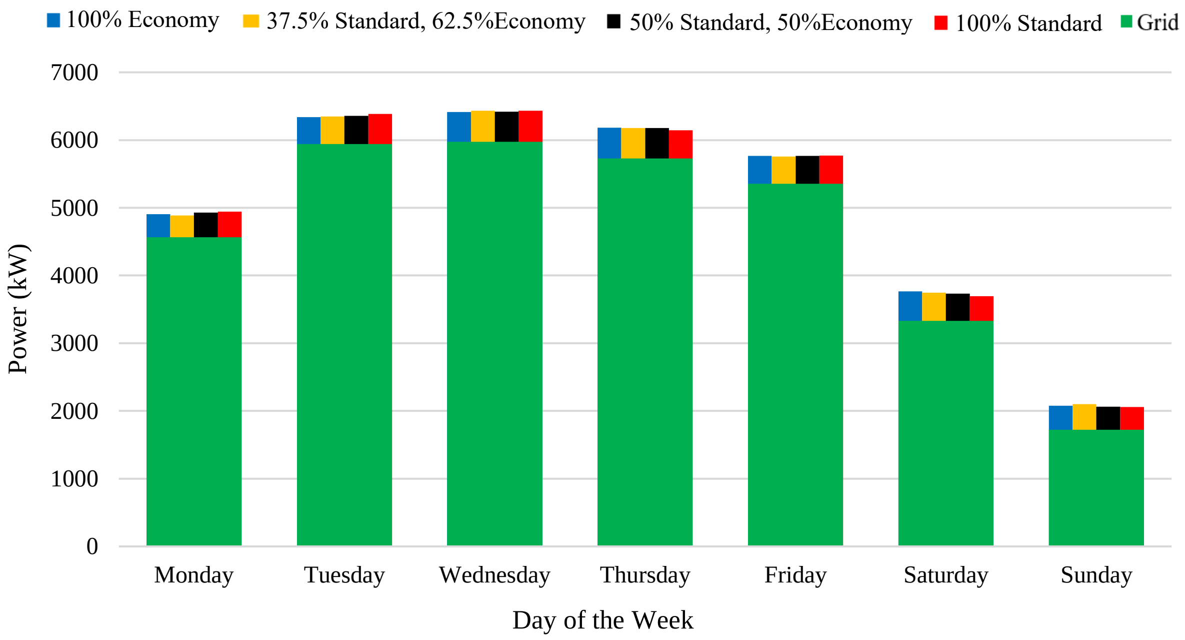


Figure 5.10: Scenarios 5, 6, 7 & 8

Figures 5.9 and 5.10 show the increase in power demand from integration of EVs is minimal, resulting in roughly an 8% increase each day. This is misleading in its presentation due solely to the instantaneous nature of power. Although the average power demand due to the EV fleet charging across the whole day is low, as shown by Figures 5.7 and 5.8, there are very large spikes lasting for short periods of time. From a grid operators' perspective, these spikes are a significant cause for concern for grid stability and efficiency. The contrast cases which highlight these spikes, and their impact, are visible in the following two approaches.

5.2.2 Highest Peak

Looking at a more conservative approach to this impact investigation on the grid, here the results for each charging scenario are used in combination with the highest peak demand seen in the WPD dataset. The highest pre-existing power demand occurred on the 08/12/202 at 20:00 with a reading of 9405 kW. The Monday to Sunday week surrounding this date (07/12/2020 – 13/12/2020) is shown in Figure 5.11.

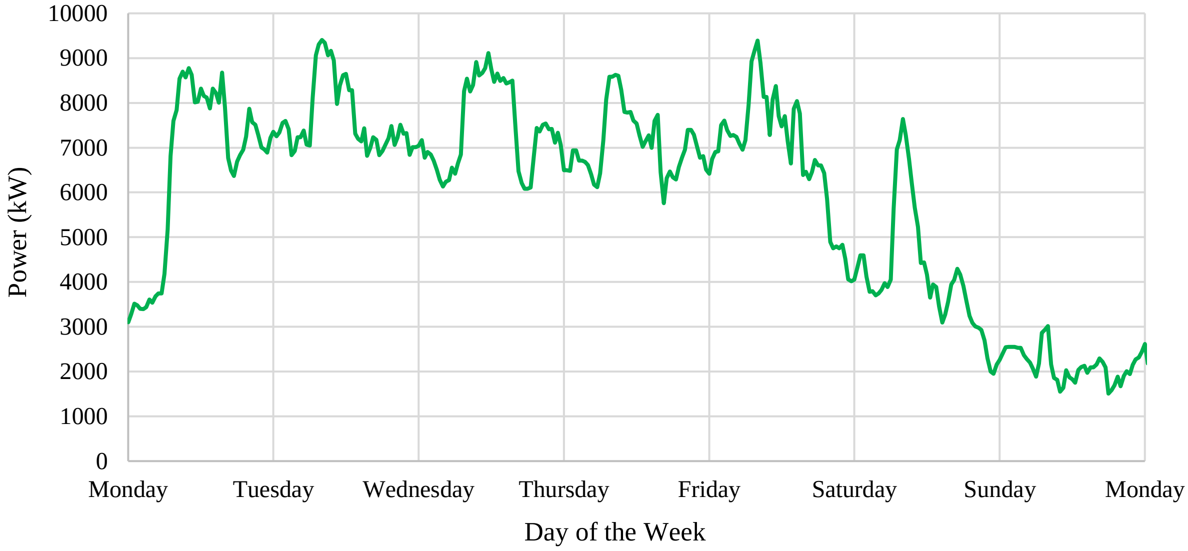


Figure 5.11: The week with the highest pre-existing power demand on the grid

Again, this section of grid data was combined with the scaled results of the EV Charging Model which can be seen in Figures 5.12 and 5.13 for scenarios 1-4 and 5-8 respectively.

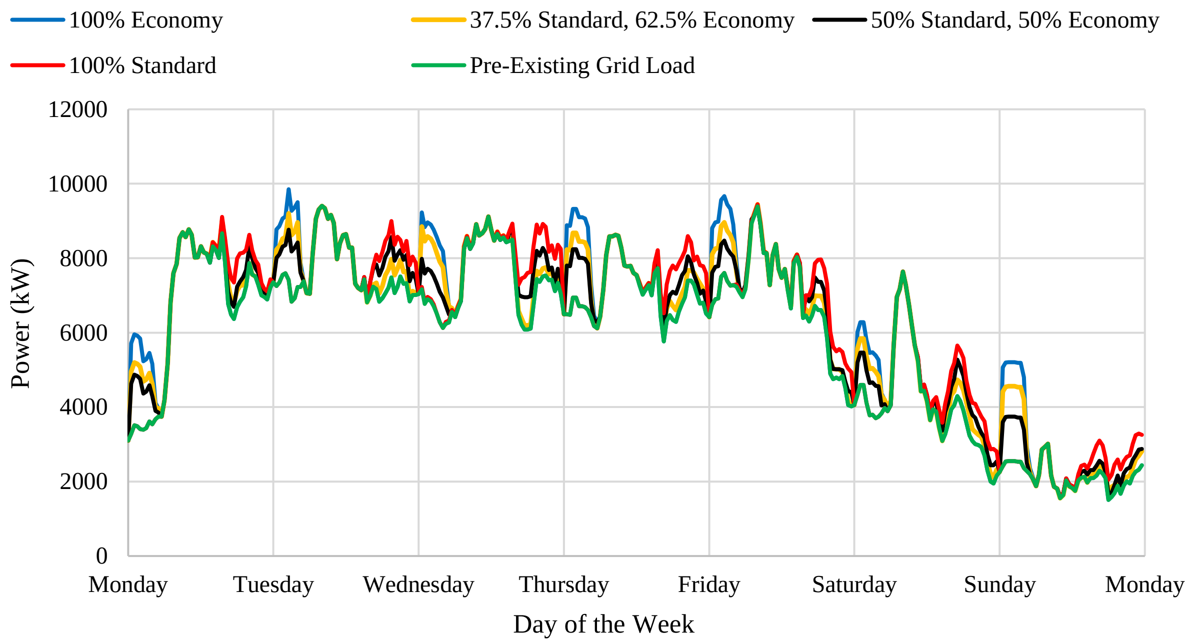


Figure 5.12: Scenarios 1, 2, 3 & 4 – Scaled EV Charging Model results combined with the largest pre-existing power demand on the grid

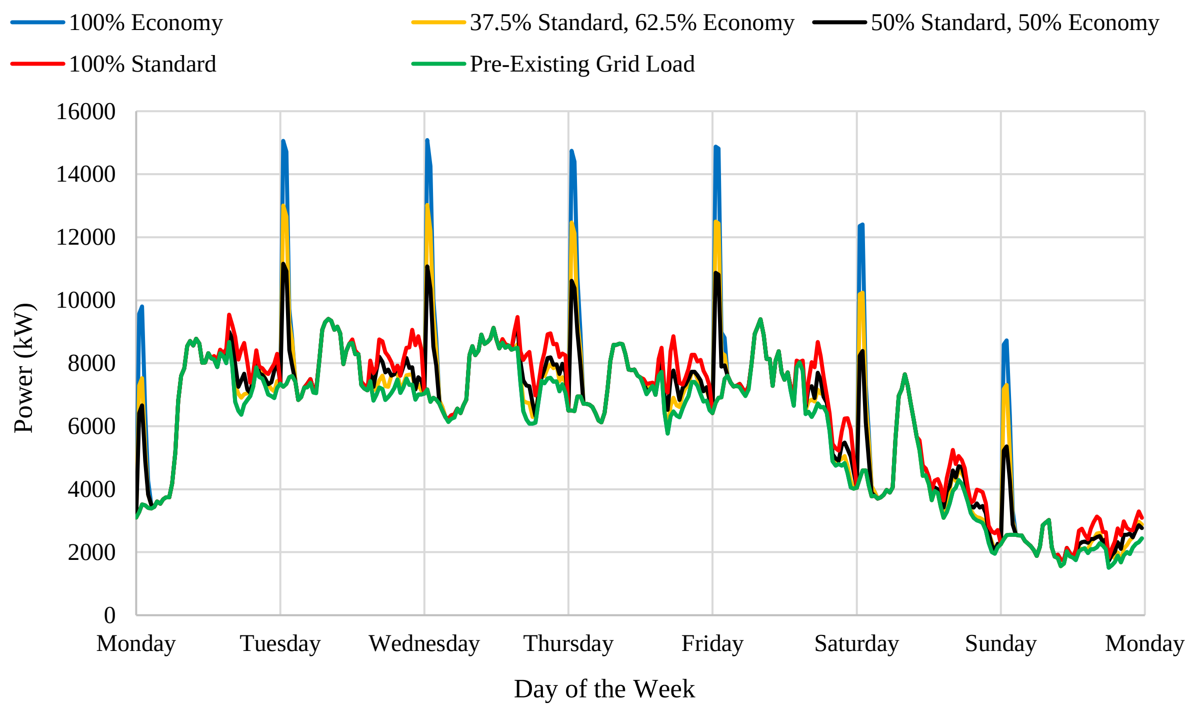


Figure 5.13: Scenarios 5, 6, 7 & 8 - Scaled EV Charging Model results combined with the largest pre-existing power demand on the grid

With the inclusion of half-hourly values, as shown in Figures 5.12 and 5.13, the fluctuations of power over time is much more evident, when compared to the daily values of the previous method. With these peaks and troughs now evident, the addition of the EV fleet demand from charging appears very differently. For scenarios 1, 2, 3 and 4, there looks to be minimal increases in the peak power demand value. As mentioned previously, the largest pre-existing power demand on the grid was 9405 kW, with the addition of EVs, this has only increased to new maximum of 9853 kW as seen in the 100% Economy scenario (scenario 1), representing a 4.8% increase.

In contrast, for scenarios 5, 6, 7 & 8, although the 100% Standard scenario follows a similar negligible impact as the previous four scenarios, as the ratio of Economy tariffs increases, the peak power demand rises drastically and becomes a significant impact and cause for concern. Scenario 5 (the 100% Economy tariff combined with charging every night) now increases the peak power demand to 15,084 kW, an increase of over 60% at the substation.

From a grid operators' perspective, these rapid changes in demand are of the most concern, and having shown the different ways the same dataset can be manipulated to indicate different grid impacts highlights the importance for accurate representation of power and its measurements as these can only ever be instantaneous in nature.

5.2.3 Weekly Average

For the purpose of this work, the decision was made to take an average week of the pre-existing grid load, as opposed to the worst-case scenario as detailed in the previous subsection. With this method in mind, the combination with the charging power requirements for the EV fleet are shown in Figures 5.14 & 5.15.

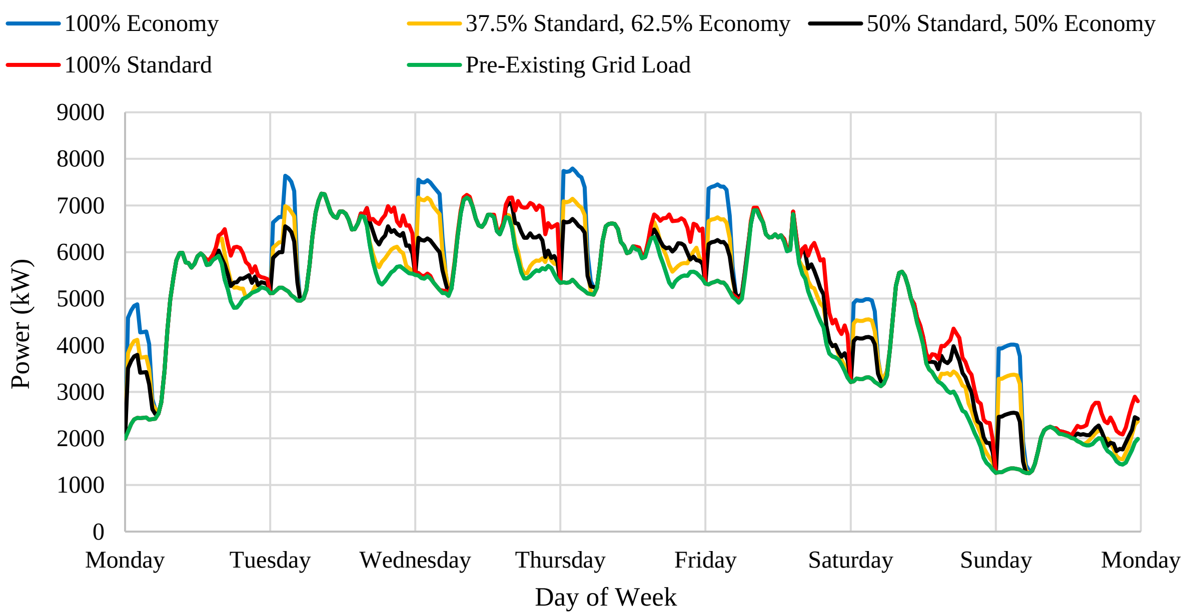


Figure 5.14: Scenarios 1, 2, 3 & 4 - Scaled EV Charging Model results combined with the average weekly pre-existing power demand on the grid

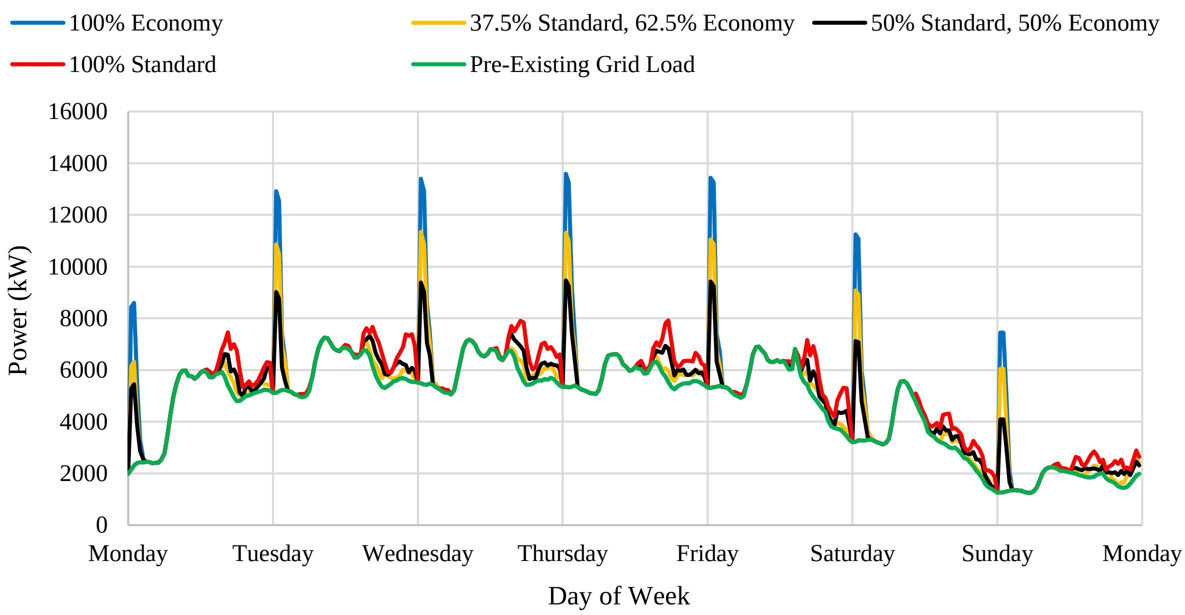


Figure 5.15: Scenarios 5, 6, 7 & 8 - Scaled EV Charging Model results combined with the average weekly pre-existing power demand on the grid

The combination of the scaled EV Charging Model results with the average weekly pre-existing grid loads follow a similar pattern to the combination with the highest peak week (Figures 5.12 and 5.13) with the major difference being the highest peak demand. With the average weekly method, the highest power demands are 7793 kW and 13,594 kW for scenarios 1-4 and scenarios 5-8, respectively. However, this method does present a more regular pattern for grid demand, having averaged across 52 weeks, as opposed to taking the solely largest week. Going forward, this method and the resulting pre-existing grid values it produces will be taken forward for further analysis into the grid impact of Bradbourne and the surrounding areas. It is important to note that infrastructure is sized to cope with the highest demand to avoid it becoming dangerously overloaded.

5.3 Investigation into Grid Overload Events

The work presented in this chapter thus far is based on the continued premise of one charge point per vehicle, which currently yields 1380 charge points connected to substation 890067. This scenario, whereby every vehicle has its own home charge point, is unrealistic due to the constraints of, firstly the type of wiring/fuses in households of the UK. A typical UK household will be fitted with a mains 100 A fuse, considering that the 7 kW Pod Point chargers presented in Chapter 4 required around 30 amps, this would limit any household to a maximum of 2 charge points under reasonable calculations given pre-existing household energy demands. Even with three chargepoints, this would leave very little current for the pre-existing household use. Secondly, the actual upfront costs for having multiple charge points installed for households with multiple vehicles may well be prohibitive.

However, investigating the case for 1380 charge points connected to this substation is still beneficial, especially as a worst case scenario. From the grid's perspective, 1380 charge points may not be unrealistic when also considering public charge points. A sensible case for 1380 charge points to be connected to the grid from within this area of interest can be made when considering not just the local population, but also tourists. Especially at weekends and on holidays where others may travel to rural areas for outdoor activities (hiking, climbing etc). In conjunction with public charge points installed at supermarkets and workplaces , a case can be made for the scenario where it is highly possible 1380 charge points could be in use simultaneously, within this larger area around Bradbourne (see figure 5.4). It should be noted that this saturated charging scenario (whereby 1380 charge points, i.e. all charge points within the simulation, are in use simultaneously) is a worst case scenario. Therefore, understanding the impact of this number of charge points on the current grid infrastructure is essential for future proofing the grid, especially understanding the impacts of grid failures. As part of the Network Capacity Map discussed in Section 5.1, specifications for each substation are detailed. Those for substation 890067 are presented below in Table 5.1.

Substation Name	Longcliffe 33 11kv S Stn
Substation Type	Primary
Substation Number	890067
Substation Firm Capacity	23.00 MVA
Substation Peak Demand	9.75 MVA
Substation Demand Headroom	13.25 MVA
Upstream Demand Headroom	4.50 MVA

Table 5.1: Demand specifications for Substation 890067 (Network Capacity Map, 2023)

As detailed by table 5.1, substation 890067 still has a demand headroom of 13.25 MVA available, however, this is limited by the upstream demand headroom, 4.50 MVA. Considering the current substation peak demand is 9.75 MVA, this indicates a grid capacity of only 14.25 MVA at this point. Applying a Power Factor Correction of 0.95 again, this is equivalent to a true power, grid capacity, of 13,538 kW. With 1380 charge points, each rated at 7 kW, if all were to be in use simultaneously, this would generate a power demand of 9,660 kW. For context purposes, the power demand forecasted for the scaled EV charging model scenarios (scenarios 1-8) saw a maximum of 3,470 kW across the 'Charging initiates once EV falls below 20% SOC' behavioural scenarios (this was seen in Scenario 1 – 100% Economy) and a maximum of 8,241 kW for the 'Charging every night' behavioural scenarios (specifically Scenario 5 – 100% Economy). This can be seen in figures 5.7 and 5.8. This indicates that the existing grid infrastructure is more than capable of meeting this increase in demand due to EV charging, however, the upstream infrastructure is a cause for concern.

With an existing grid capacity of 13,538 kW and taking the EV Charging demand to be a maximum of 9,660 kW, this would leave only 3,878 kW for the pre-existing grid load. Which as shown in Table 5.1, would not be enough for the already peak demand of 9,750 MVA (9,263 kW). These calculations are illustrated below in figure 5.16.

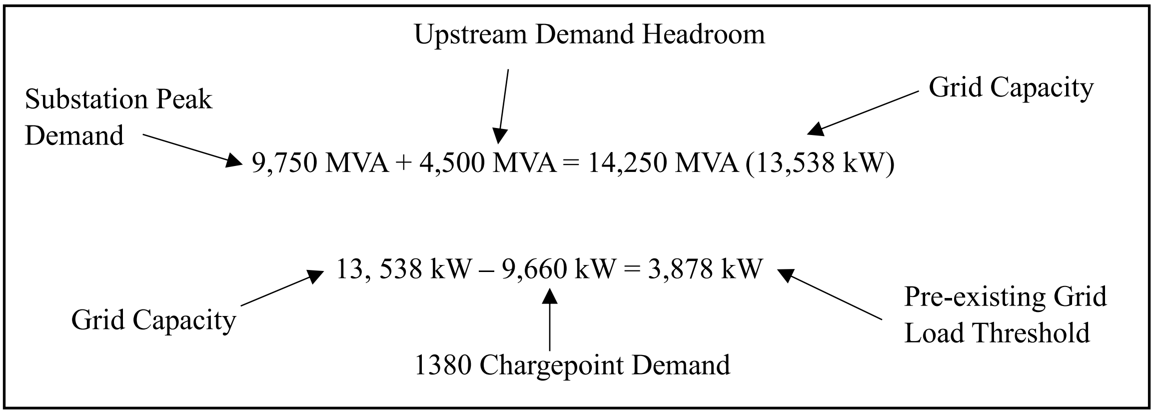


Figure 5.16: Substation 890067 headroom calculations

Given the upstream constraint on the grid system is 4.50 MVA (4,275 kW), it was calculated how many times, throughout the WPD's year of data, the grid infrastructure would not be able to cope with demand. This would be anytime the pre-existing grid power exceeds 3,878 kW. The WPD data for substation 890067 contains 18,040 data points of power measurements, comprising of meter readings every 30 minutes. Considering the 3,878 kW threshold, the grid would have exceeded this threshold 12,064 times (i.e. 12,064 half-hour segments during the year). The distribution of these grid threshold breakthroughs by the total consecutive half hour segments at any one time are shown in figure 5.17.

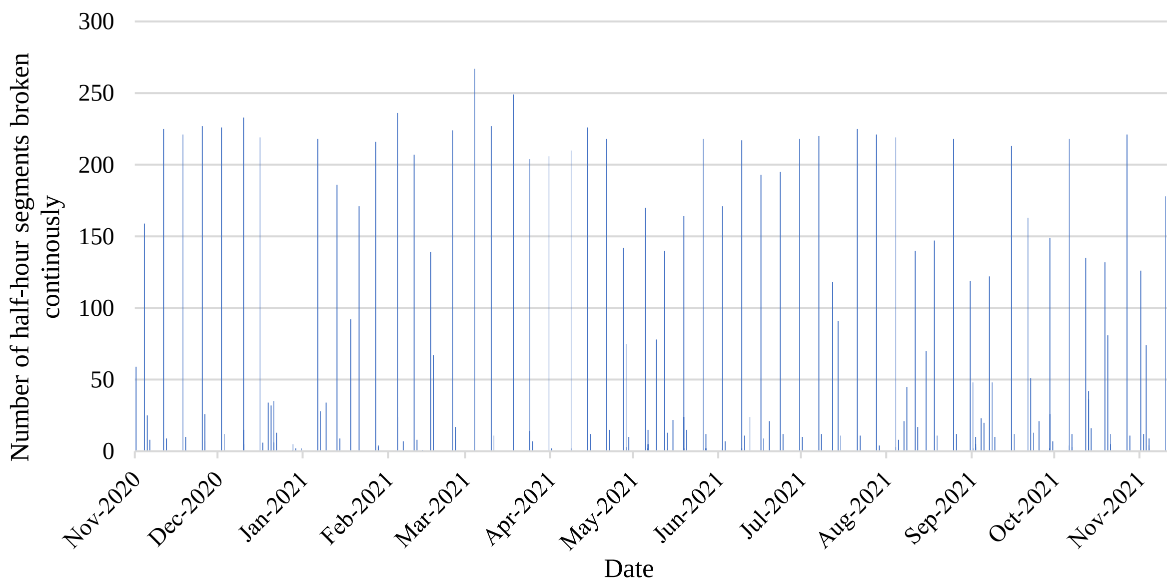


Figure 5.17: Grid Overload Points over the course of the Western Power Distribution dataset

The work presented in this section reserves the grids capacity for the 1380 charge points first and then calculates the breaches caused from any other load. In reality, this is the other way around, the demand from the EV chargepoints would cause the breaches and consequential potential overloads. This ‘order’ was chosen in order to conduct the calculations of threshold breaches quicker and directly using the WPD dataset.

Figure 5.17 highlights not just the large number of times this threshold is exceeded during the course of the year, but also, more concerningly the duration of some of these potential grid overloads. The longest non-stop period whereby this threshold is broken lasts for 267 half-hour segments, equivalent to 133.5 hrs (5 days 13.5 hrs). If the breakthrough of this grid threshold was to result in a power outage, due to overload of a transmission transformer for example, these long durations of power outages would be a major concern for EV owners. These breakthrough points have been grouped today into five categories; 12hr, 24hr, 36hr, 48hr, and 48hr+ and presented in table 5.2.

Half-Hour Groupings	Number of Occurrences
0-24 (12hr)	117
25-48 (24hr)	13
49-72 (36hr)	4
73-96 (48hr)	6
97+ (48hr+)	52

Table 5.2: Grid Threshold Breakthrough

The largest category of threshold breakthrough are those under a 12hr duration, which constitute 117 of the 192 breakthrough events highlighted. As the duration of breakthrough increases, the numbers of such cases continue to fall, with the final category (48hr+) combining many more instances into one and thus resulting in a larger number. Considering the figures used in the calculation of this grid threshold were taken from the upstream source of substation 890067, as per Table 5.1, the resulting impact should a threshold breakthrough occur would be much greater than just the sole area served by substation 890067. Rather, a much larger area would be impacted if this upstream transformer was to exceed its rating. This upstream transformer feeds, alongside 890067, a further 6 substations; covering a much larger area. This poses more cause for concern given the small headroom available for such a large area of coverage, should this area adopt solely EVs at some point in the future.

5.4 Timeline for Chargers

Having conducted a comprehensive assessment into the impact of this rural EV fleet within Bradbourne and the surrounding area on the local grid infrastructure, this section will provide a forecast for the timeline for when these impacts are likely to become a realisation. The focus thus far has been on 1380 vehicles, and by extension charge points, connected to substation 890067 which has been shown to be a cause for concern, however this is not an immediate concern. It will take time for this level of adoption to be reached, should it ever be reached.

Effort was therefore made to forecast when this level of adoption may become reality. However, determining a forecast for home charge point installation is difficult, due to the lack of publicly available data. Zapmap are the UK's leading digital platform for EV drivers to search for available public charge points, having 95%+ of public charge points mapped (Zapmap, 2023a). They offer the most accurate estimate for the number of charge points in the UK year on year. Between 2016 and 2021, the charge point network grew four-fold from 6,500 to more than 28,000 devices (Zapmap, 2022).

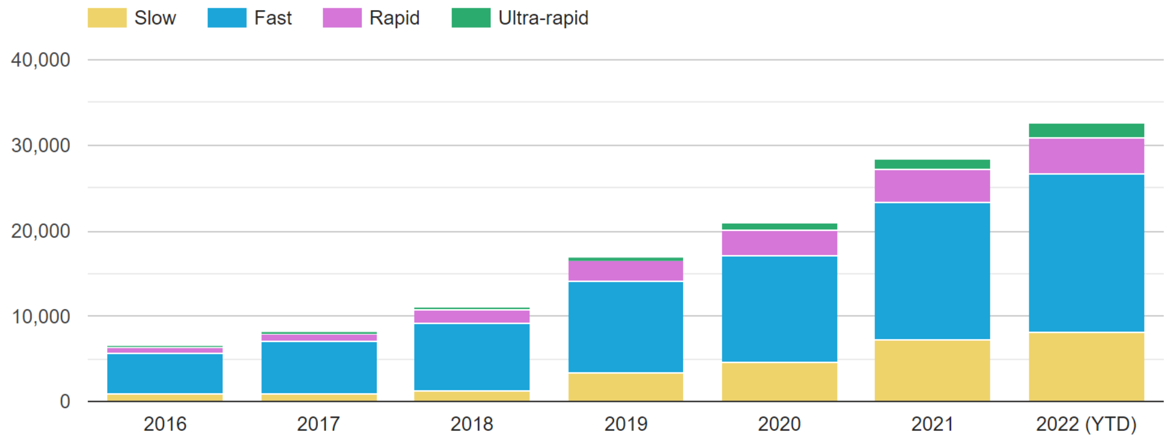


Figure 5.18: Number of chargepoints in the UK (Extracted from Zapmap, 2023b)

Whilst Figure 5.18 provides insight into how the availability of public charge points is changing over time, this does not necessarily correlate with private, 'home' or workplace, chargepoints. As per figure 5.18, there are 33,000 public UK charge points mapped as of 2022, however, in terms of private charge points there is estimated to be more than 400,000 (Zapmap, 2022). This indicates that the number of private charge points in the UK is likely much closer to the actual number of EVs registered in the UK (see Table 5.3). Which, during this early adoption phase of EVs is unsurprising, due to most UK households only having one vehicle and having not replaced all their current ICE vehicles with an EV. Therefore, the rate of increase for EVs themselves in the UK was chosen to be used as the basis for this forecast model. Table 5.3 presents the cumulative number of battery electric vehicles in the UK from 2016 till 2021 according to Zapmap statistics, which has been plotted and extrapolated using excels inbuilt functions enabling the determination of a trendline to use for forecasting in figure 5.19.

Year	Cumulative no. of battery-electric cars in the UK
2016	30,669
2017	44,266
2018	59,740
2019	97,565
2020	205,770
2021	396,497

Table 5.3: Cumulative number of battery-electric cars in the UK (Zapmap, 2022)

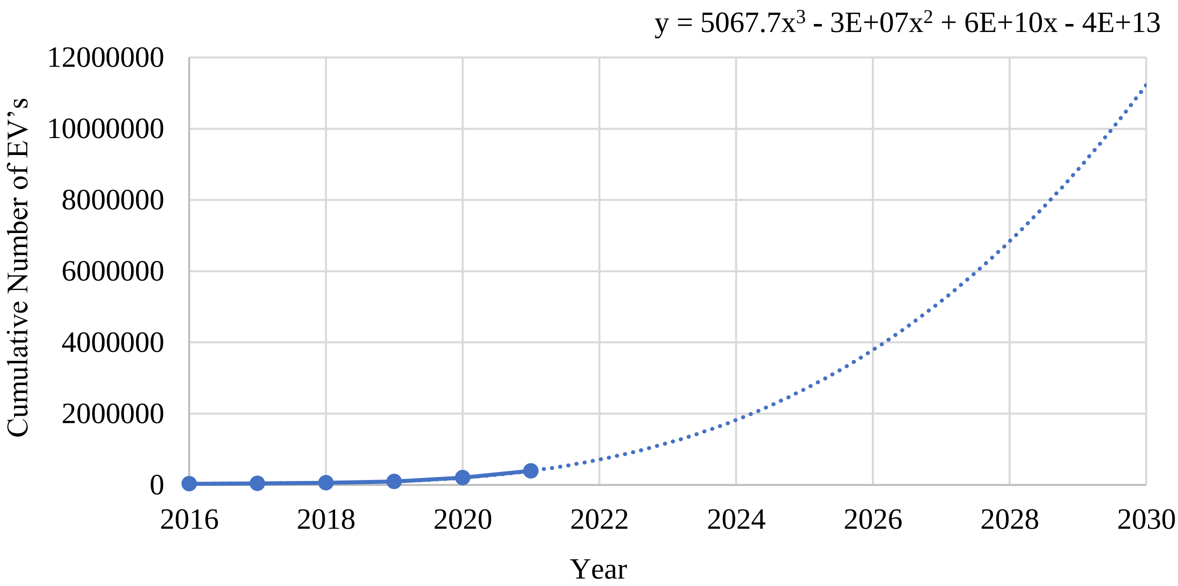


Figure 5.19: Extrapolated cumulative number of EVs in the UK with trendline

Following the determination of this trendline, the current number of private charge points is required. With the focus of this chapter, and in particular the work analysing the grid impact having been on the larger area surrounding and including Bradbourne, the timeline forecast will also reflect this. As well as receiving power related data from WPD, details on the devices connected to substation 890067 was also included (Western Power Distribution, 2022b). These devices included Biofuels, Waste Generation, Solar, Wind and the number of EV Chargers. Per this dataset, at the time of writing, there are 9 EV chargers connected to substation 890067. However, it is unsure if these are private home chargers or public charge points. To overcome this, effort was made to determine a more conservative approach and so provide a range for the time until 1380 chargepoints are connected to the larger area substation. Treating these 9 chargepoints, as per the WPD data, as the public charge points, using a ratio of 1:12 (calculated from the ratio of public to private chargepoint estimates per Zapmap), indicates a possible 109 private chargepoints currently connected to substation 890067. With these two start points, 9 and 109, along with the trendline illustrated in figure 5.19, a forecast for future chargepoint numbers in the area has been conducted. The results of these two start points are presented below in Table 5.4 and 5.5.

Year	No. of Chargers
2022	9
2023	16
2024	27
2025	41
2026	61
2027	86
2028	117
2029	155
2030	201
2031	255
2032	390
2033	473
2034	567
2035	673
2036	791
2037	922
2038	1067
2039	1226
2040	1401

Table 5.4: Forecast for the number of home chargepoints connected to substation 890067 based on a starting point of 9

Year	No. of Chargers (Cumulative)
2022	109
2023	196
2024	324
2025	502
2026	738
2027	1041
2028	1419
2029	1880
2030	2433

Table 5.5: Forecast for the number of home chargepoints connected to substation 890067 based on a starting point of 109

Table 5.4 and 5.5 suggest that it will take between 6 and 17 years for 1380 chargepoints to be connected to substation 890067 and by extension convert the predictions for their grid impact into reality. This is of some concern as 6 years is a relatively short period of time for major infrastructure upgrades to occur. However, it should be worth mentioning that although in the early stages of EV adoption, the rate of home charge point uptake is likely to follow a similar pattern to the sale of EVs themselves, during higher market penetration levels, EV owners may not choose to install multiple charge points at their properties when having multiple EVs and so this correlation will change. Therefore, resulting in a longer period of time for charge point numbers to reach a concerning number from a grid operators' perspective.

With current grid infrastructure and its present specifications, as detailed in Table 5.1, the available headroom on substation 890067 serving this area of investigation is 13.25 MVA. This is limited by an upstream demand headroom of 4.5 MVA. Accounting for Power Factor Correction, using 0.95 again, this would indicate an available headroom of 12,587 kW at the local infrastructure level and 4,275 kW upstream. Considering solely 7 kW charge points, substation 890067 could withstand a total of 1798 charge points before potential issues arise. Considering the limiting factor of the upstream demand headroom, this is reduced to only 610 charge points. Referring to the charge point installation timelines presented in tables 5.4 & 5.5, they indicate that local infrastructure, due to the upstream demand constraint, would face issues by 2026 under aggressive assumptions and 2035 under conservative assumptions.

5.5 Chapter Summary

This chapter has presented a comprehensive investigation into the impact EV Charging will have on local grid infrastructure, typical to rural environments. Having acquired substation meter reading data from WPD, this enabled a direct examination for the results of the EV Charging Model (presented in Chapter 4) which focused on the village of Bradbourne and the current grid load of Bradbourne and the surrounding areas.

As highlighted by the results presented in Chapter 4, the power requirements for a rural EV fleet in Bradbourne was shown to be of higher concern over energy. With this in mind, the work in this Chapter focused solely on the power perspective, a decision reinforced by the data from WPD only containing power readings. Due to the instantaneous nature of power, its actual impact can be masked depending on how you present the data, as detailed in Section 5.2. This chapter presented multiple methods for which to present the power data from WPD to highlight this aspect in detail and should be noted for any further work.

After determining a suitable method for which to combine the acquired data from a local substation to Bradbourne and the results of the EV Charging Model, which had to be scaled to coincide with the power meter readings from substation 890067. Although the case study of this thesis has been focused on the village of Bradbourne, it is important to highlight the applicability of these methods for any rural area. Given its use of publicly available data (UK Census) on rural locations, any location can be used as an input for this methodology to assess the impact of EVs. This can be extended to the WPD dataset also if similarities between 'Vehicle Availability' and 'People per Household' can be made with a location of interest, as per the scaling methodology developed in this Chapter.

Section 5.2's analysis showed scenarios 1-4 integrated well with the pre-existing grid load, whereas scenarios 5-8, which are arguably the most realistic set, showed serious cause for concern with large power demand spikes at various points. Given roughly the same amount of energy is being 'refuelled' over the simulation period in question, the results of this chapter pose many considerations for policy makers, EV charge point operators and grid operators. Arguably, the main contributing factor for the refuelling behaviour to change from that simulated in scenarios 1-4 to scenarios 5-8 is the long charge times of EVs. If charging speeds continue to improve, this could mitigate some of the issues highlighted in this chapter. Nevertheless, it is vital to assess the impact of today's technology. Given these large spikes forecasted, the worst case scenario (whereby all 1380 chargepoints are in use at the same time, a scenario closely reflected by scenario 5 – 100% Economy) was investigated further. Results indicated multiple voltage violations throughout the WPD year-long dataset, when considering this threshold imposed upon substation 890067 by the upstream demand headroom. This is a substantial cause for concern for not just grid operators but EV drivers, and thus the public also. Voltage violations may lead to power cuts, which has serious implications for a transport sector so dependent on electricity. Mitigations of such events and also exploration for feasibilities of EVs in these events is required, this will be investigated in the following chapter.

This chapter's content concluded with a simple forecast model to indicate when this level of EV adoption is likely to occur and by extension when the potential issues highlighted during this chapter may become a reality. Depending on how conservative certain parameters were made, the high level of adoption discussed in this chapter is between 6 and 17 years away. These timescales do provide time for grid operators and other institutions to ensure rural areas, such as Bradbourne, are prepared for the EV future.

With the combination of power requirements from a rural EV fleet and local grid pre-existing demand, the work presented in this chapter fulfils '*Objective 3a*', as detailed in Chapter 1. The following chapter seeks to further examine particular nuances of grid behaviour when considering the addition of charging loads from EV uptake in rural areas. This includes the impact of power outages and mitigation strategies for the increased load, in an effort to achieve '*Research Aim 3*'.

CHAPTER 6: FURTHER EXPLORATION OF EV CHARGING RESILIENCE IN RURAL AREAS

The previous chapter saw the combination of results from the EV Charging Model and the pre-existing loads on the grid local to Bradbourne and the surrounding areas. Results showed a wide range of changes to the grid supply demand due to EV uptake in rural areas, dependent on factors such as electricity tariffs and charging behaviours. Most notable from the previous chapter was the identification of large spikes in power demand which may be a result from large EV uptake.

This chapter aims to continue the investigation into the impact on power demand of the grid due to EVs and how EVs may cope if pre-existing grid infrastructure fails to meet requirements. This chapter will begin with a comprehensive investigation in Section 6.1 into the impacts of power cuts, unplanned and planned, on EV Charging ability. Section 6.2 examines possibilities for mitigating these and other consequences of largescale EV adoption in rural areas through the utilisation of Demand Side Management techniques. The chapter concludes with Section 6.3.

Material presented in this chapter has been published previously, or currently under review, in the following papers: McKinney et al., (2023c, d).

6.1 Power Outages

The material presented thus far in this chapter focuses on the capabilities of the current grid infrastructure surrounding Bradbourne and how a rural EV fleet may integrate with this. Having seen that the simple addition of this EV fleet could cause major problems in terms of potential grid overload, this is a worrying outcome for an electrified vehicle future.

Therefore, it is imperative to investigate what impacts power outages would have on rural communities, such as Bradbourne, dependent on their EVs for daily transport. Power outages are still witnessed today, albeit a less than common occurrence in the UK, however more prevalent in rural areas due to the weaker grid infrastructure (Western Power Distribution, 2022a). The additional nuance for a rural area without power is the typically longer duration of power outages, due to the more remote nature of the infrastructure when considering accessibility for repair, etc. Power outages for this research have been categorised into two groups: (1) Unplanned, and (2) Planned. Both of these categories have been investigated.

Additionally, this analysis will also consider the direct impact power outages will have on EV owners themselves, via their vehicles SOC. Only the 84 vehicles of Bradbourne will be considered as it is at this level that the data for each, and every vehicle has been generated via the TDM (Chapter 3) and the EV Charging Model (Chapter 4). This section will initially outline the methodologies used to examine both unplanned and planned power outages. Subsequently, the results and discussions for unplanned power outages will be covered in section 6.1.2, followed by those for planned power outages in section 6.1.3.

6.1.1 Methodologies for Unplanned and Planned Power Outages

This section will first begin with presenting the methodology employed for investigating unplanned power outages on the village of Bradbourne. A range of suitable length power outages has been investigated. This will then be followed by the methodology for investigating planned power outages, which involved the incorporation of the Electricity Supply Emergency Code (ESEC) (GOV.UK, 2019).

As shown in Chapter 4, the scenarios based on 'Charging initiates once EV falls below 20% SOC' behaviour (scenarios 1, 2, 3 & 4), which aimed to align with more traditional ICE refuelling regimes, did not prove optimal. The battery charge of many vehicles was unable to keep up with the required travel demand. Consumers are likely to realise these issues, and others highlighted by the results of Chapter 4, and therefore adapt their charging behaviour accordingly. Thus, the decision was made to focus on the 'Charging every night' scenarios (Scenarios 5, 6, 7 & 8) from here-on-out.

Unplanned Power Outages

Unplanned power cuts can be caused by all manner of incidents damaging grid infrastructure, i.e. poor weather, sabotage, and accidents. These unplanned power cuts can vary in their durations, dependent upon how much damage is caused.

To understand the impact of unplanned outages on EV charging and by extension the usability of individual vehicles, a range of power outage durations have been simulated: 12hr, 24hr, 36hr and 48h, the duration categories as devised in Table 5.2 of Chapter 5.

For each of the power outage scenarios (12hr, 24hr, 36hr & 48hr), custom python scripts were written which enabled the manipulation of the EV Charging model results from scenarios 5, 6, 7 & 8. A random number generator was used to select the timing (a specific timestep within the 4 week simulation period) for when the power outages would begin, which would remain the same across each scenario for comparative reasons. The power outages were all scheduled to begin at 7:30pm on '*Fri1*' of the 4 week simulation period. The python scripts inserted the power outages at this moment of the simulation period, not allowing for any more charging events to occur during this period, followed by recalculations for the remainder of the simulation period of the charging events based upon the parameters detailed in Chapter 4 as before.

Planned Power Outages

To contrast the work undertaken on unplanned power outages, the decision was made to also investigate planned power outages, prompted by recent global events and threats to domestic energy supply. Geopolitical statuses are a probable threat to domestic power and energy availability in the UK. At the time of writing, the current war in Ukraine with Russia has led to a gas shortage worldwide, not only affecting prices and thus the running costs of an EV but have resulted in renewed media attentions for the UK Governments planned blackouts protocols (The ESEC) (The Guardian, 2022a).

The ESEC details plans should a prolonged electricity shortage affect a specific region, or the whole country (GOV.UK, 2019). This code outlines the process to ensure fair distribution nationally of what electricity supply is available using a process known as “rota disconnections”. This has brought about a significant amount of concern for UK citizens (The Guardian, 2022b), and most notable will have an impact on electric vehicle owners when recharging. Therefore, it was decided to investigate the effects these proposed planned blackouts would have on the results from the EV charging model.

The “rota disconnections” propose to split the days into 3hr segments and depending on your postcode location and house, the electricity supply will be cut during different segments. This is to ensure reduced energy use during these times of limited supply. Multiple disconnection levels have been planned, ranging from 1 to 18, which depict varying degrees of energy rationing, see Appendix C. Furthermore, for the area undergoing electricity rationing should the ESEC be invoked, the households of such a region are split amongst 18 groups (A-U) to ensure fair distribution of what electricity supply there is to different households at different times. There groups will henceforth be referred to as ‘area groups’.

These proposed disconnection level blackouts range from loss of electricity for a few 3hr slots per week (Level 1), to complete, continuous, blackout (Level 18). The disconnection levels proposed by the ESEC can be seen in Appendix C, of which Levels 1, 5, 10, 12 & 15 have been chosen to be simulated. These levels were selected to offer a comprehensive investigation into various degrees of disconnection that a community might experience. Levels beyond 15 were not considered due to the extremely low probability of such worst-case scenarios occurring. Additionally, from an impact analysis standpoint, blackouts nearing a week in duration would effectively result in no EV charging while they persist.

To minimize the computational and time requirements of conducting this investigation of the multiple disconnection levels, only previously described Scenario 6 (37.5% Standard, 62.5% Economy) was selected upon which to base this work. This was the most realistic electricity tariff distribution scenario, as presented in Chapter 4. The 45 households of Bradbourne which have vehicles, and thus an EV within these simulations, were randomly assigned an area group, ranging from A to U. The result of this process can be seen below in Table 6.1.

ESEC Block	House ID
A	17, 23, 29, 45
B	14
C	6, 7, 11, 37
D	9, 12, 34
E	10, 28, 33, 38, 47
G	32, 46
H	19
J	5, 21
K	16, 18, 22

ESEC Block	House ID
L	25
M	26, 41
N	15, 31, 43
P	13
Q	8, 48
R	24, 36, 39, 44
S	27
T	35
U	20, 30, 40, 42

Table 6.1: Area group assignment for each Household of Bradbourne – only households with vehicles (House ID 5-49)

Custom written python scripts were used to simulate these planned power outages detailed by the ESEC. This involved the input of the EV Charging Model results (as per Chapter 4), combined with the ESEC disconnection levels (Appendix C). The algorithm would initially check all pre-existing charging events, dictated by the EV Charging Model to determine if these events would still be possible under the current ESEC scenario being simulated. If a planned charging event was scheduled to occur during a power outage period, the vehicles variables for the timesteps of that power outage would be recalculated. Following periods of power outage, when the power returns, should vehicles require charging, and should its position (i.e. at home) allow for a charging event also, then recalculations will also take place to account for this.

Two charging regimes were developed and chosen to again investigate differing behavioural types; electricity tariff dictated and opportunistic. Electricity tariff dictated follows the same protocols set out in Chapter 4, where the charging events of a household depend on the electricity tariff. As scenario 6 was chosen as the basis for this work, this means 62.5% of household on economy tariffs would only charge between 00:00-07:00, regardless of the disruption caused by the planned power outages. However, as an attempt to mimic more human behaviour, another behavioural pattern was chosen to simulate; opportunistically charging. This behavioural pattern assumed that, should these planned blackouts go ahead, individuals would cease to follow their EV tariff pricing structure and opt for a more opportunistic approach whereby they would elect to charge at any time in order to maximise the available state of charge of their vehicle at any one time, therefore ensuring their continued use of their vehicles was possible. To simulate these two charging regimes, it was assumed that all household's EV chargers would have a time delay function (smart functionality). Allowing vehicles to be plugged in but wait till the next available charging opportunity arose.

Having presented the various parameters and methodologies for simulating both unplanned and planned power outages, the results, pertaining to the EV fleet of Bradbourne itself, will now be presented for both in Sections 6.1.2 and 6.1.3 respectively. As this work builds directly upon the output of the EV Charging model results from the previous chapter, the results for both unplanned and planned power outages have been presented for the selected time periods for each scenario that was detailed by Table 4.6 of Chapter 4.

6.1.2 Results and Discussion for Unplanned Power Outages

This section will present and discuss the results from simulating 12, 24, 36 & 48hr unplanned power outages durations, building upon the EV Charging Model of Chapter 4.

12hr Outage

Figure 6.1 below shows the impact a 12hr power outage, beginning at 7:30pm on Friday, has on the overall charge across all 84 EVs of Bradbourne. All four electricity tariff distribution scenarios were modelled and the comparison between the original (solid lines) and 12hr outages (dashed lines) are displayed. It should also be noted that for the rest of Section 6.1.2, with regards to figure legends, ‘E’ and ‘S’ indicate Economy and Standard electricity tariffs respectively.

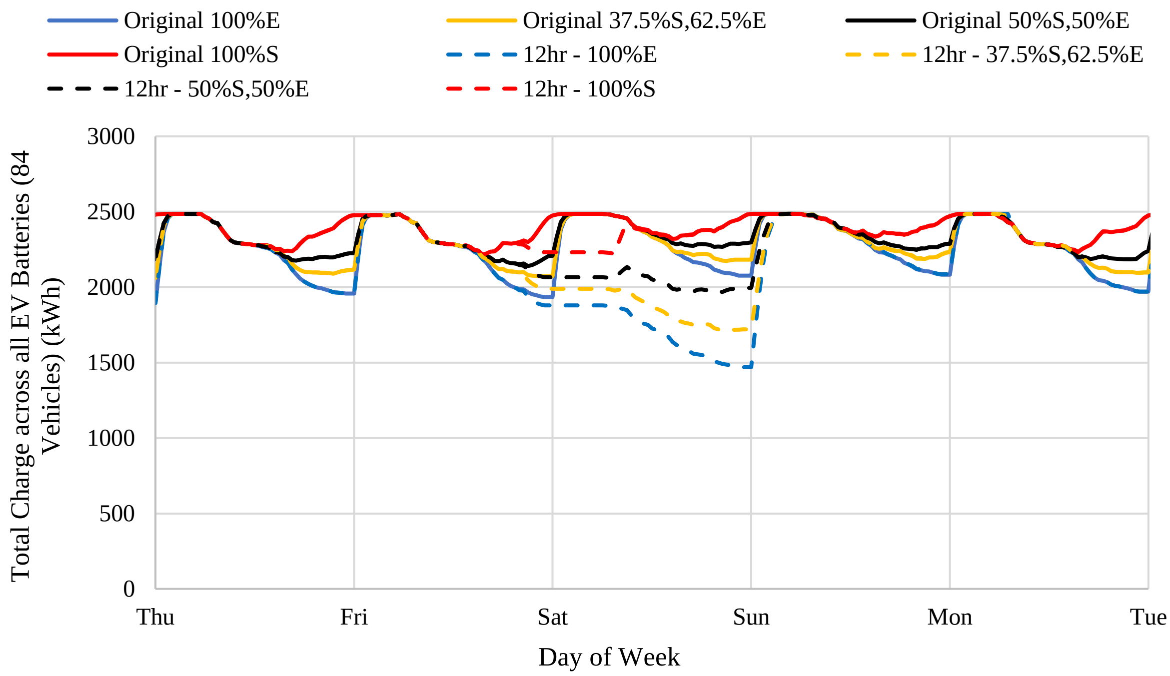


Figure 6.1: Total Charge across of all EV Batteries of Bradbourne’s vehicle population over time for scenarios 5-8 with and without a 12hr power outage

As one would expect, all scenarios have been impacted by the power outage, with the 100% Economy scenario witnessing the largest effect. This scenario has seen a drop of almost 500 kWh across the fleet of 84 vehicles. This is due to this scenario having essentially ‘missed’ its daily charging opportunity once midnight passes, and the Economy tariff charging events are initiated. In contrast, as the ratio of households with a Standard electricity tariff increases, the impact of the outage becomes decreased, with negligible affect for the fleet deployed on the 100% Standard scenario. With regards to the 100% standard scenario, we can see a straight flat line during the period of the power outage before vehicles are then able to recharge once again, indicating a period of zero vehicles in use. Although, the data presented in Figure 6.1 is reassuring from a grid's perspective, and at first glance may indicate that this impact of this power outage is less severe than it actually is, as the fleet only loses roughly 500 kWh in total. Investigating the impact to individual vehicles and by extension the EV owners themselves shows a different story.

To review the impact on a more individual level, Figure 6.2 shows the minimum, maximum and average SOC profiles for each scenario with and without the power outage. The minimum and maximum profiles were determined through selecting the EV whose SOC dropped to either the minimum value, or the maximum value, respectively, during the selected time period. If an EV reaches 0%, for the continuation of the simulation, the vehicle does not go below 0%, but is able to 'continue' the journey and return home to begin charging (electricity tariff dependent for the timing of the charging event itself) from 0%. In reality, it is recognised this would be extremely problematic for the vehicle owner as they would be unable to drive home, and the vehicle may have to be recovered. The average SOC profile is an average of all 84 vehicle's SOC at each half-hour timestep during the simulation period.

Figure 6.2 demonstrates that the vehicle's SOC never drops to 0% during the selected time period, even in the face of a 12-hour power outage. This duration is identified as the most common length of power outage, as indicated by the findings in Table 5.2 of Section 5.3, thus enabling EV owners to maintain their usual travel patterns despite the outage. Most notably from figure 6.2, is the impact of the electricity tariff on the SOC profile during the simulated power outage. During the power outage runs of the simulation, the minimum SOC profile belongs to House 48 – Car 1, which, by chance, is served by an Economy electricity tariff for all the scenarios whereby there is a ratio including both Economy and Standard tariffs. However, this is not the case for the 100% Standard scenario which allows the households to begin recharging as soon as the power outage is over. In this scenario, the minimum SOC profile now belongs to House17 – Car 1, the same as the original case without a power outage. The lowest SOC reached is just under 7% which causes concern for any longer duration power outages which will be presented next.

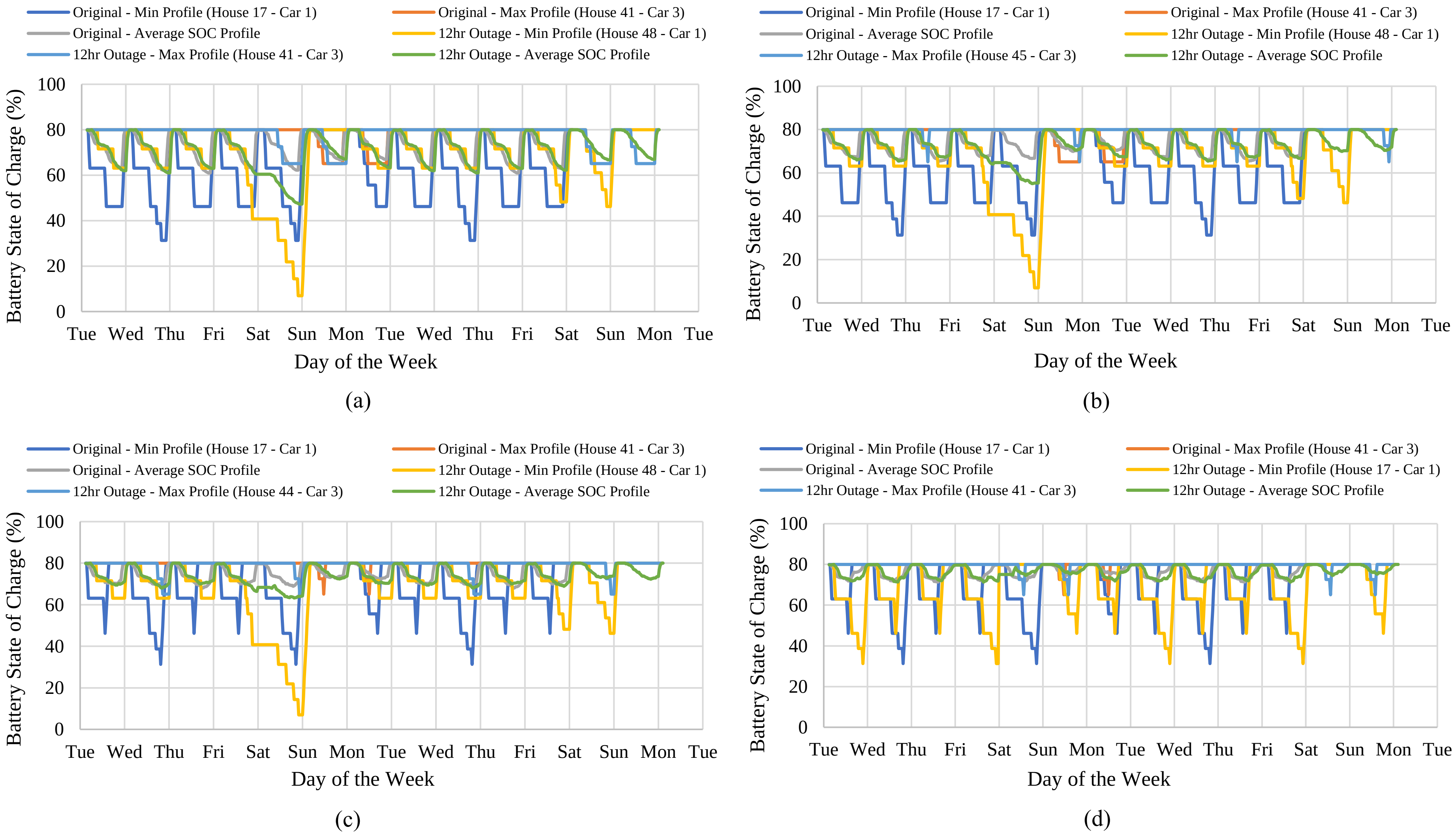


Figure 6.2: Min, Max, and Average Individual Vehicle SOC plot for (a) 100% Economy, (b) 37.5% Standard, 62.5% Economy, (c) 50% Standard, 50% Economy, (d) 100% Standard

24hr Outage

The next duration of power outage simulated was 24hr, the results for the whole EV fleet can be seen in figure 6.3 below. This duration produced results very similar to the 12hr power outage, especially the 100% Economy scenario, with more of an impact seen for the other three electricity tariff distribution ratios. The is due to the inclusion of standard electricity tariffs in these scenarios which now with a 24hr power outage results in a large decline in fleet total charge.

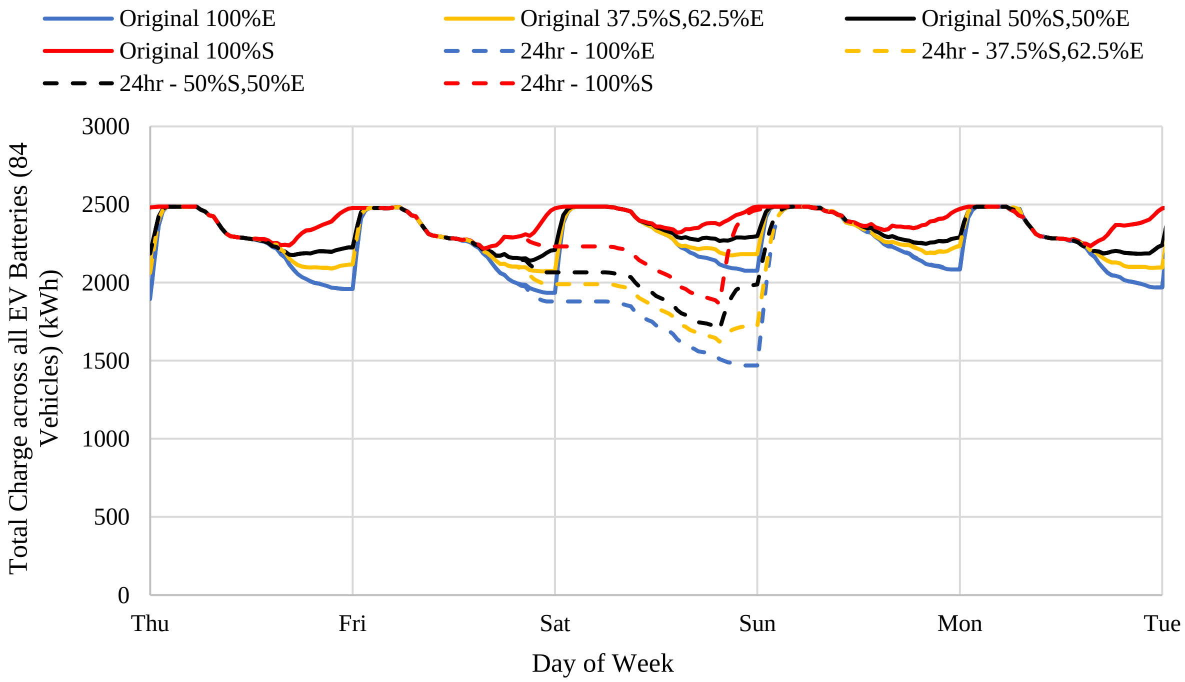


Figure 6.3: Total Charge across of all EV Batteries of Bradbourne's vehicle population over time for scenarios 5-8 with and without a 24hr power outage

Comparing figures 6.3 with 6.1 (the total charge of the EV fleet when witnessing a 12hr power outage), what is interesting is the fact that the impact due to a 24hr power outage is the same as the 12hr power outage for the 100% Economy scenario. This is due to the hours of charging that are dictated by the economy tariff. Given the start of the power outage is 7:30pm, for economy 7 tariff households, the charging events which would be affected are those beginning at midnight Friday/early Saturday morning. When considering the 12hr outage, the households would regain power at 7:30am, but wait until midnight on the Saturday for their next charging event. Now a 24hr power outage scenario has been simulated, this continues the power outage until 7:30pm on the Saturday, where still the next available charging event for the economy 7 tariff households would be at midnight. Therefore, as economy 7 tariff households base case is recharging every 24hrs at midnight, the impact of either a 12hr or 24hr power outage would be the same. This is predicted to be the same, for the 100% economy scenario, for the 36hr and 48hr power outage cases with those two scenarios resulting in the same impact.

Again, figure 6.3 would suggest the vehicles are minimally impacted and so little concern for EV owners, however when highlighting individual vehicles, this shows, again, larger impacts and concerns. Figure 6.4 shows the minimum, maximum and average SOC profiles for a 24hr power outage across all electricity tariff distribution scenarios with comparisons to their respective originals (no power outages). The most significant difference between the figure 6.4 representing the 24hr power outage and the graphs presented in figure 6.2 for the 12hr power outage is the 100% Standard scenario. The 24hr causes a much larger reduction in SOC, in both the average profile and, more interestingly, the maximum profile than was the case with the 12hr outage.

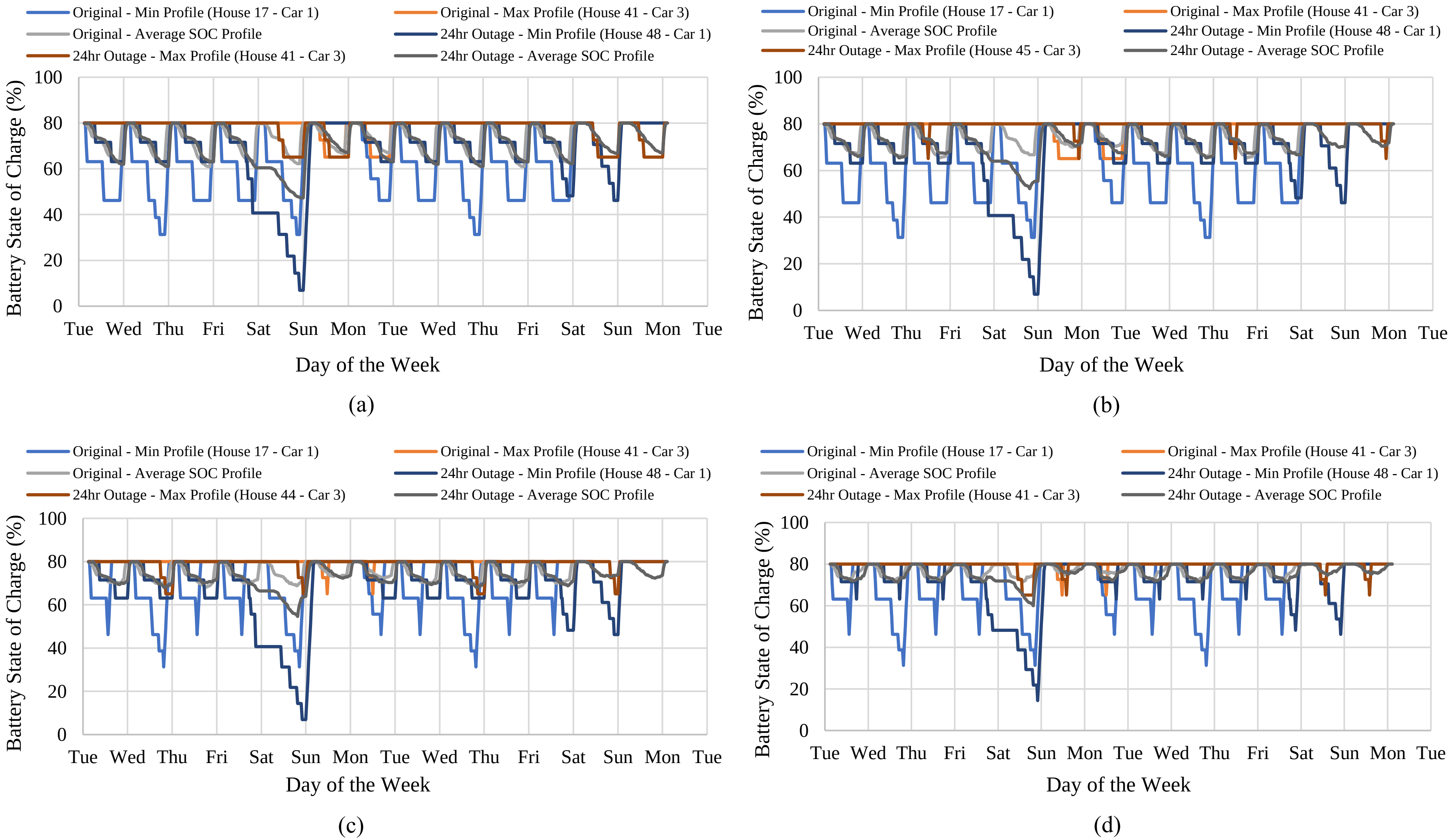


Figure 6.4: Min, Max, and Average Individual Vehicle SOC plot for (a) 100% Economy, (b) 37.5% Standard, 62.5% Economy, (c) 50% Standard, 50% Economy, (d) 100% Standard

36hr Outage

The results for the 36hr power outage simulation are shown below in figure 6.5. With the power outage now lasting longer than a day, the impact has become much more significant. As the underlying charging behaviour for these scenarios is ‘Charging Every Night’, all 84 vehicles studied will have lost a day’s opportunity for a charging event. This has led to a significant reduction in the charge of each vehicle, and by extension the total charge across all batteries.

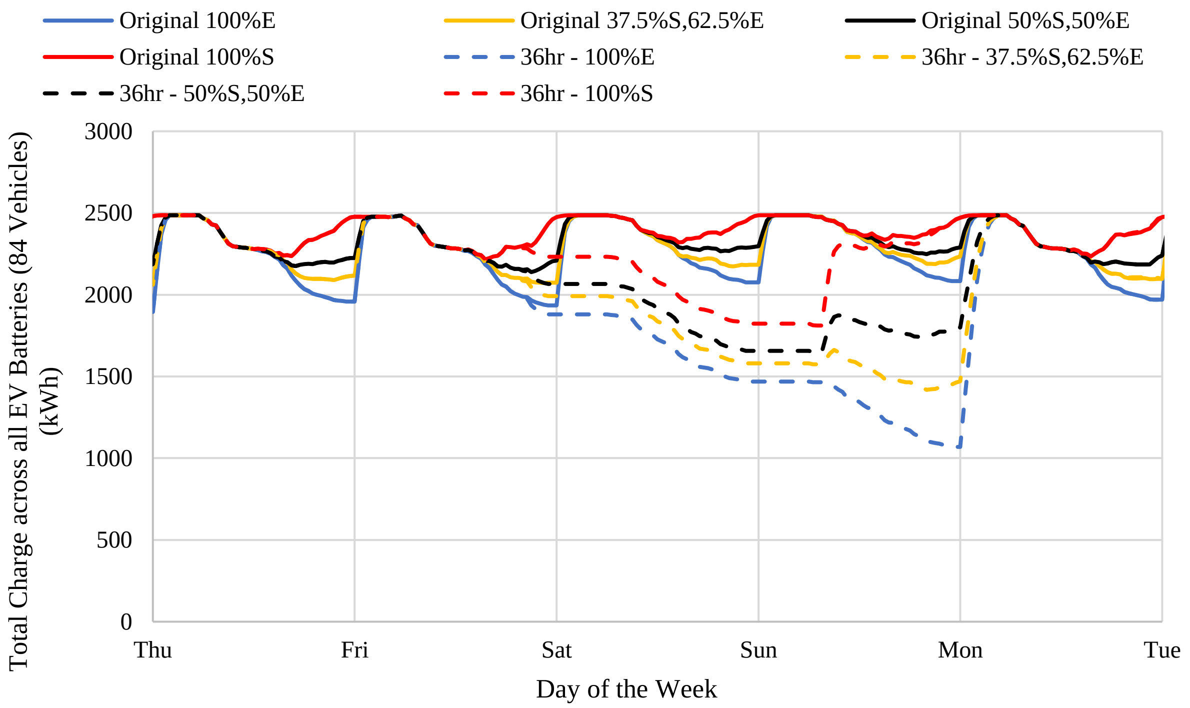


Figure 6.5: Total Charge across of all EV Batteries of Bradbourne’s vehicle population over time for scenarios 5-8 with and without a 36hr power outage

Given the large push for EV owners to have EV specific tariffs, which largely follow an Economy tariff structure, figure 6.5 highlights, contrastingly, the benefits of standard tariffs and charging at any time during periods of atypical circumstances, such as a power outage. For the scenarios with larger Standard tariff distribution ratios, we see the impact of the power outage reduced drastically. This is particularly relevant to the scenario where the power outage starts at 7:30pm. In the case of a 36hr power outage under the Economy tariff, similar to the 12hr and 24hr scenarios, vehicles are subjected to an additional 12hr outage. This results in an increased inability to recharge before continuing further journeys according to the established travel patterns. The impact of this becomes evident in figure 6.6, where the minimum vehicles now reach 0% for all electricity tariff distribution scenarios.

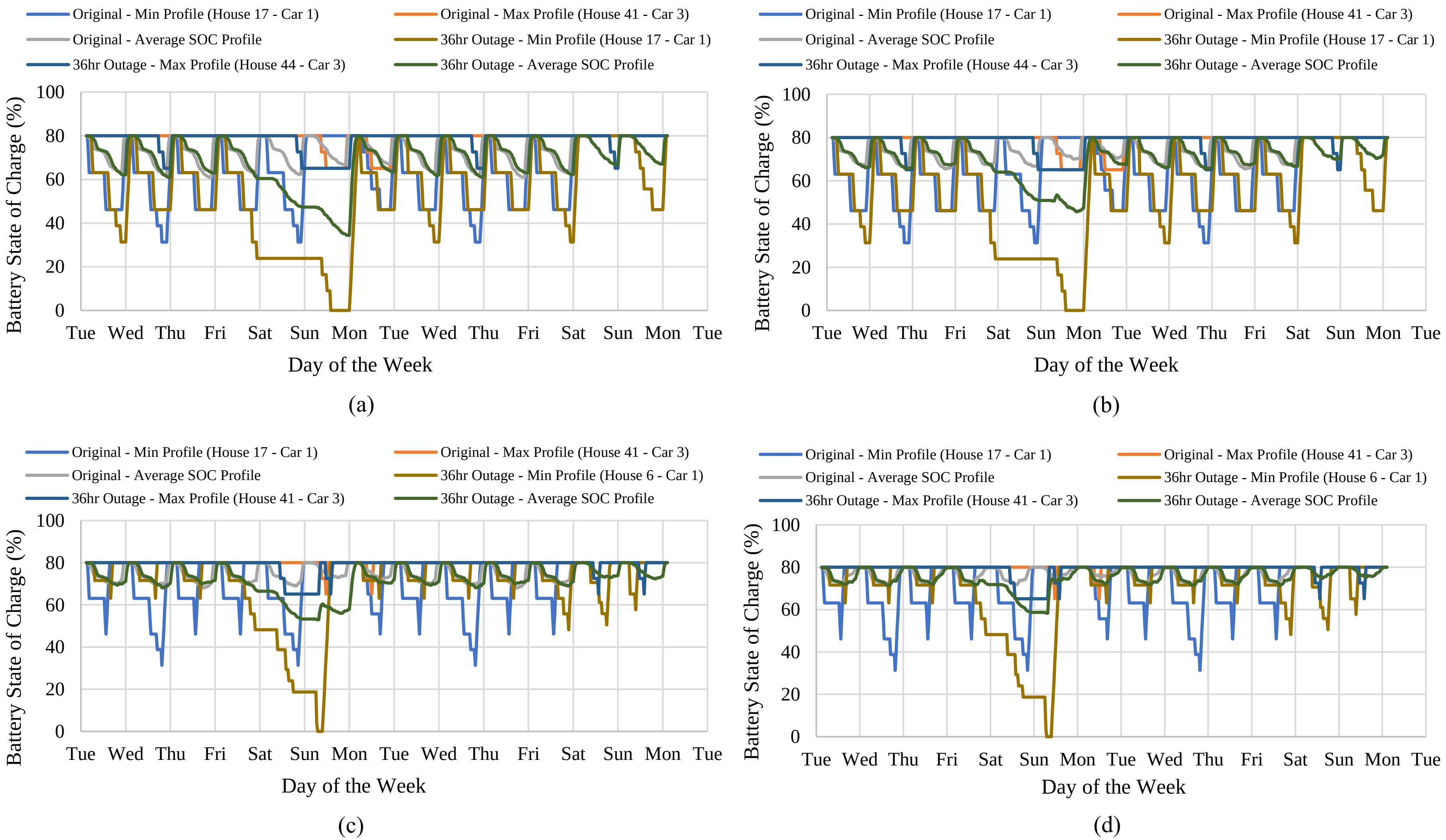


Figure 6.6: Min, Max, and Average Individual Vehicle SOC plot for (a) 100% Economy, (b) 37.5% Standard, 62.5% Economy, (c) 50% Standard, 50% Economy, (d) 100% Standard

48hr Outage

The last and longest duration of unplanned power outage simulated was 48hrs, the results of which can be seen in figure 6.7.

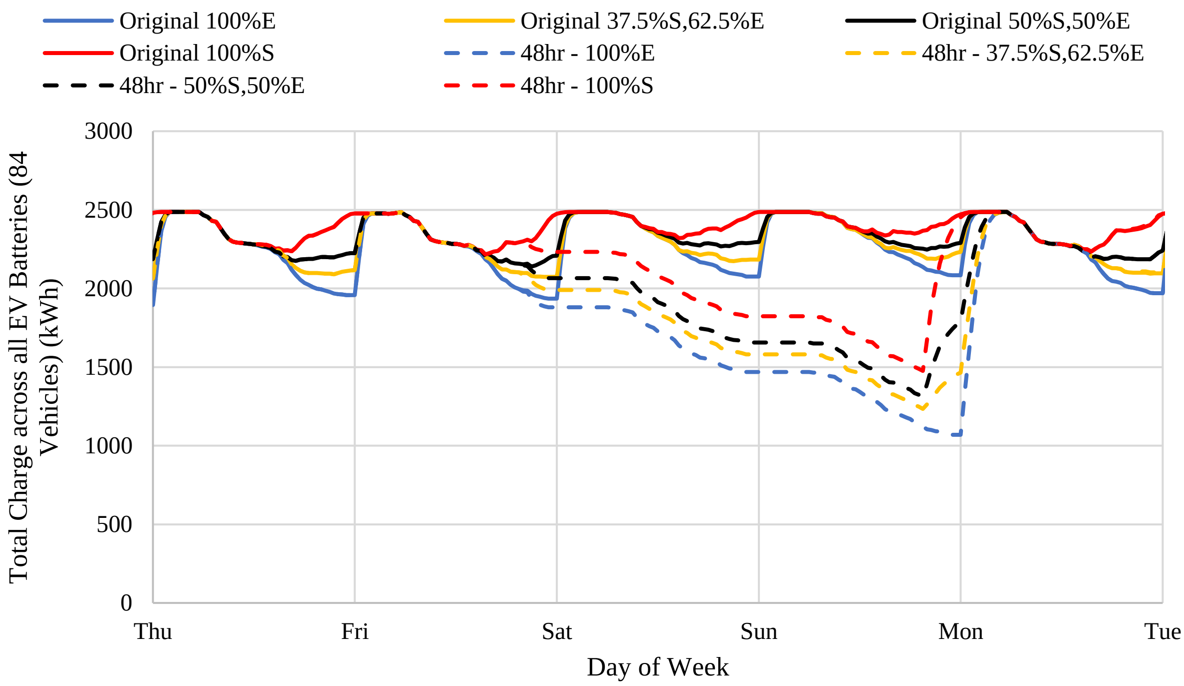


Figure 6.7: Total Charge across of all EV Batteries of Bradbourne's vehicle population over time for scenarios 5-8 with and without a 48hr power outage

As pointed out in the 24hr power outage scenario and for the same reasons, the 100% Economy scenario with a 48hr power outage is the same as for the 36hr power outage. However, as per figure 6.7, the other three electricity tariff distribution scenarios (100% Standard, 50% Standard, 50% Economy and 37.5% Standard, 62.5% Economy) all see the total charge of the EV population drop considerably during the course of the power outage. Contrary to the previous durations, the 100% standard is now severely affected also. This is also highlighted by figure 6.8 which details the SOC profiles for individual vehicles during this simulation.

The work presented in this section reflects the kind of power cuts we are familiar with in the UK, i.e. those caused by damage to infrastructure, whether that be due to weather or accident. However, current geopolitical affairs have brought about the UK Governments need to draw up plans for planned black-out periods.

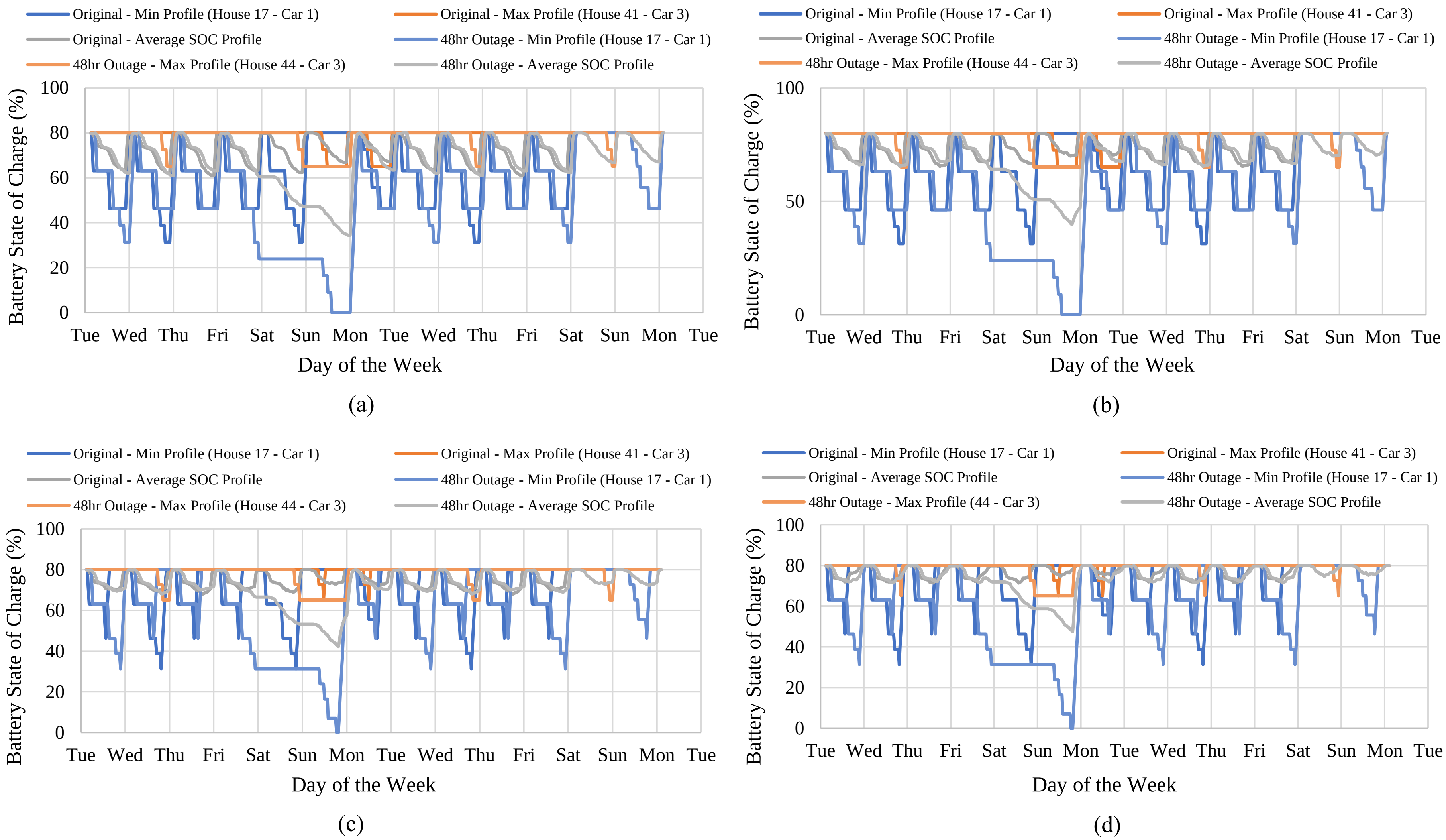


Figure 6.8: Min, Max, and Average Individual Vehicle SOC plot for (a) 100% Economy, (b) 37.5% Standard, 62.5% Economy, (c) 50% Standard, 50% Economy, (d) 100% Standard

6.1.3 Results and Discussion for Planned Power Outages

The presentation and discussion of results from simulating planned power outages are structured as follows: Initially, two charging regimes, as previously mentioned, have been simulated. To demonstrate the effect of these regimes, a brief presentation of results for an individual vehicle is provided. This is followed by an analysis of various factors over the simulation period, including battery capacities, charging energy, required energy demand and consequent electricity generation needs, power demand and its impact on grid supply, and finally, the implications for individual consumers and their EV capabilities. A 4 week simulation period was chosen to allow initial transients to stabilise, and the data for slightly over a week is presented.

For each avenue of investigation, two sets of results are shown. The first set focused on the battery capacity of the EV fleet, and the second set examines the energy demand from the 84 charge points in Bradbourne within the simulation. For both sets, a combined presentation of all results is provided for comparison, followed by two separate plots that distinguish the outcomes of the two charging regimes.

Electricity Tariff Dictated and Opportunistic Charging Regimes

To understand the impact of these two charging regimes and highlight the difference in results they produce, one of the more severely affected vehicles of the population, House 17 – Car 1, and the impact of each of the chosen levels of disconnection for both the 'electricity tariff dictated' and 'opportunistic regimes' over one week of the simulation have been presented in Figures 6.9 and 6.10, respectively.

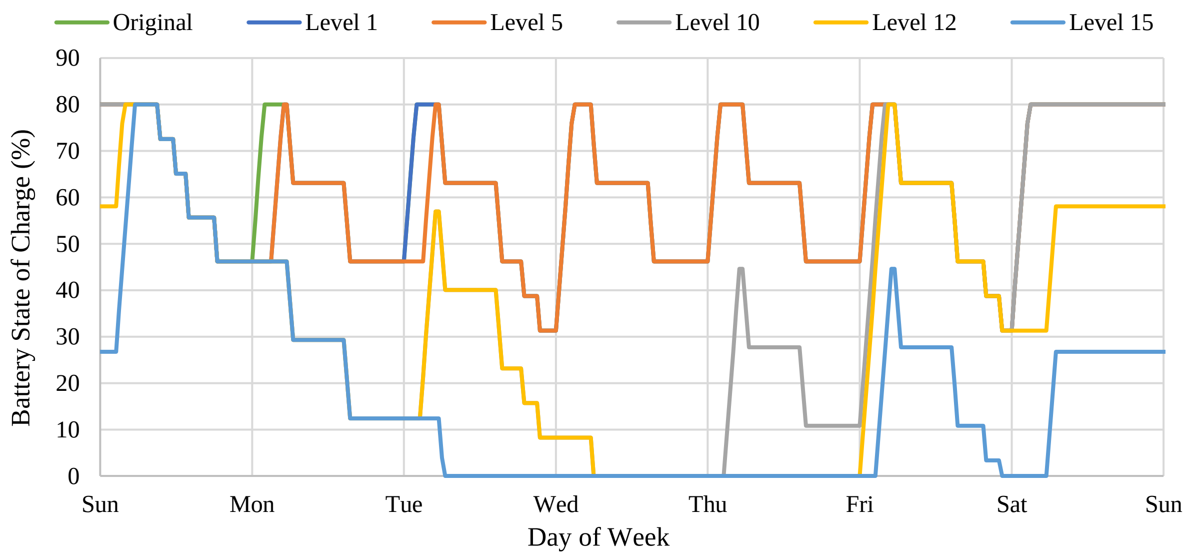


Figure 6.9: State of Charge for House 17 – Car 1 EV over time under 'Electricity Tariff Dictated' charging regime

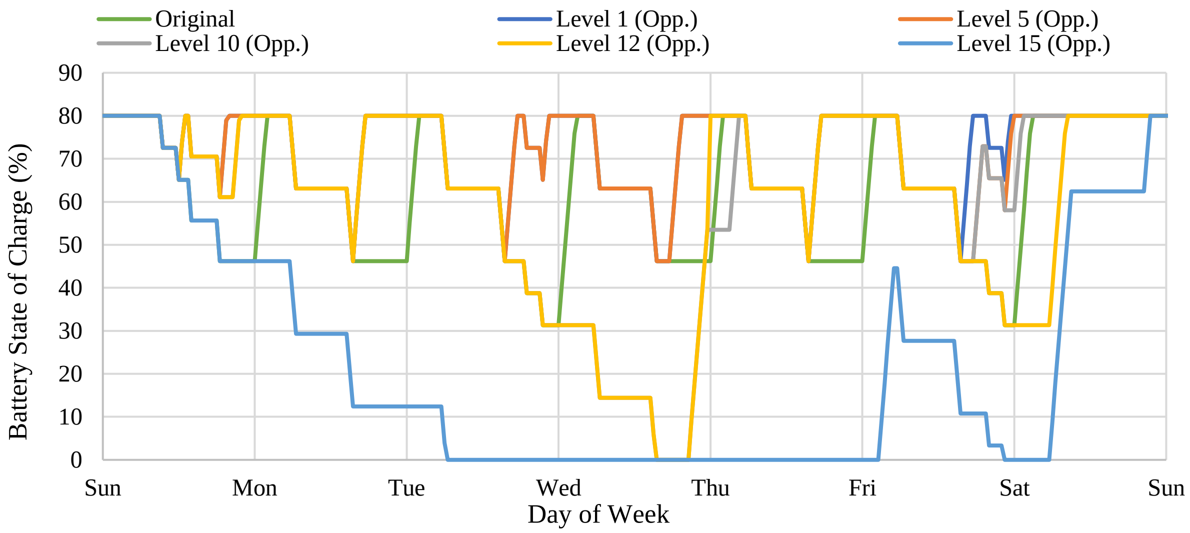


Figure 6.10: State of Charge for House 17 – Car 1 EV over time under ‘Opportunistic’ charging regime

House 17 is served by an Economy tariff, as presented during the EV Charging Model in *Chapter 4*, and therefore charging events can only occur between 00:00 and 07:00, however, for the purposes of these planned power outage simulations, if the charging for tariffed households was not to reach 80% by 07:00, the charging would continue if possible. This would be until either another blackout occurred, or the vehicle left home. This primarily results in a few half-hour timesteps following on from the 07:00 timestep where charging at an Economy household would still continue. This decision was made to again reflect the need an EV owner under an Economy tariff household would have for charging their vehicle, although not fully transitioning into the opportunistic charging regime.

As House 17 is served by an Economy tariff, the major impacts come from disconnection levels which switch off power during these crucial charging, economy, hours i.e. the early hours of each day. For reference, as per Table 6.1, this household is under ESEC block A. As highlighted by Figures 6.9 & 6.10, the impacts of these two charging regimes is significant. For the electricity tariff dictated charging regime, this vehicle reaches 0% multiple times at Level 10 disconnection, with even Level 5 reducing the SOC down to levels just above 30%. In contrast, utilising an EV owners more realistic behaviour through the opportunistic charging regime, enables more charging events to occur, and the disconnection levels now become an issue with this EV in question reaching 0% SOC at only Level 12 and 15.

Additionally, when considering these two charging regimes, and the underlying electricity tariffs serving each household, as the ESEC is a public document and if enacted, individuals themselves would know the times and durations of their power cuts. Therefore, it is unlikely that individuals would try to correlate their original EV charging patterns (forecasted by the EV Charging Model), with the reduced periods of time when power is on. Instead, EV owners would choose to charge or conduct their journeys at different times and thus alleviate this impact of such power outages furthermore. Therefore, it is reasonable to take this work as a worst case scenario.

Battery Capacity

Figure 6.11 shows the EV fleets total level of charge over time for the original scenario as well as both the charging regimes. From the weekly trend, although there are recharging events occurring in available periods where the power is on during the week, due to the underlying travelling patterns having more mileage travelled during the weekdays, as opposed to the weekends (see *Chapter 3*), this has resulted in a weekly undulating profile. Whereby the total battery charge capacity over the course of the week slowly declines, to be replenished to the highest levels at the weekend.

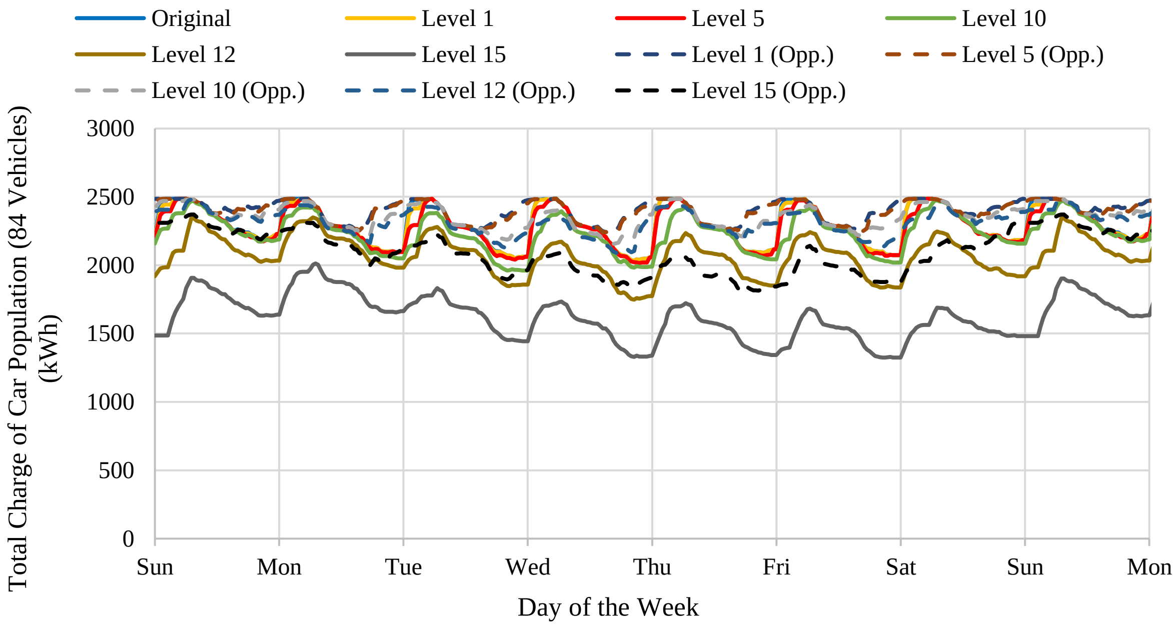


Figure 6.11: Total Battery Capacity of entire EV population of Bradbourne for both 'Electricity Tariff Dictated' and 'Opportunistic' charging regimes

As expected, disconnection level 15 under the 'Electricity Tariff Dictated' charging regime had the largest impact with a considerable reduction of almost 40% in the total battery charge capacity of the fleet. Figures 6.12 and 6.13 present these results but separated by charging regime.

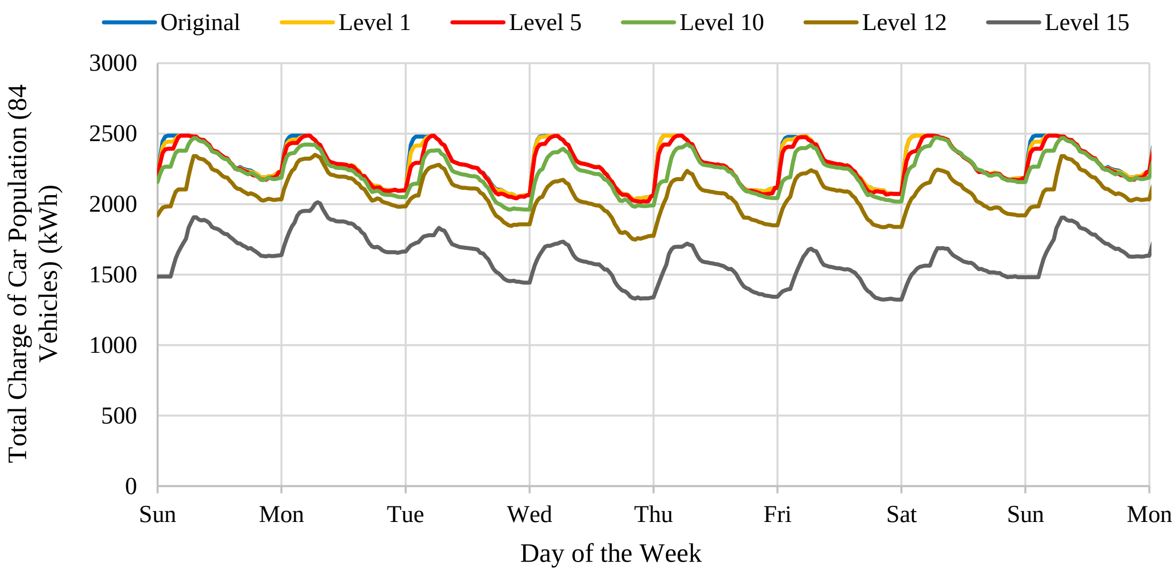


Figure 6.12: Total Battery Charged Capacity of entire EV population of Bradbourne for the 'Electricity Tariff Dictated' charging regime

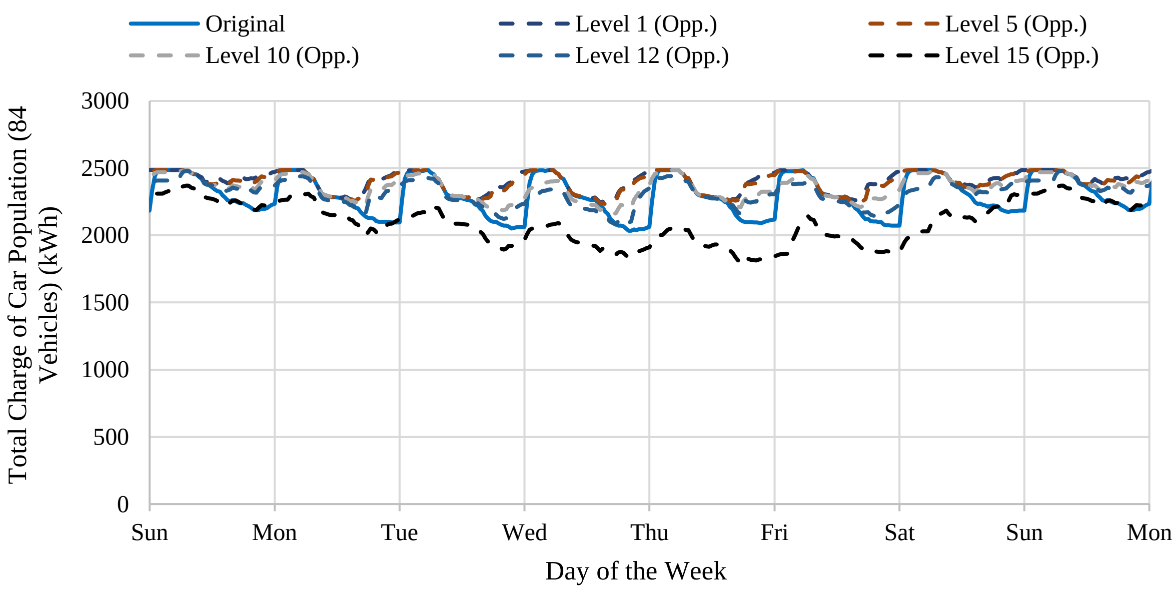


Figure 6.13: Total Battery Capacity of entire EV population of Bradbourne for the 'Opportunistic' charging regime

Compared to the original scenario, all but the highest disconnection level simulation, disconnection level 15, for the opportunistic charging regime method actually improved the overall battery capacity of the fleet. This highlights why this charging behaviour was first developed, to simulate how charging behaviours may change during periods of planned power outage. EV owners could act more conservatively and thus charge more in the hours that allow them to do so, and so the battery capacity of every vehicle remains at a higher average SOC.

However, these graphs are deceptive, as they suggest that there is no real concern to even the higher level disconnection levels. As per figure 6.13, this shows roughly a 10% decrease in the total battery charge capacity across all EVs when averaged across the whole 8 days presented (Sun-Mon), which is true. However, the individual vehicles that constitute this total capacity are all impacted in different ways depending on their travelling habits and charging capabilities. This will be discussed in further detail shortly.

Charging Energy

In contrast to figure 6.11 suggesting that the total battery charge capacities are minimally impacted by the various disconnection levels and therefore the batteries must be recharged significantly even with the planned power outages, figures 6.14, 6.15 and 6.16 show the total charging energy at each timestep (every half-hour) due to all the recharging events occurring during the simulation. These figures show large decreases in the energy demand spikes compared to the original scenario, especially for the opportunistic charging regime based scenarios.

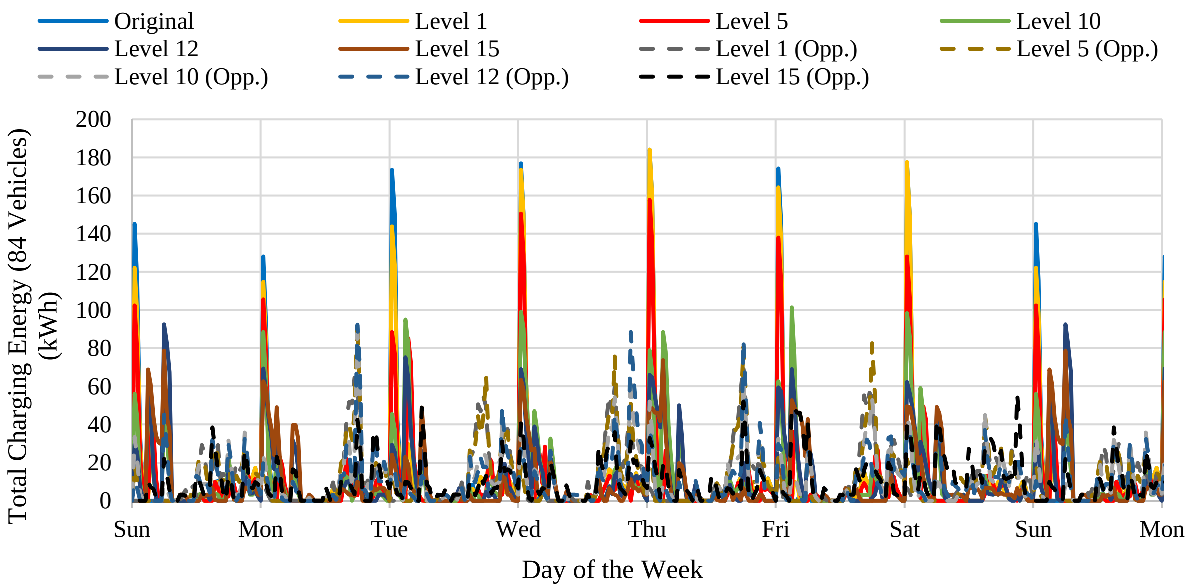


Figure 6.14: Charging Energy for both 'Electricity Tariff Dictated' and 'Opportunistic' charging regimes

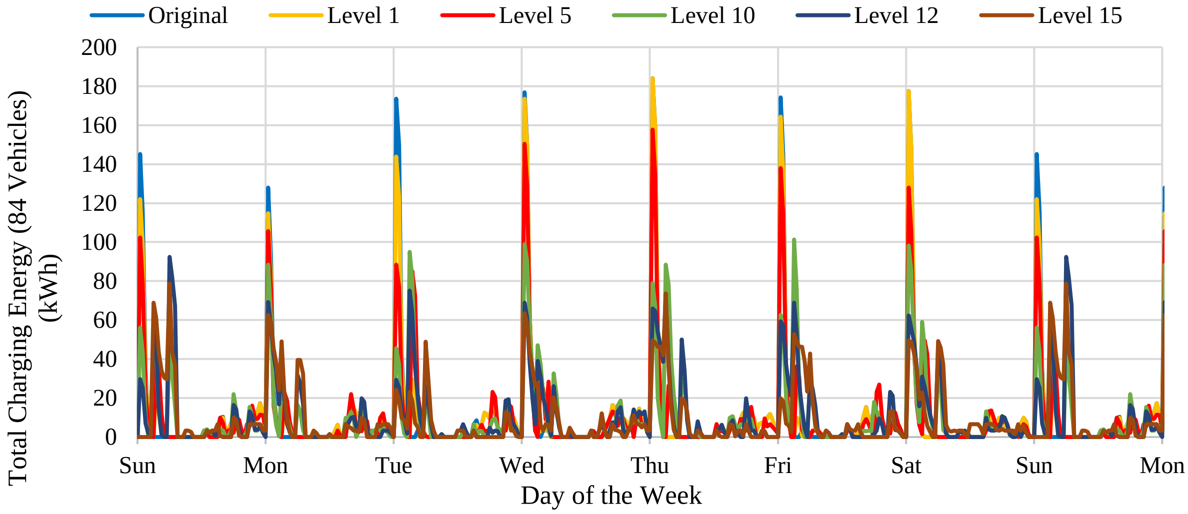


Figure 6.15: Charging Energy for Electricity Tariff Dictated regime

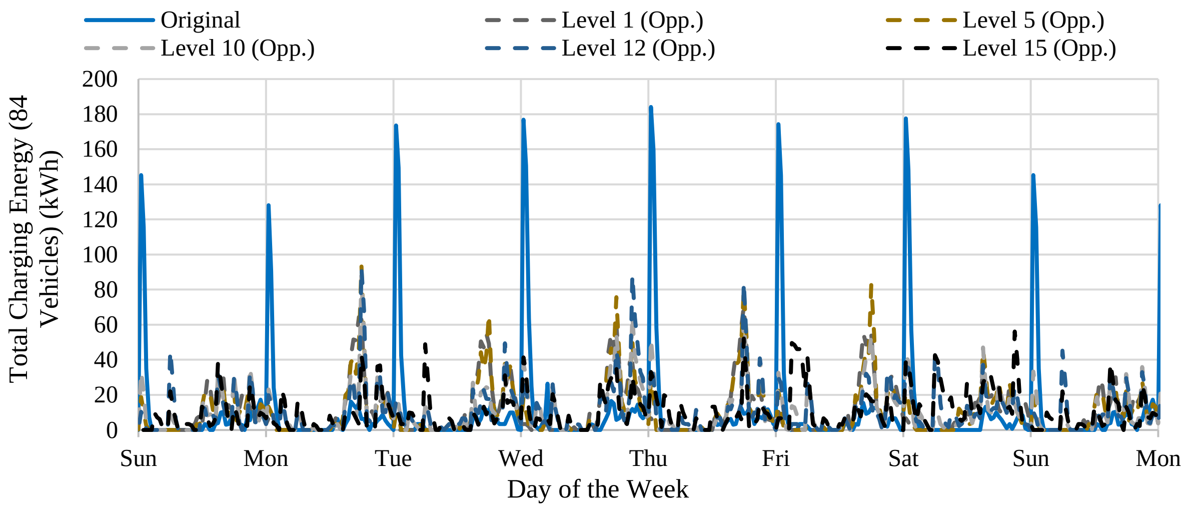


Figure 6.16: Charging Energy for Opportunistic Charging regime

When considering the impact of power outages, the impact of such will differ depending on if the perspective is from the electricity generation capability to the capabilities of the physical grid infrastructure, to how the end user, the EV owners themselves, will be affected. The impacts of these planned power outages for each group will now be discussed.

Generation

From a generation perspective the total energy charged during the 4 week simulation period for each scenario is detailed in table 6.2 below.

Charging Regime	Disconnection Level	Total Energy Charged (kWh)
Original	-	14,007.87
Electricity Tariff Imposed	Level 1	14,007.87
	Level 5	13,607.24
	Level 10	13,662.64
	Level 12	13,458.49
	Level 15	11,729.52
Opportunistic charging	Level 1	13,994.39
	Level 5	13,998.54
	Level 10	13,917.35
	Level 12	13,857.40
	Level 15	13,513.59

Table 6.2: Total Energy Charge during the total time of simulation for each scenario

The difference in total energy being charge between each scenario is not significant, with the worst scenario, disconnection level 15, under the electricity tariff imposed charging regime only charged 2278 kWh below the original level, representing a loss of only 17.7% in energy to the system over 4 weeks. Considering the ESEC is a technique for electricity rationing during periods of reduced output, these disconnection levels have not reduced the total energy consumed by very much. Therefore, it could be argued that the purpose of the ESEC has been thwarted, from the EV perspective, by the need to claim energy for travel, albeit at a higher expense than charging off-peak.

As expected, the opportunistic charging regime scenarios have maintained the total energy put into the system far better than the electricity tariff imposed regime. This is due purely to the behaviour, and EV owners taking any opportunity they can to recharge their vehicles. Although, by extension this has caused the energy rationing to be in-effective.

Grid Infrastructure

As shown earlier, when determining the impact on grid infrastructure, power is the more significant factor, when compared with energy. This can be seen in the following figures, figures 6.17, 6.18 and 6.19 below.

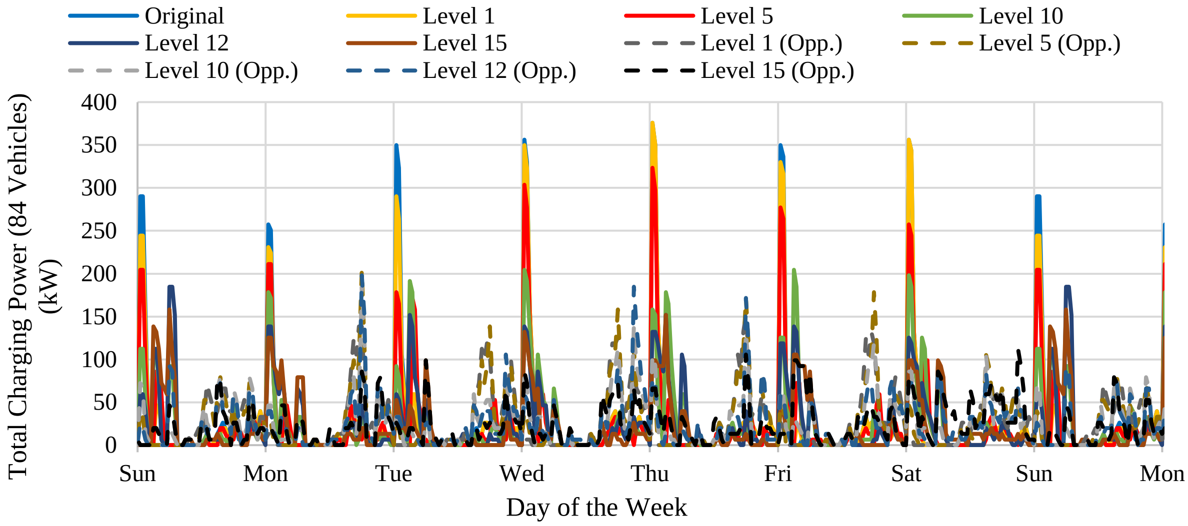


Figure 6.17: Charging Power demand for both ‘Electricity Tariff Dictated’ and ‘Opportunistic’ charging regimes

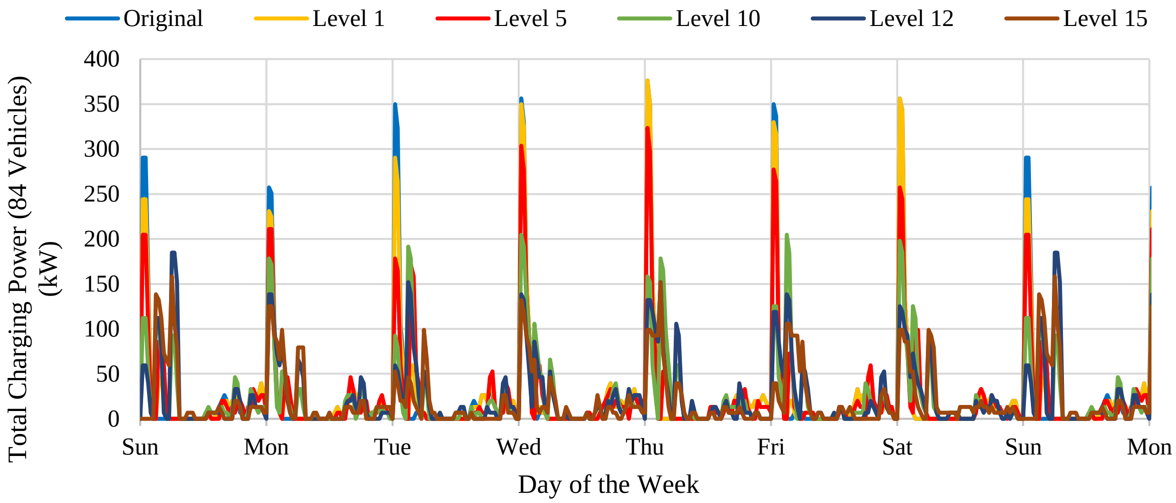


Figure 6.18: Charging Power demand for the ‘Electricity Tariff Dictated’ charging regime

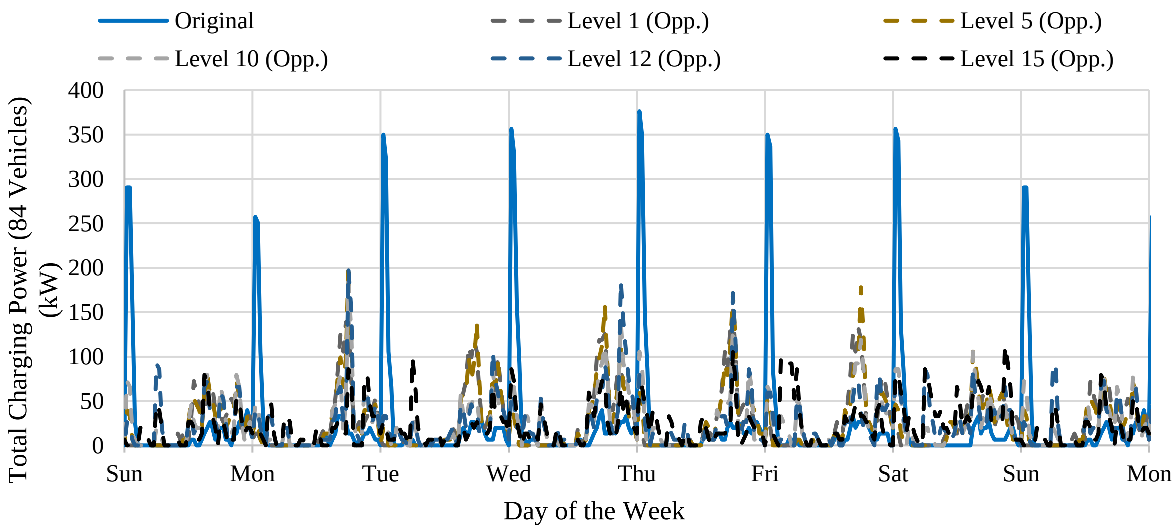


Figure 6.19: Charging Power demand for the ‘Opportunistic’ charging regime

As per figures 6.17, 6.18 and 6.19, the charging demand profiles for the charge points during these simulations follow the same patterns as the energy profiles. This is expected due to the relationship between energy and power. In all cases the peak power demand has been reduced, which from a grid's infrastructure, and by extension a grids operator's, perspective is very beneficial. The following section, Section 6.2, will examine other methods and techniques which can be used to reduce the peak demand spikes causes by EV uptake in rural areas.

Building upon this work, to further investigate the impact on the local grid infrastructure around Bradbourne, these charging power profiles have been combined with dataset received from WPD, previously detailed in Section 5.1.1. Again, the results from these simulations have been scaled by a factor of 16.43 to reflect the vehicle population size of the area covered by the substation to which the WPD dataset pertains, see figures 6.20, 6.21 and 6.22.

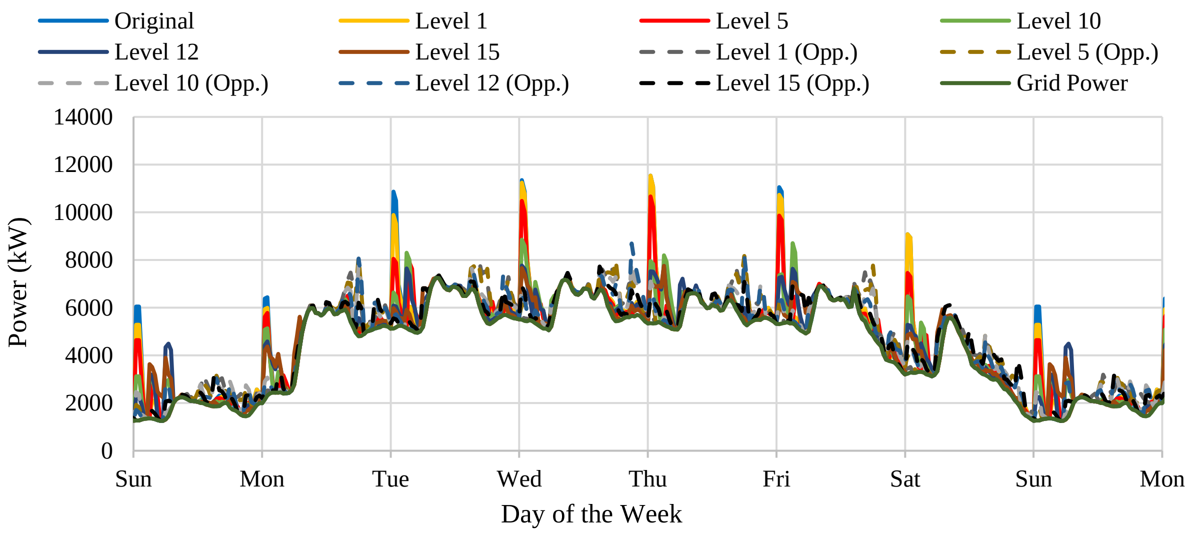


Figure 6.20: Charging power demand combined with the pre-existing grid power demand for both 'Electricity Tariff Dictated' and 'Opportunistic' charging regimes

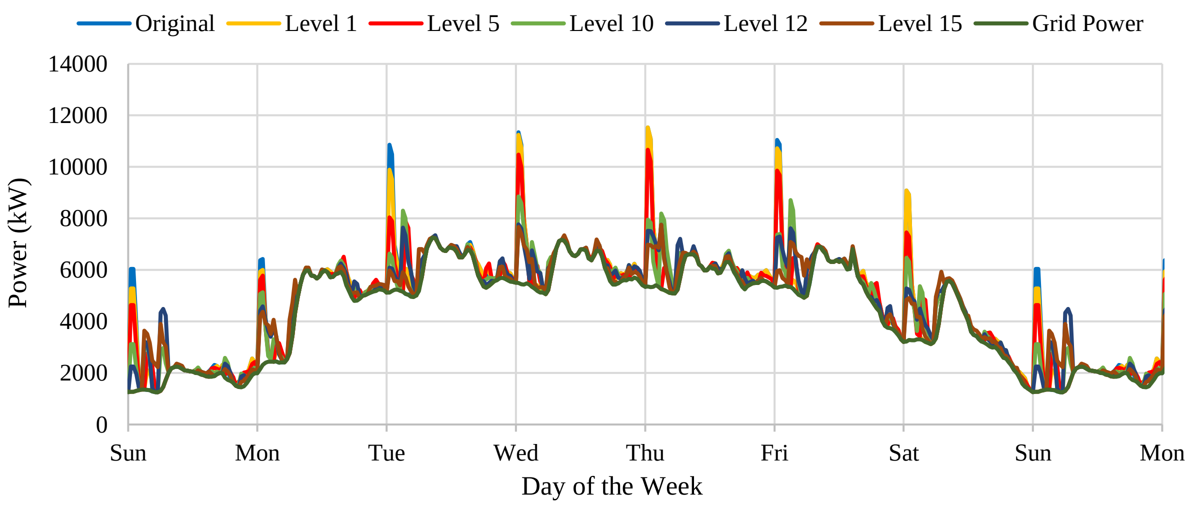


Figure 6.21: Charging power demand combined with the pre-existing grid power demand for the 'Electricity Tariff Dictated' charging regime

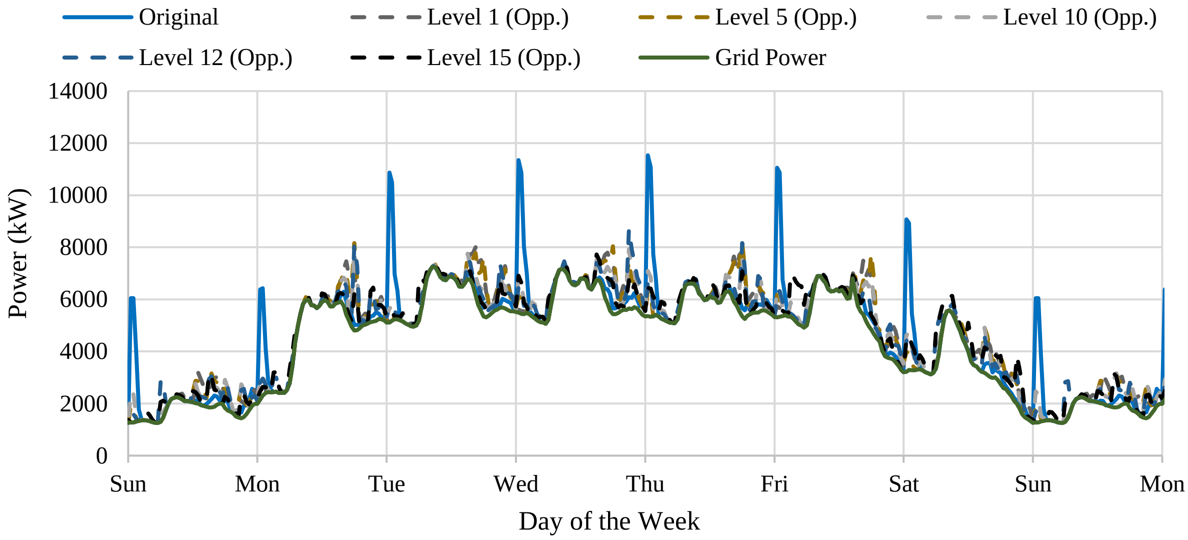


Figure 6.22: Charging power demand combined with the pre-existing grid power demand for the 'Opportunistic' charging regime

Consumer

As mentioned previously, the total battery charge capacity plots shown in figures 6.11 initially suggest little cause for concern for the impact these ESEC planned power outages will have on EV usability in rural areas. However, when considering the individual vehicles which constitute this total battery capacity of the fleet, some vehicles fare better than others. Table 6.3 shows the number of EVs which reach 0% SOC during some point within the 4 week simulation period.

Charging Regime	Disconnection Level	No. of Cars reaching 0% SOC
Electricity Tariff Dictated	Level 1	0
	Level 5	0
	Level 10	1
	Level 12	3
	Level 15	25
Opportunistically	Level 1	0
	Level 5	0
	Level 10	1
	Level 12	1
	Level 15	6

Table 6.3: The number of EVs that hit 0% SOC at some point during the 4 week simulation of each scenario

From table 6.3, multiple EVs do in fact reach 0% SOC, which is hidden through the total battery charge capacity presentation approach. From a consumer perspective, only when high level disconnection scenarios were simulated does this occur. Scenarios which are unlikely to occur in real life should planned power outages ever be invoked per the ESEC. Table 6.3 also highlights the impact the opportunistic charging regime has, when compared to the base scenario of the electricity tariff dictated charging regime. When considering disconnection level 15 for both charging regimes, there is a huge reduction from 25 to 6 vehicles that ever reach 0% SOC during the 4 weeks of simulation.

Figures 6.23, 6.24 and 6.25 present the average SOC of all 84 vehicles over the entire simulation period, again, reinforcing the findings previously. Highlighting the concealment of individual vehicles reaching 0% SOC during the simulation period, but also how the 'Opportunistic Charging' regime improves the average SOC throughout.

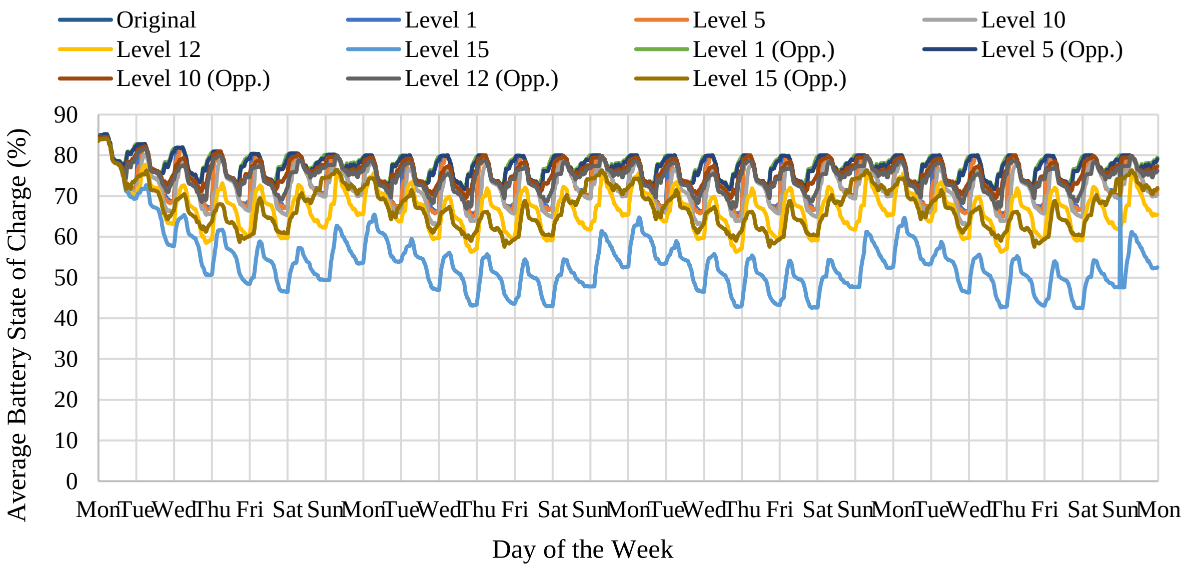


Figure 6.23: Full 4 week simulation period for the average battery SOC of the simulated EVs of Bradbourne during the ESEC planned power outages for both the 'Electricity Tariff Dictated' and 'Opportunistic' Charging regime

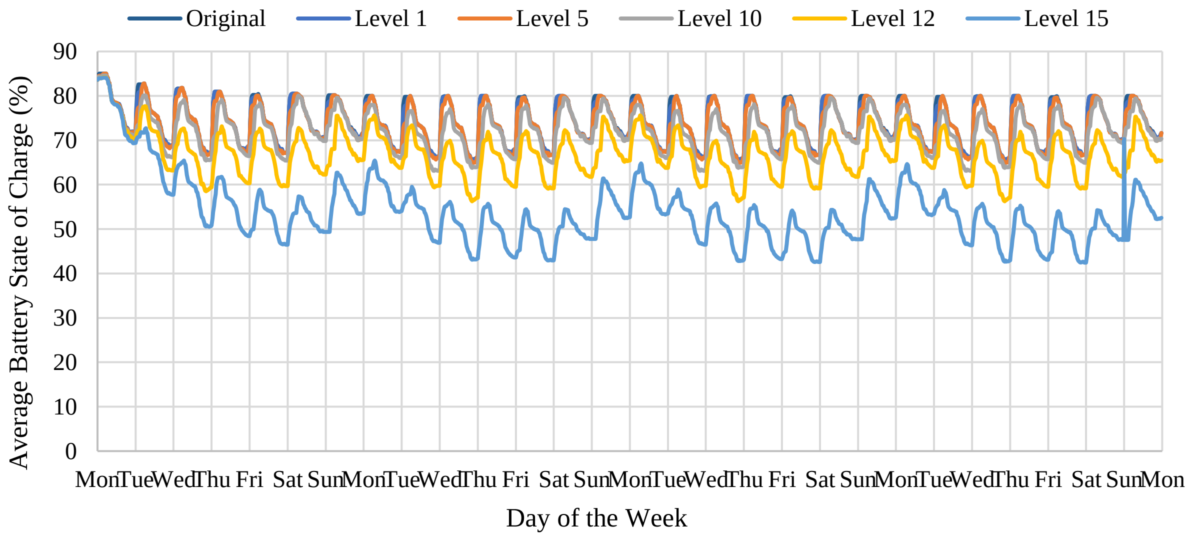


Figure 6.24: Full 4 week simulation period for the average battery SOC of the simulated EVs of Bradbourne during the ESEC planned power outages for the 'Electricity Tariff Dictated' Charging regime

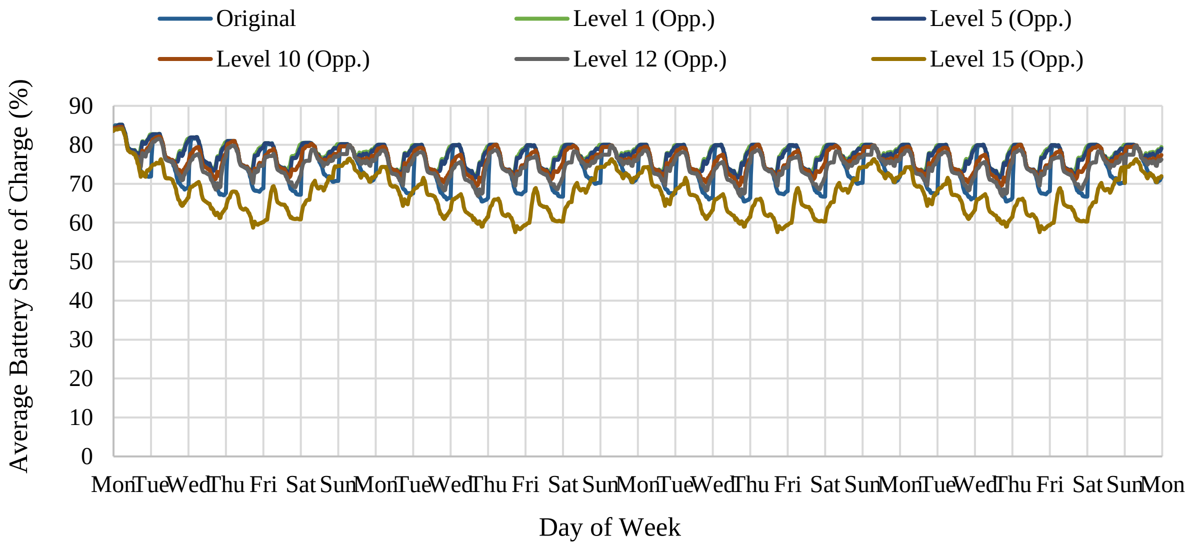


Figure 6.25: Full 4 week simulation period for the average battery SOC of the simulated EVs of Bradbourne during the ESEC planned power outages for the 'Opportunistic' Charging regime

There are some limitations to this methodology, as it would be reasonable to assume that the travel patterns would also change to accommodate the planned power outages as they would be known (planned) occurrences. Individuals therefore would be able to plan to always be at home, where possible, when they had power on in order to charge, for example. However, these scenarios are currently beyond the scope of this work and could be addressed under further work, this will be discussed in Chapter 8.

6.2 Demand Side Management

As shown in this chapter, the impact of EVs on the grid is considerable, including greater demand for electricity, both from an energy and power point of view, and the repercussions this could bring. Currently, grid operators have developed two mechanisms designed to maintain the balance of power supply and demand in a cost-effective way. The first mechanism is based on the integration of energy storage systems into the grid, and the second mechanism is focusing on minimising the peak load by encouraging end-users to change their power usage behaviours with incentivised benefits (Aoun et al., 2019). This process is called Demand Side Management (DSM) (Aoun et al., 2019).

DSM seeks to alleviate this issue, through strategies and technologies which encourage consumers to shift their demand and optimize their energy use. Thus reducing the peak demands and smoothing out demand over a longer period of time in general. With rural areas threatened by power outages more so than their urban counterparts, especially in terms of the impact a power outage will have, creating a more reliable and flexible grid is not just in the grid operators' interest but EV owners themselves.

Referring back to figure 5.15 in Section 5.2, the ‘charging every night’ scenarios (scenarios 5, 6, 7 & 8) have the largest peak demands due to the integration of EV charging, with Scenario 5 (100% Economy) indicating the worst impact. The results of this scenario have been repeated below in Figure 6.26 for reference. Therefore, DSM Strategies will only be investigated around this scenario as this represents the worst case.

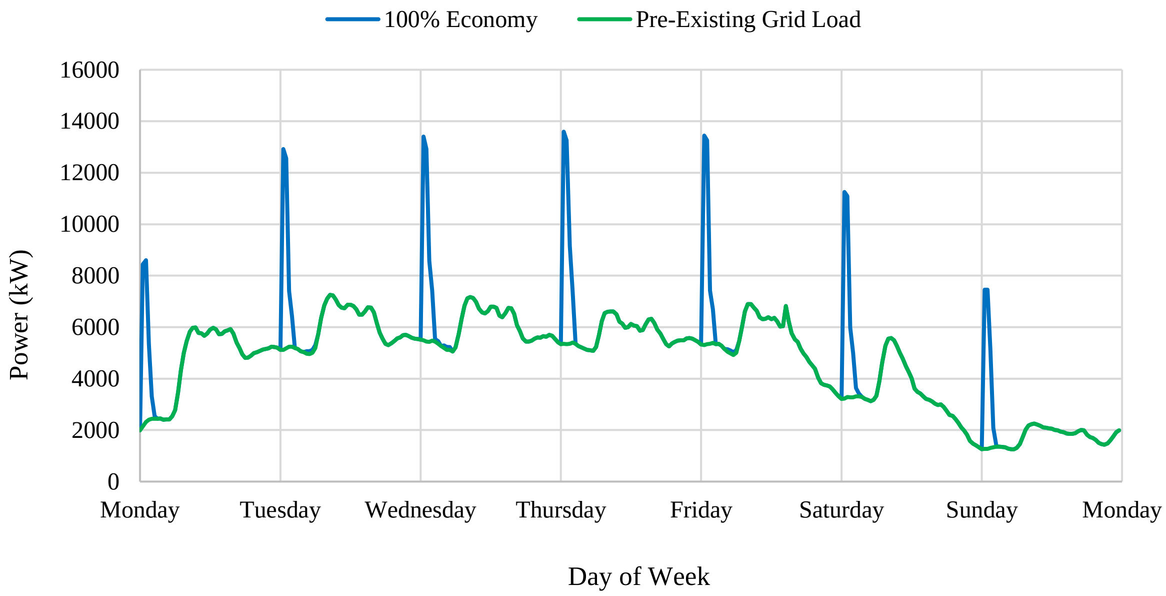


Figure 6.26: Combination of Pre-existing Grid Load and EV Charging results for the 100% Economy scenario

6.2.1 Development of Strategies for DSM

As this work directly involves the grid, this body of work is based on the larger area including and surrounding Bradbourne – the area presented in figure 5.4 of Chapter 5. However, as the DSM strategies developed will directly impact charging events of individual vehicles, the methodology employed in the previous sections of scaling the results would not work. Therefore, each of the original 84 vehicles simulated for Bradbourne were duplicated 16.43 times (with the 0.43 constituting a random selection of 36 vehicles from the population of 84). This provided 1380 vehicles with individual travel patterns and charging profiles, upon which the DSM strategies could be applied. Three DSM Strategies have been proposed for this body of work:

Strategy 1 - A first come, first serve approach: Whereby the first individual charge points to be utilised for a charging event see no power reduction, but once the grid supply power threshold value has been reached, any additional vehicles that are plugged in will not be able to start charging until others finish.

Strategy 2 - Lowest Battery charge has priority: A smart system whereby all SOCs of each vehicle are reviewed at 30 minute intervals, with only the lowest SOC vehicles being able to charge up to the grid constraint, again, no power reduction at the chargers.

Strategy 3 - Equal Distribution: All vehicles are recharged when plugged in, but the power at individual charge points is reduced (shared) to align with the total threshold limit/constraint imposed (Ciabattoni et al., 2021).

Across each scenario, multiple threshold limits are applied to the local substation, i.e. to simulate potential limits grid operators may impose on their energy distribution network. These thresholds are 8000 kW, 10,000 kW and 12,000 kW and signify the total power that can be drawn from the local substation at any one time, which in this instance would be a combination of the pre-existing grid load and the power requirements from EV charging. Applying DSM strategies requires a global approach, i.e. from perspective of the transformer. For this reason, at each 30 minute interval timestep the headroom between the pre-existing grid load and the current threshold limit being simulated was calculated. This headroom is then compared to the total power demand from all 1380 vehicles in this instant to see if there is enough power for the pre-determined charging events of that timestep. If not, and the imposed grid thresholds have reduced the capacity of the transformer to such a level whereby the number of desired charging events cannot occur then the implementation of one of the DSM strategies currently being simulated can begin. The process for this simulation is illustrated in figure 6.27 below.

6.2.2 DSM Simulation Process

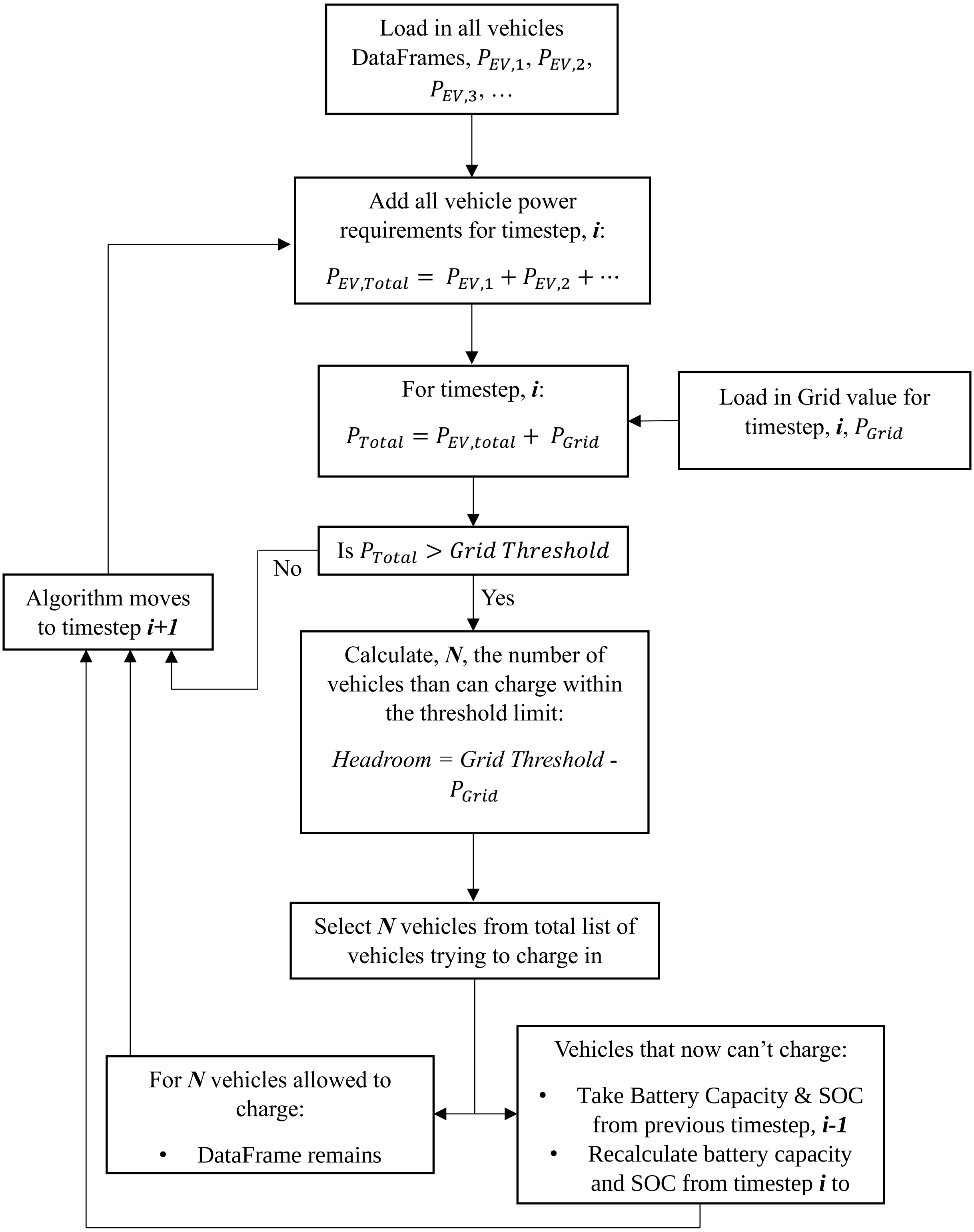


Figure 6.27: Flowchart representing the Simulation Process for DSM Strategy 1

As detailed in figure 6.27, every vehicle, and their individual results from the EV Charging Model, act as an input to the DSM system. During each 30 minute interval over a 4 week period, the simulation compiles the total power required by each vehicle/charge point ($P_{EV,Total}$). This is then added to the pre-existing load on the local grid infrastructure (P_{Grid}) to calculate the total power demand, P_{Total}. This is then compared with the imposed threshold limit. If P_{Total} is larger than the imposed grid threshold, then the DSM strategy currently being investigated is implemented in order to decrease this total load to below the limit.

In building the Demand-Side Management (DSM) methodology upon the EV Charging Model, it is important to clarify that the charging framework remains consistent. Specifically, the model presupposes that each vehicle is paired with its own charging station. Thus, the scheduling of charging sessions adheres to the timelines established by the EV Charging Model. This arrangement implies that in households with multiple vehicles, each one is equipped with a separate charger. As a result, the DSM model treats vehicles in multi-vehicle households no differently than those in single-vehicle households, ensuring that the number of vehicles does not influence the charging strategy or its impact within the DSM framework.

Figure 6.27 illustrates the process for Strategy 1 specifically, whereby 'N' number of vehicles are selected from the total list of vehicles attempting to charging during this timestep. These vehicles are then given priority should they wish to continue charging in the next timestep. Strategy 2's process would involve a review of all the vehicles trying to charge at each timestep and selecting 'N' number of vehicles with the lowest State of Charges. Strategy 3 would continue to allow all vehicles wishing to charge to continue doing so, however the power drawn from each of those vehicles would be equally reduced in order to decrease P_{Total} below the imposed grid threshold currently being run. Custom written python scripts were used to compute the above processes for each strategy. To align with the results of the EV Charging model, these simulations ran for a period of 4 weeks to allow for the assessment of the feasibility for these DSM strategies over a longer time period.

6.2.3 Results of DSM Strategy 1

This strategy utilized a first come first serve approach, whereby at each timestep, out of the vehicles wishing to charge, only the first 'N' vehicles are allowed to charge, with further priority given to those already charging from the previous timestep. The overall impact from the grid's perspective can be seen in figure 6.28 below.

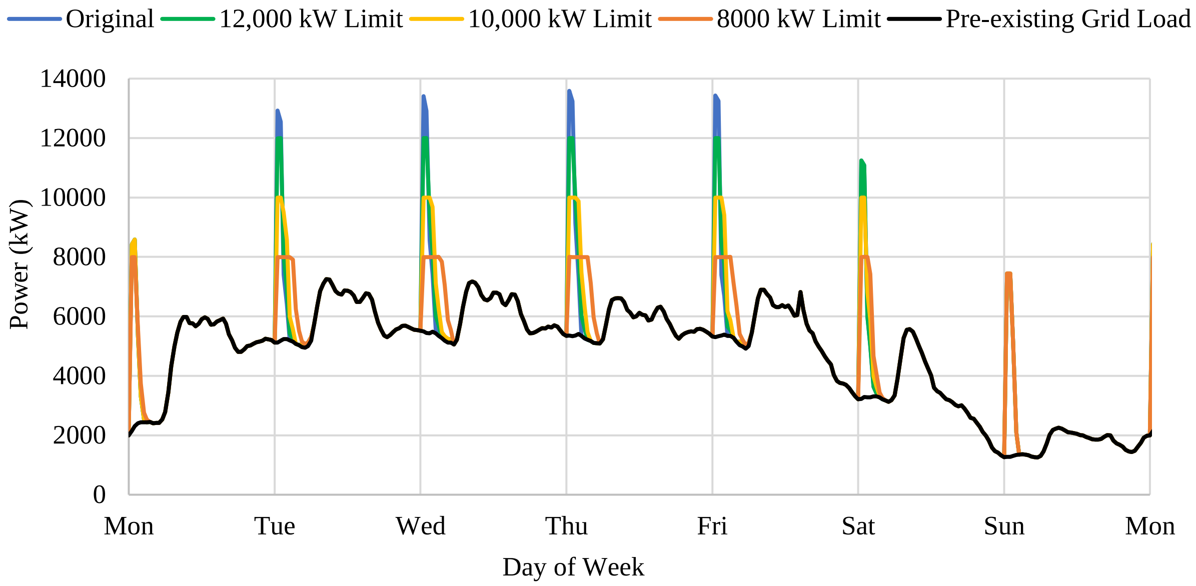


Figure 6.28: Total power drawn from grid for Strategy 1 across the three threshold limits

As per figure 6.28, the duration of charging events across the population of vehicles increases as the imposed threshold is lowered. However, regardless of the threshold, all vehicles received enough charge to fulfil the following days scheduled travel activities. This is largely due to the impact the Economy 7 tariff has on EV charging, which acts as a form of DSM in the first instance. Due to this electricity tariff, most charging events were scheduled during a period of low demand in terms of the pre-existing load on the grid. This allowed for the use of pre-existing headroom to the threshold limits, when comparing the highest grid demand. Although from the grid operators' perspective this achieves the required outcome of reducing those peak demands and curtailing any voltage violations, for the EV owners themselves, there may be issues with acceptance. Although many home charge points come with delay-start charge time functionality to align with EV specific electricity tariffs, using this function is an EV owner's choice. Strategy 1 supposes grid operators' responsibilities for the delay in charging caused to some owners, however the focus of this work was the investigation of the end results from DSM implementations and not the methods by which this would be achieved. The duration of time that charging took place across the different threshold scenarios saw the most significant impact, see Table 6.4.

	Original	8000 kW Limit	10000 kW Limit	12000 kW Limit
Time (hrs)	2.5	4.5	3	3

Table 6.4: Average charging durations for Strategy 1

All imposed threshold scenarios saw an increase in the duration whereby charging events took place, with the most severe being that caused by the 8000 kW threshold, as expected. Given the start time for charging events, as dictated by the Economy 7 tariff was midnight, even at the lowest threshold, this still allowed for all vehicles to finish their charging events by the early morning.

6.2.4 Results of DSM Strategy 2

Instead of a first come, first served approach, this strategy prioritized those EVs with the lowest state of charge. As shown by figure 6.29, the results are similar to those seen in Strategy 1. However, when considering the time over which charging events occur during strategy 2, Table 6.5 shows that this duration has decreased with comparison to the results from strategy 1. Again, all vehicles gained the necessary charge to sustain their scheduled travel and so from an EV owner's perspective, satisfaction from this standpoint alone has been achieved.

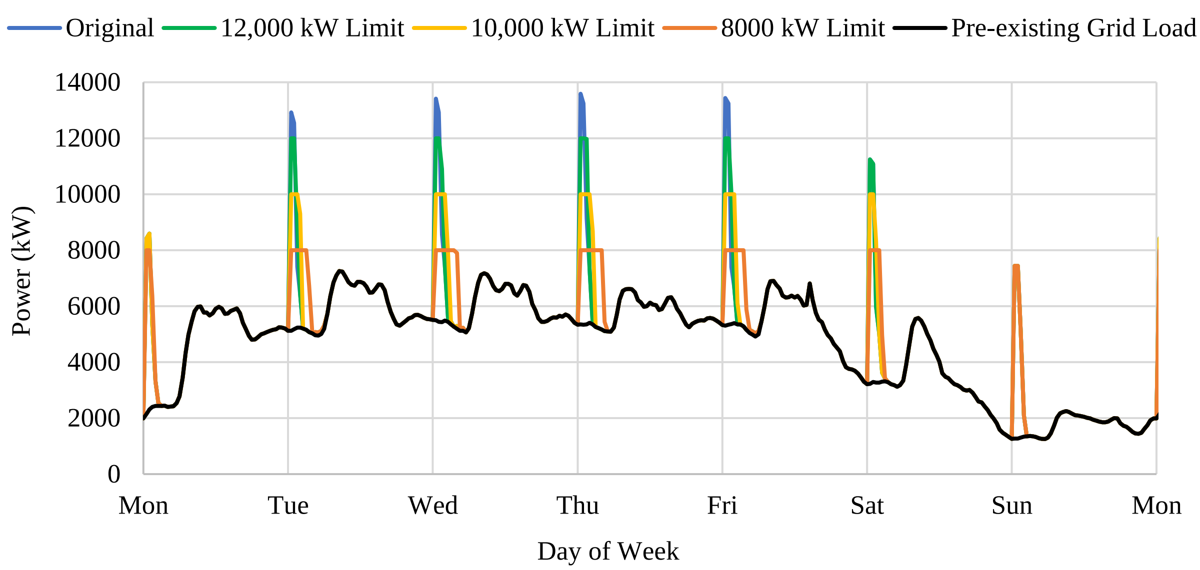


Figure 6.29: Total power drawn from grid for Strategy 2 across the three threshold limits

	Original	8000 kW Limit	10000 kW Limit	12000 kW Limit
Time (hrs)	2.5	3.5	2.5	2.5

Table 6.5: Average charging durations for Strategy 2

By focusing on the lowest charged vehicles first, this has allowed for maximum capacity of charge to be deployed to the vehicles. This is due to the relationship between power and energy and the fidelity of the results – readings every 30 minutes. With the use of 6.6 kW chargers, this yields a maximum of 3.3 kWh charge every half hour for the vehicles. However, if a vehicle requires less than 3.3 kWh to reach the upper 80% SOC limit (i.e. fully charged), this simulation timestep would still require 6.6 kW of power from the grid. By prioritizing the lowest SOC vehicles initially, these vehicles will more likely require a full 3.3 kWh of charge each half hour, and so maximum charging efficiency of the system is achieved. This will then be followed by the last few half-hour timesteps of charging events occupied with lower efficiency (<3.3 kWh charge) charging events, when compared to strategy 1 which would have these timesteps scattered across the whole duration. This results in savings of an hour of overall charge event duration when comparing strategy 2 and strategy 1. There is also a social aspect to strategy 2 which needs to be considered with regards to understanding its acceptance amongst the user community. Strategy 2 provides an opportunity to understand how consumers may react to scenarios whereby charging does not initiate directly after plugging in, but with an understanding that this is due to someone with a lower charge on their EV which may hinder their next day's requirements.

6.2.5 Results of DSM Strategy 3

This strategy employed what is possibly a more equitable strategy – to equally distribute the available headroom below the imposed thresholds, between all vehicles requiring charging. This would be employed via considering the power requirements of the whole EV population, and if this was above the threshold value all chargers would remain operational albeit at a lower output power compared to their rating. Each EV charger's power output would be reduced equally in order to reduce the total load on the grid. Again, the threshold limits of 8000 kW, 10000 kW and 12000 kW were imposed upon the system. The results of strategy 3 can be seen in figure 6.30.

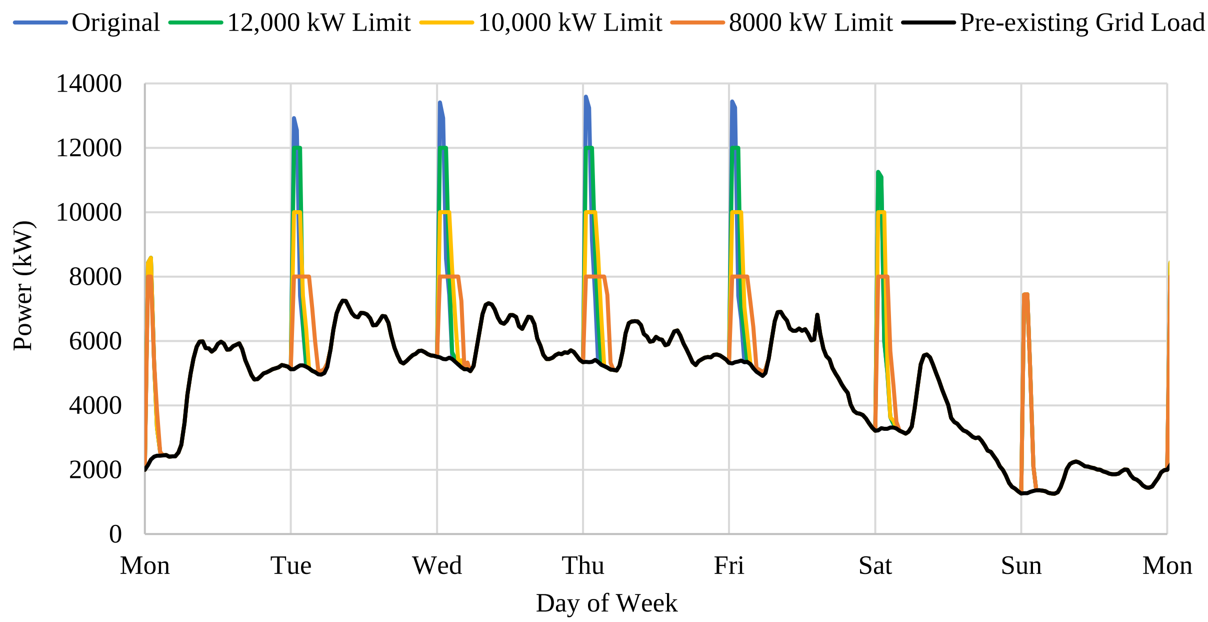


Figure 6.30: Total power drawn from grid for strategy 3 across the three threshold limits

Strategy 3 is assumed to be the most socially accepted form of DSM investigated, as again for grid operators the power demand spikes have been reduced significantly to that more in-line with pre-existing loads, however, in addition this strategy holds the fairest approach for EV owners themselves, should their communities power supply be limited or controlled.

	Original	8000 kW Limit	10000 kW Limit	12000 kW Limit
Time (hrs)	2.5	4	3	2.5

Table 6.6: Average charging duration for Strategy 3

The duration over which charging events occur, as concurrent with the other two strategies has increased, see table 6.6. However, there is more of a linear relationship between each imposed threshold limit on the grid, compared to strategies 1 & 2. Overall, all DSM strategies have proven their feasibility in reducing the peak load due to EV charging, whilst still allowing EV owners to maintain their current travel patterns.

6.2.6 Discussion and Comparison of all DSM Strategies

To provide an insight into how each DSM strategy impacted individual vehicles, the results from Vehicle 33 within the simulation have been presented, see figure 6.31. For reference, Vehicle 33 belongs to House ID 29, a '*Two Person, Two Vehicle*' household. The TDM simulated this vehicle to travel for '*Work*' full time, 5 days per week, conduct two '*Other*' trips, as well as completing four '*Shopping*' trips during the week. As recalled in Section 6.2, all households within the DSM simulations were served by an Economy electricity tariff, and thus aimed to complete charging events in the early hours.

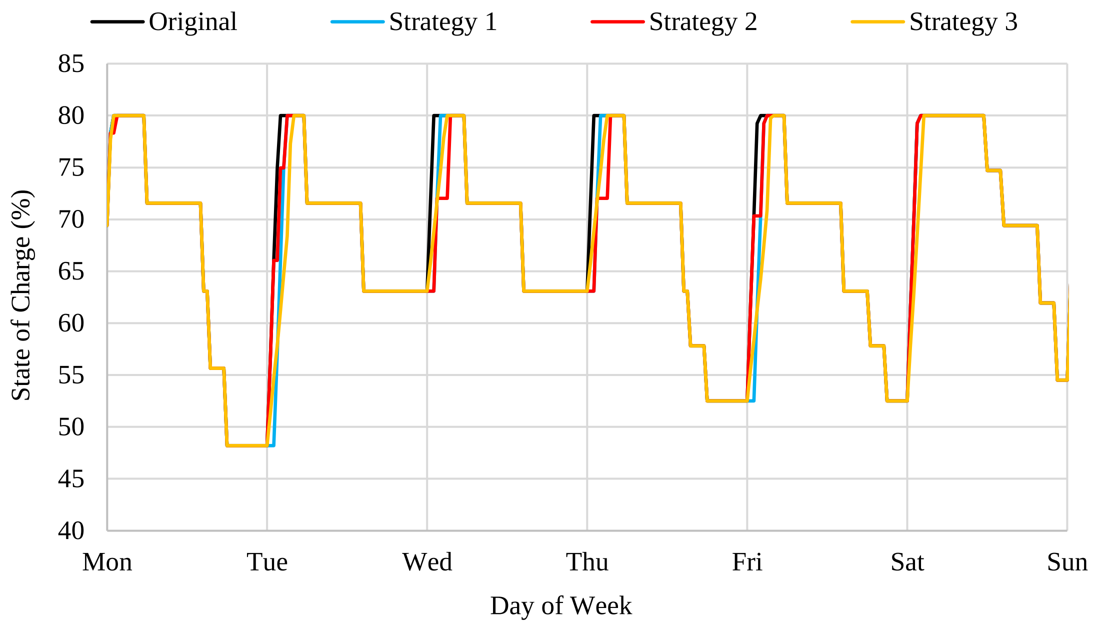


Figure 6.31: State of Charge over one week across each DSM strategy for Vehicle 33

As shown by Figure 6.31, the largest impact the different strategies have is on recharging time. In this case (vehicle 33), and all the other vehicles, sufficient charge was provided to meet the travel demands of EV owners. However, the various strategies implemented had differing effects on different days of the week. Strategy 3 illustrates the different rate of recharge compared to strategies 1 and 2, due to the relationship of power and energy as discussed earlier, which is expected to change not just daily, but at each half-hour timestep. This is due to the 'Headroom' changing for each timestep with respect to what the pre-existing load on the grid is, which allows for differing reductions in power of each charge point. Although for strategy 3, we are now reducing the power output of each charge point itself, and thus reducing the maximum amount of energy that can be recharged within each timestep, which has not resulted in the slowest DSM strategy when compared with the original. All DSM strategies did extend the duration of charging events, as expected (shown by tables 6.4 – 6.6), however, figure 6.31 shows that depending on the day of the week, strategy 3 is not the slowest overall, as one might expect. Strategy 2 results in the slowest DSM on some days for vehicle 33 in this example. This is due to the 'step-changes' as dictated by strategy 2 which can be seen in figure 6.31. These are timesteps during this vehicles timeline when it no longer had one of the lowest SOC's, when compared to the rest of the fleet (1379 other vehicles with chargepoints connected to substation 890067). In this instance, charging would have ceased on vehicle 33 and another vehicle begins. This alludes towards the fairness of this strategy, which attempts to give everyone within the community of Bradbourne a minimum level of charge. The biggest limitation extends from the EV charging model underpinning this work, specifically the number of charge points parameter. If the number of charge points was restricted this would, in of itself, act as a 'natural'/real-life form of DSM. However, having focused on a total number of charge points of 1380, derived from the number of vehicles in the area (*Section 5.2*), this figure does represent a realistic value. Although 1380 home charge points, as assumed in this work, is less likely, for a future scenario with 100% EV market share with numerous home chargers installed, with the addition of public charge points (located at workplaces, shops etc.) this figure would become more likely.

6.3 Chapter Summary

This chapter explored the impacts of power outages, both unplanned and planned. Firstly, with regards to unplanned power outages, multiple durations, ranging from 12hrs to 48hrs, were simulated. These showed interesting links between electricity tariffs and the impact of power outages, with the households served by a Standard electricity tariff fairing the best in terms of the vehicles SOC and maintaining travelling patterns. However, for power outages longer than 36hrs, vehicles within the simulation of Bradbourne's population began reaching 0% SOC at various times. Planned power outages highlighted the UK Governments ESEC, which given recent global affairs at the time of writing, are receiving a lot of attention. A selection of the ESEC proposed disconnection levels were simulated for a period of 4 weeks and their impacts investigated, from a generational, grid operators and EV owners perspectives.

Given the concern that large scale EV adoption has shown to implicate rural grid infrastructure in the UK, mitigation of such issues was investigated. Utilising demand side management techniques to stabilise the grid, three strategies were developed; a first come, first served approach, lowest battery has priority, and an equal distribution. Each strategy enabled the reduction of peak demands drastically down to sufficient levels that would leave grid operators satisfied and alleviate any of the issues presented during this chapter. However, investigations into the fairness and satisfaction of each strategy from EV owners and consumers perspective would be needed to make any further recommendations on approaches.

A large part of what the findings presented in this Chapter and Chapter 5 previous, is the mitigation of concern that rural residents and transition to EVs should take from this. The findings presented in the last two chapters directly assess how consumers, rural residents, shall experience EVs and the over-arching takeaway will hopefully be that of less concern. As detailed in Chapter 2, literature exposed multiple barriers towards the adoption of EVs, as well as nuance aspects for rural communities, which only exacerbate these. With these nuances taken into consideration, this thesis has shown rural residents may own and operate EVs with confidence. EVs have been shown to be more than capable at carrying out the average daily travel requirements of rural residents, even considering power outages. However, to ensure a smooth transition, infrastructure upgrades are paramount and should not be taken less seriously following the findings of these last few chapters. This thesis argues that with the timeline predictions, this should only spur on policy makers and infrastructure operators to ensure the rural areas are equipped for the future. The material presented in this chapter, and the previous, offer a comprehensive review and technical analyses for EV uptake in a rural area. Thus aiding in the understanding of the impact this transition will have for rural communities. Alongside the previous chapter, '*Research Aim 3*' has now been achieved with the material in this chapter fulfilling '*Objectives 3b and 3c*'.

Although, an imperative part of this EV transition, as with all large-scale socio-techno transitions, is stakeholder engagement. When it comes to the EV transition in rural areas, this specifically involves the rural demographic themselves. Stakeholder engagement cannot simply justify assumptions and predictions from models and the theoretical approach, it also highlights any unforeseen issues, all of which coalesces for a smoother transition. This will be the focus of the next chapter.

CHAPTER 7: UNDERSTANDING THE RURAL DEMOGRAPHIC AND ELECTRIC VEHICLES

Thus far, the work presented in this thesis has been from a largely theoretical standpoint, i.e. simulations and modelling. To fulfil the objectives of this thesis as outlined in Chapter 1, a data collection phase was included to underscore the real-world relevance of this research. This phase also considers rural communities, a frequently neglected stakeholder group, in the understanding and development of strategies for the EV transition in these areas. This data collection stage took the form of a survey which was distributed to rural communities, seeking to gather information on their current vehicle usage, the use of EVs and associated technologies such as charge points and electricity meters, as well as the demographic themselves.

This chapter will be presented in a different manner to the previous ones, due to its nature of incorporating primary empirical data. It will begin with an introduction to the survey itself in Section 7.1, this will include its makeup, the decisions surrounding the choice of questions that went into it, as well as discussing the methodology, including the ethical approval stage and distribution methods. A short cross-reference to Stakeholder theory and its influence on this work will also be discussed. Section 7.2 will present the results of the survey for each question, with the discussion on its relation to the previous work within the thesis, including validations of the models previously presented and publicly available datasets. Section 7.3 will follow; this section will discuss the wider implications of the findings from the survey in relation to other similar studies which have been conducted. The chapter will conclude with Section 7.4.

Material presented in this chapter has been published and presented previously at the 2023 Logistic Research Network (LRN) conference (McKinney et al., 2023e).

7.1 Development of Survey

The survey was developed in Google Forms software. This was chosen, over for instance other survey specific software such as Qualtrics and Survey Monkey, due to its accessibility through the university and the requirements of this data collection stage. These requirements exclude the advanced statistical analysis of the responses, which survey specific software offers. Questions were designed in such a way to easily allow for validation of the models presented previously in this thesis, enabling easy comparison. Google Forms offered a user-friendly approach, from both its design and participant perspectives and allowed for the easy export of responses to Microsoft Excel, in which all sufficient data manipulation could be conducted. The additional time and resources that would have been required to undertake this exercise in a survey specific software was not justified by any additional statistical abilities it may have provided. The contents of the survey itself, the ethical approval process it underwent, and its distribution will now be discussed.

7.1.1 Contents

This survey consisted of 18 questions, split across 5 sections related to the EV transition and rural areas. These sections were as follows: (1) Demographic, (2) Your Cars and Travel, (3) Electric Vehicles, (4) Charging and (5) Electricity Tariffs. A full copy of the survey can be found in Appendix D.

The first section, ‘Demographic’, recorded information pertaining to the area of the respondent, as well as the number of people and their respective ages living at the household. It is important to note that a distinctive aspect of the survey was its design to be completed from a household perspective, rather than that of an individual, when capturing this data.

The second section, ‘Your Cars and Travel’, was incorporated to discern car availability and usage for each household. These questions enabled direct comparisons with the results of the Travel Demand Model presented in Chapter 3. The aim is to validate not only the inputs used by this model, but also its outputs, and by extension those from the EV Charging Model (presented in Chapter 4).

The ‘Electric Vehicles’ section was used to understand not just awareness of EVs and the transition to EVs within the rural community, but also ascertain their acceptance of this transition. Additionally, questions related to local public transport were also included to identify alternative means of transport and accessibility.

The following section, ‘Charging’, provided an opportunity to investigate charge point allocation and capabilities for rural households in terms of parking, anticipated number of chargers individuals would desire, and where they envisage charging their EVs. These questions were framed to be answered regardless of current EV ownership status, and so instead invited participants to contemplate a future scenario whereby they did have an EV.

The final section, ‘Electricity Tariff’ was included to understand associated EV technologies, such as EV specific electricity tariffs and meters. This section also enabled insight into their adaptability for change, change that could maximise EV potential and reduce running costs.

The survey concluded with an option for participants to receive a ‘results report’ upon the surveys completion. This report not only included various results from the survey, but also information pertaining to the EV transition itself and the various technologies raised in the survey. Thus, informing the rural community so that they themselves may become a more prominent stakeholder. A copy of the results report which was emailed to participants (upon request) can be seen in Appendix G.

7.1.2 Ethical Approval

Research ethics applies to all aspects of data collection and analysis, which only becomes more stringent when research involves human subjects or research participants (Bell et al., 2022). To ensure ethical integrity is adhered to, this body of qualitative work underwent review from the University of Sheffield's ethics committee (Ethics Application ID: 044759).

The ethical review process was also beneficial for improving the survey, in particular the phrasing of questions. To ensure high completion levels, questions required layman's language, however this did detract from the level of detail questions could delve into. For instance, first attempts for understanding when vehicles are in use and for what trip purposes they complete, in order to validate the TDM, saw multiple questions requiring participants to complete essentially a full week travel diary at 30-minute intervals, as per the TDM. Through the ethical review process it became clear that in order for this question to be successful, and by extension the survey itself, the complexity would have to be reduced. This resulted in minimal questions to understand total weekly mileages undertaken by participants. Although the high level validation is not possible, this ensured survey completion and an ability to validate the low level findings from the TDM.

With regards to integrity of the survey itself, the ethical review process also highlighted the need to consider data protection and personal information. Although no personal information was collected by this survey, protocols were still set in place for participants to be informed, through a participant information sheet (Appendix E) and understand how the data collected would be managed and utilised.

7.1.3 Distribution

The focus of this thesis is on rural communities and ensuring that the EV transition does not result in life becoming more difficult for them. Therefore, potential participants were required to meet a single criterion – they live in a rural area. To align with the work presented thus far in this thesis, areas of the Peak District again were chosen from which this data collection would take place. A flyer was developed to advertise the survey in this area – purposive sampling.

Purposive sampling is a technique used in qualitative research to select a specific group of individuals or units for analysis. A key advantage with this technique is the quality of the resulting data collected. As data is collected from participants who are particularly interested in and experienced with the topic (i.e. living in a rural area), this results in the collection of rich, detailed and meaningful data. This does however mean, that since the sample is not randomly selected, the findings from purposive sampling cannot be statistically generalised to the broader population. Though given the focus of this thesis is specifically rural areas, deeper insights into this focus is preferential over broader generalisation, which would be to include other population areas. Additionally, this does present a challenge for replicability. The purposive sampling technique also enables greater flexibility, allowing the collection, particularly from an areas POV, to adapt and focus on emerging patterns should they appear. However, with the participation criteria also subjects the data collected to bias and subjectivity. Attempts were made to minimise any bias through the use multiple avenues of distribution, which will be discussed in more detail shortly, to ensure everyone within the rural area(s) of interest, were contacted about the survey. This contact was done so through a flyer.

The flyer had a QR code and website address, with which individuals who wished to participate would be able to access the Google Form survey. For an already harder to reach community, this may have incurred some limitations due to accessibility and technology. Individuals who may lack technological knowledge, or Internet access altogether (more likely in rural areas), may result in a lower response rate than in person survey conducting methods. However, the wide geographic coverage for the flyer distribution helped to address this limitation.

Multiple distribution methods were employed over a period of 9 months, with the total data collection stage lasting 11 months. Utilising services such as Royal Mails Door-to-Door Campaign service, local parish councils, hand delivery and contacting local schools in the area, were used to distribute flyers to households in the area of interest. A full breakdown of the contacts used for this distribution can be found in Appendix F.

Distribution methods were also staggered throughout the total time of data collection. This was as a result of periodically increasing the area of interest to capture more data. Initially, efforts were focused on solely the village of Bradbourne and some additional surrounding villages; the areas highlighted in red in figure 7.1.

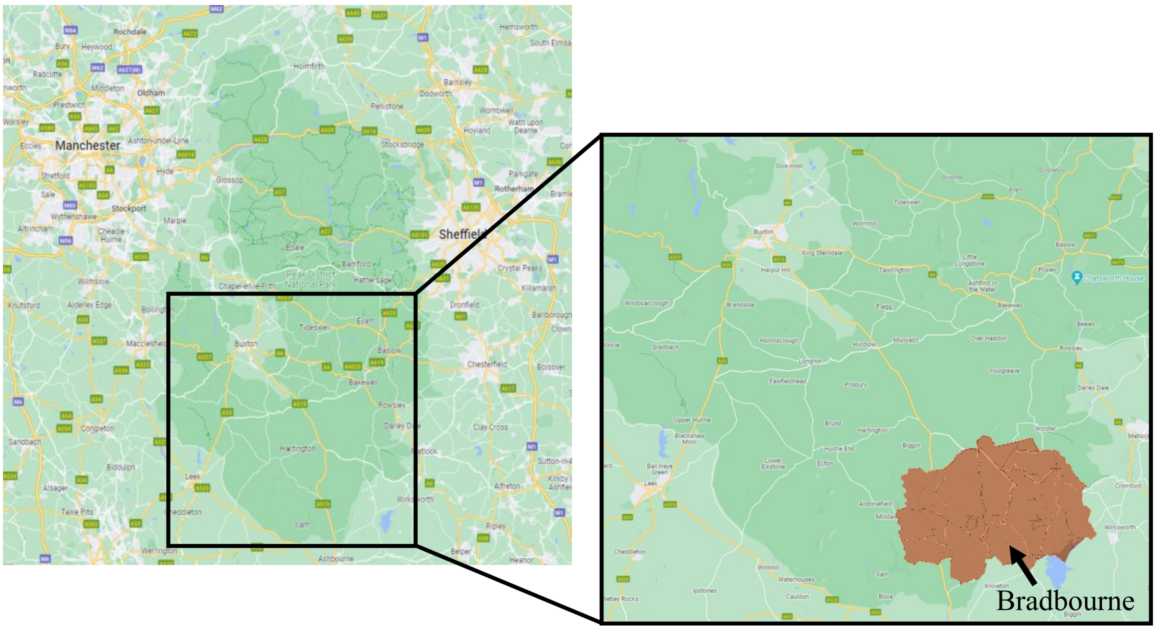


Figure 7.1: Initial distribution area (Area includes that highlighted in red)

For the area highlighted in Figure 7.1, distribution methods included local parish councils and schools as well as some hand delivery of flyers through household letterboxes. Following low uptake levels, the decision was made to increase this area of distribution. Based on local census output areas (ONS, 2023), additional parish councils and school districts were contacted. The distribution area increase can be seen in figure 7.2.

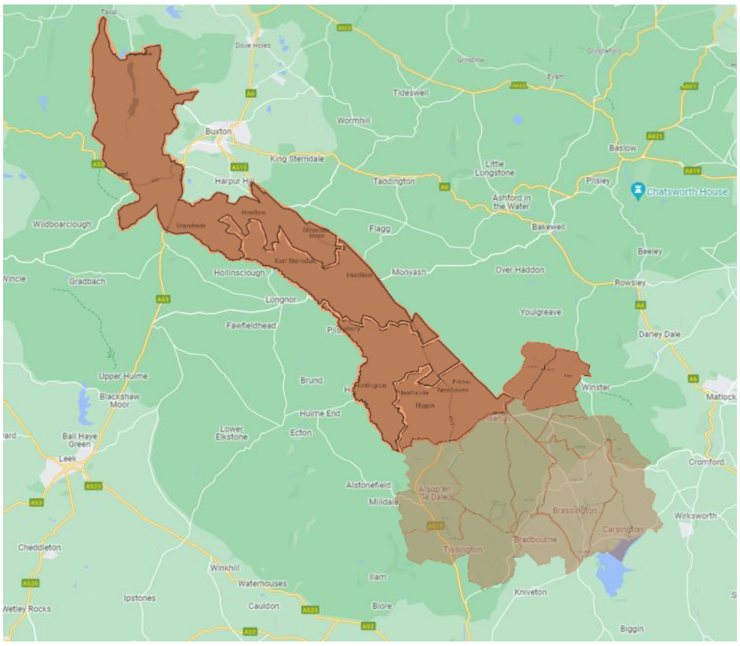


Figure 7.2: Increased flyer distribution area (new area in bold red)

Hand delivery of flyers through household letter boxes proved to translate into the highest response rate. Therefore, Royal Mails Door-to-Door service was utilised to deliver almost 12,000 flyers, split between two batches, covering various postcode areas of the Peak District (see Appendix F). These areas are highlighted in figure 7.3.

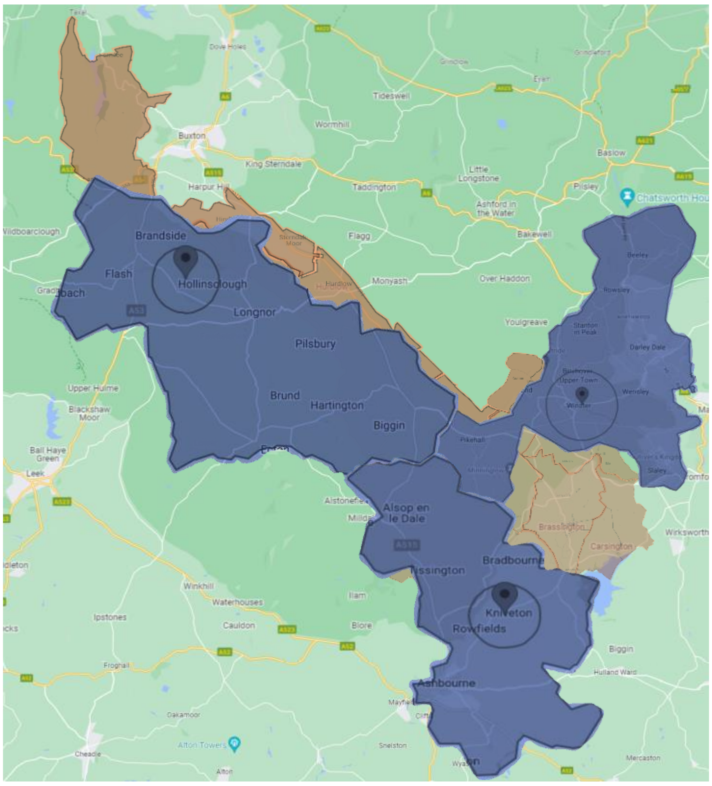


Figure 7.3: Royal Mail Batches (area highlighted in blue)

To note, the inclusion of the Royal Mails Door-to-Door service, in particular the post code area which serves Bradbourne (DE6 1) also extended far past the boundaries of the Peak District and into a much more populated area – the large town of Ashbourne. This led to two factors which will need to be considered going forward.

Firstly, the flyer is titled "Sheffield University Research on Car Usage in Rural Areas". Individuals from these now more populated areas may not feel this applies to them and so believe the survey is not applicable to them. Changing of the flyer however would have required resubmission of an ethics application and reapproval. This requires a large lead time and would have delayed data collection and so was deemed not beneficial.

Secondly, the work of this thesis and the data collection stage itself is to focus on rural areas, having widened the distribution area to now include a more populated area may undermine this aim. However, as discussed previously, the 'Demographic' section of the survey includes indicating the participants local area. This allows for the segregation of the responses into areas and having now included more populated area will in fact provide useful comparisons.

7.2 Results and Discussion of Survey

Over the course of 11 months, over 12,000 flyers were distributed to households across the Peak District. From which 192 responses, corresponding to 192 households were received. This captured data pertained to over 500 individuals and 376 vehicles, the results of which will now be presented and discussed. Data from the survey will henceforth be referred to as 'Data Collection' in figure legends. Alongside the presentation of the results from this survey, comparisons and validations against the previous simulation findings presented in this thesis will be made. The timeline for responses can be seen in figure 7.4, including indications for when large advertising and distribution efforts occurred.

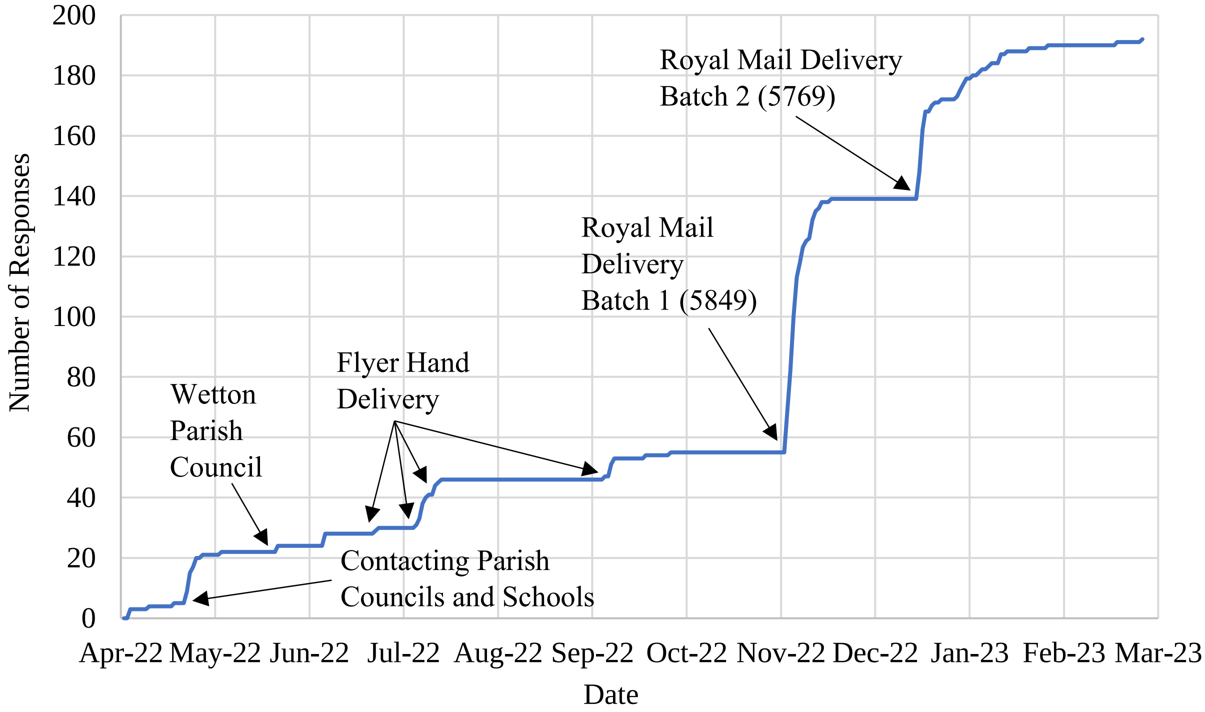


Figure 7.4: Timeline for Responses

With data collection taking place over the span of 11 months, responses have captured data at multiple times throughout the year. This includes bank holidays, school holidays, months of the year, and by extension, weather conditions. These are all factors which will impact responses on various questions, such as vehicle usage, which is very different during summer compared to winter for example. Although attempts were made to instruct participants to provide an average estimate when answering questions, it is important to note there may be an underlying bias.

As previously discussed, to ease the ethical review process, no identifiable information was collected as part of this data collection stage. The highest level of detail requested from participants was the area you lived, so as to allow for geographical analysis of results. This required participants to select their closest settlement from a list provided. Figure 7.5 plots the location of all 192 household responses as a heat map. It is important to note, as highlighted in figure 7.5, the data collected from this survey included responses from the town of Ashbourne. Ashbourne is a far more heavily populated area, concurrent of a more urban environment which may skew the results presented from this survey.

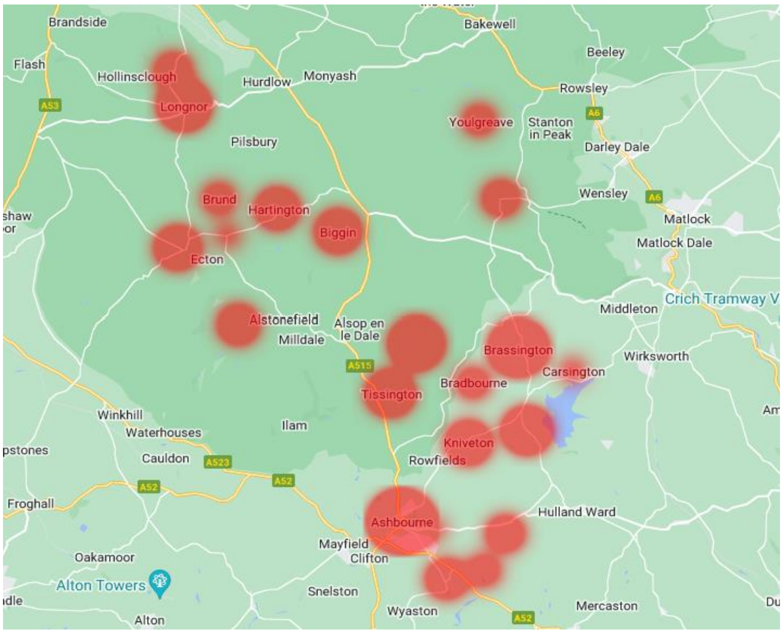


Figure 7.5: Heat Map

7.2.1 Demographic

As described in Chapter 7.1.1, the first section of the survey gathered data on the demographics. Figure 7.6 presents the distribution of household occupancy for each household, compared with the 2011 UK census. Figure 7.7 then presents the age profile of respondents, again compared with the 2011 UK Census. Both datasets that serve as inputs for the TDM presented in Chapter 3.

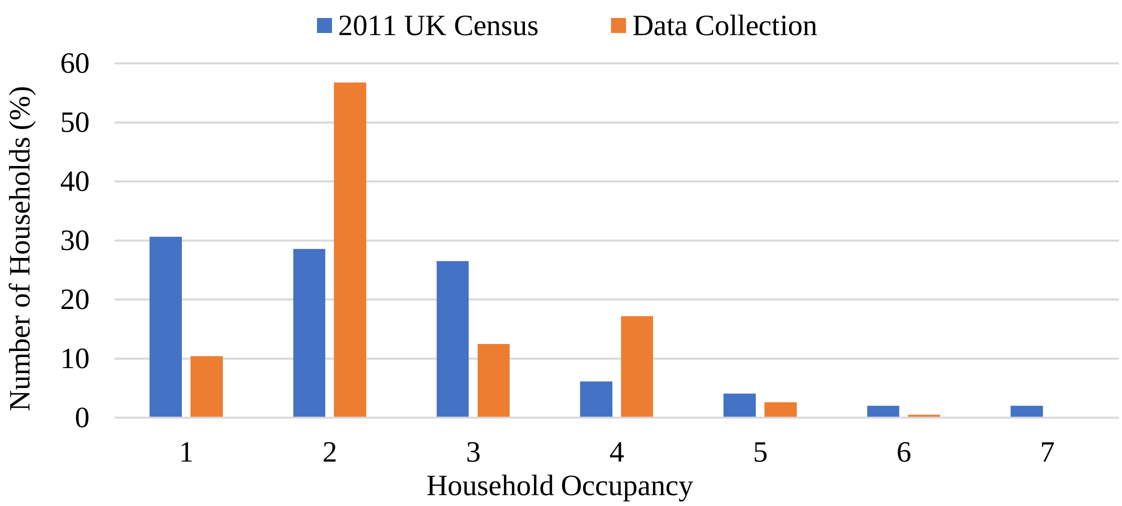


Figure 7.6: Household Occupancy

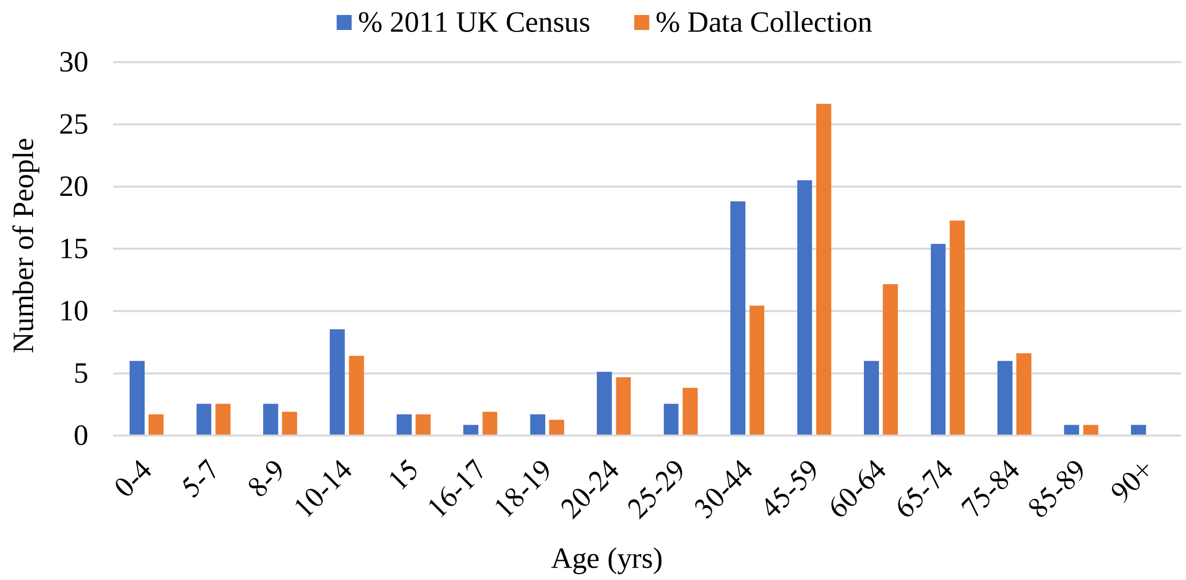


Figure 7.7: Age of individuals captured by participants

The 2011 UK Census data presented in figures 7.6 & 7.7 pertain solely to the village of Bradbourne, the centre of focus for the TDM. As shown, the data collected is in line with that collected by the Census, indicating the survey has reached a representative nature in terms of the households that responded for the wider area. The disparate nature of the age ranges, presented in figure 7.7, are those used by the UK Census. The results from this data collection were categorised into similar groups so as to allow for easy comparison. Given the high level of similarity for the age profile of the area, shown in figure 7.7, indicates that there has been little change in this communities age profile over the last 12 years. This highlights the possibility to consider other aspects of the UK census which would still be applicable for use today, even though the data is 12 years old.

When considering a comparison of the age profile makeup that was incorporated with the TDM developed in Chapter 3, this model utilised lifestyle scenarios which were randomly assigned to households with particular occupancy levels. Within these lifestyle scenarios, only three categories of age were specified: (1) <5yrs, (2) 5-18yrs, and (3) Adults (18yrs+). Table 7.1 presents a comparison for the total number of individuals within each age group for all three data sets: (1) 2011 UK Census, (2) Data Collection, (3) Travel Demand Model.

Age	2011 UK Census	Data Collection	Travel Demand Model
0-4	7	8	6
5-7	3	12	24
8-9	3	9	
10-14	10	30	
15	2	8	
16-17	1	9	
18-19	2	6	87
20-24	6	22	
25-29	3	18	
30-44	22	49	
45-59	24	125	
60-64	7	57	
65-74	18	81	
75-84	7	31	
85-89	1	4	
90+	1	0	
Total	117	469	117

Table 7.1: Age profile comparison

Figure 7.8 considers solely the TDM and the results from the data collection combined into the same age categories.

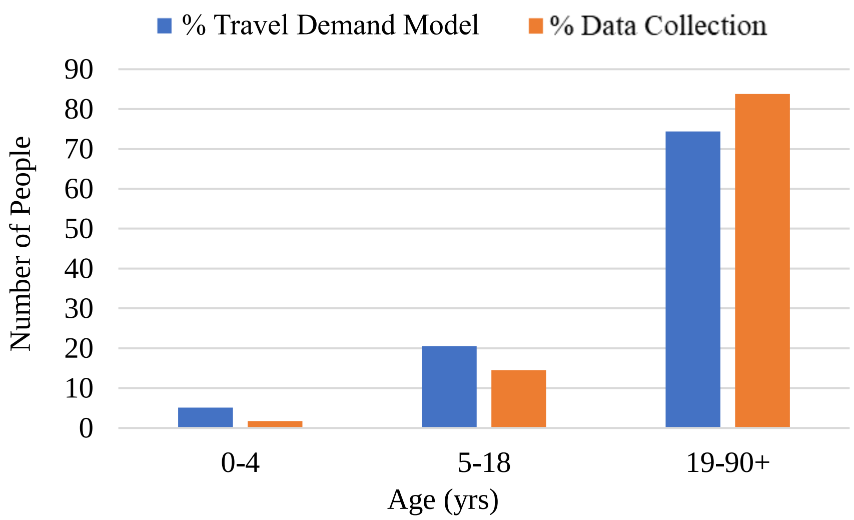


Figure 7.8: Age Category comparison between the Travel Demand Model and the Data Collection

7.2.2 Your Cars and Travel

Across the 192 households that responded, 376 vehicles were owned. This averages out to 1.99 vehicles per household, slightly higher than the 1.2 vehicles per household average across the UK (NTS, 2022). This is expected due to the higher car dependency in rural areas of the UK (Newman et al., 2014). However, it should be noted, it could be likely that those without a vehicle, i.e. 0 vehicles at the household, may have been likely not to complete the survey due to it being tailored to understand car usage in general in rural areas. This may explain the very few households which participated in the survey with 0 vehicles, and the discrepancy between the UK census results. The full distribution is shown in figure 7.9.

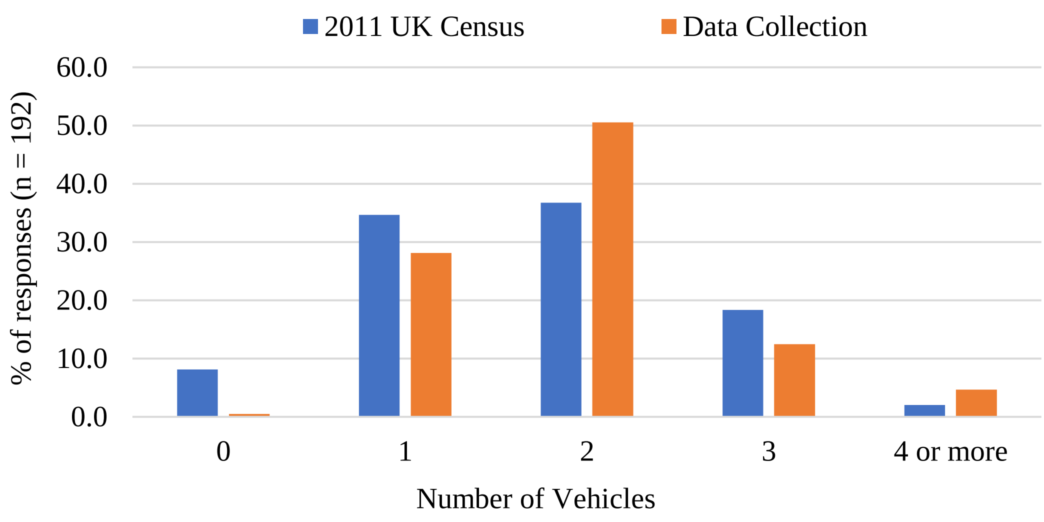


Figure 7.9: Number of Vehicles per Household

Of these 192 households, 33 had EVs already, corresponding to a total of 38 individual EVs out of the 376 vehicles captured. When considering solely households which owned an EV, the average number of vehicles per household increased to 2.12. This is not surprising as EV households are much more likely to be multi-vehicle households (DfT, 2022a). Only 7 households (3.6% of total respondent households) had an EV as their only vehicle. Due to the phrasing of this EV related question, there was no way to determine what type of EV participants had, i.e. battery, hybrid etc. This could have led to individuals questioning if their vehicle warranted selecting an option to indicate they owned an EV or not.

With regards to vehicle usage, each household travelled an average of 214 miles per week. When considering only the 33 households with EVs, this increased to an average of 280 miles per week. Again, indicative, and likely due to the higher number of vehicles typically associated with EV households; more vehicles typically results in more miles driven by that household. From an individual vehicle perspective, each of the 376 vehicles average 110 miles per week. The 84 vehicles as part of the simulation conducted by the Travel Demand Model, to represent Bradbourne, average 161 miles per week. This may be due to long-lasting effects from COVID-19 which reduced vehicle usage and by extension miles driven since the pandemic (GOV.UK, 2022c). The TDM was built upon statistics from the 2019 National Travel Survey, which would have captured data and behaviour pre-pandemic. Additionally, the lower average mileage per week could be due to participants underestimating their weekly driving in general.

As highlighted by this thesis, a crucial part of assessing the feasibility of EVs in rural areas is understanding the impact they will have on local grid infrastructure. The TDM (Chapter 3) and consequent EV Charging Model (Chapter 4), sought to predict when vehicles would be in use and by extension when they would charge. This survey sought to validate these predictions through understanding when vehicles are available throughout the day. This was done via asking participants when their vehicles would not be at home.

Some pre-processing stages were conducted in order to clean the gathered dataset, for instance, all responses with blanks or N/A were removed. Additionally, one respondent household had 0 vehicles and were disregarded from this analysis. This decision was made to align the comparisons with the previous work of this thesis which focused solely on households with vehicles. The TDM has a time resolution of 30 minutes, and so required some post-processing to align with the time resolution within these survey questions. This also required reducing the number of time slots from the TDM results.

When undertaking this data manipulation, the highest percentage seen within the combination of hours was taken as the value for the whole of the duration. For example, if combining one hour (10:00 - 11:00) with another (11:00 - 12:00), and hour 1 reported 10% whilst hour 2 reported 20%, the combined time slot (10:00 - 12:00) would take a value of 20%.

During phases of the distribution, some distribution bodies, such as potential schools and individuals themselves expressed discomfort with this question. Schools who declined to be a part of this study, which shall rename anonymous, highlighted the discomfort they envisaged some of their attending children's parents would have with regards to the location and vehicle usage questions. This did also become evident with some private individuals who completed the survey, in particular, one vehicle households. One example of discomfort for someone else knowing when their vehicle would be at home or not was expressed, nevertheless they still did complete the survey.

To ease these discomforts, as touched upon in Section 7.1.2, it would be impossible to personally identify a person/address/vehicle for two reasons; (1) this type of information was not collected, and (2) results were aggregated. This information was also made clear in the participant information sheet that was attached to the Google Form Survey and submitted as part of the ethical review application. However, the distrust of individuals for surveys and personal information is highlighted here by the continued unease to participate following this information.

Additionally, failure to complete these questions pertaining to vehicles at home could also be due to very little vehicle activity, and so a vehicle belonging to a respondent may sit idle at their household for most of the time. This is indicated by the higher level of 'N/A' responses for the question pertaining to the weekend days than the weekday days. Another consideration, as previously discussed in Section 7.1.2, is due to the low level detail of this question following ethical review, i.e. the simplification of the question and how it was asked to achieve higher response rates at the expense of a more detailed and thorough understanding/result. Vehicle travel patterns represent dynamic behaviour which is hard to predict. This can make reporting an average day's travel patterns difficult, leading to participants failure in completing the question due to difficulty.

The results for when vehicles are not at home for an average weekday day and an average weekend day are presented in figures 7.10 & 7.11, respectively. These have been combined with the aggregated results of the TDM, presented in Chapter 3 (Figure 3.21). Results are presented as percentages of the total number of vehicles reported, respective of either the 84 vehicles of the TDM or the 376 vehicles captured by the survey.

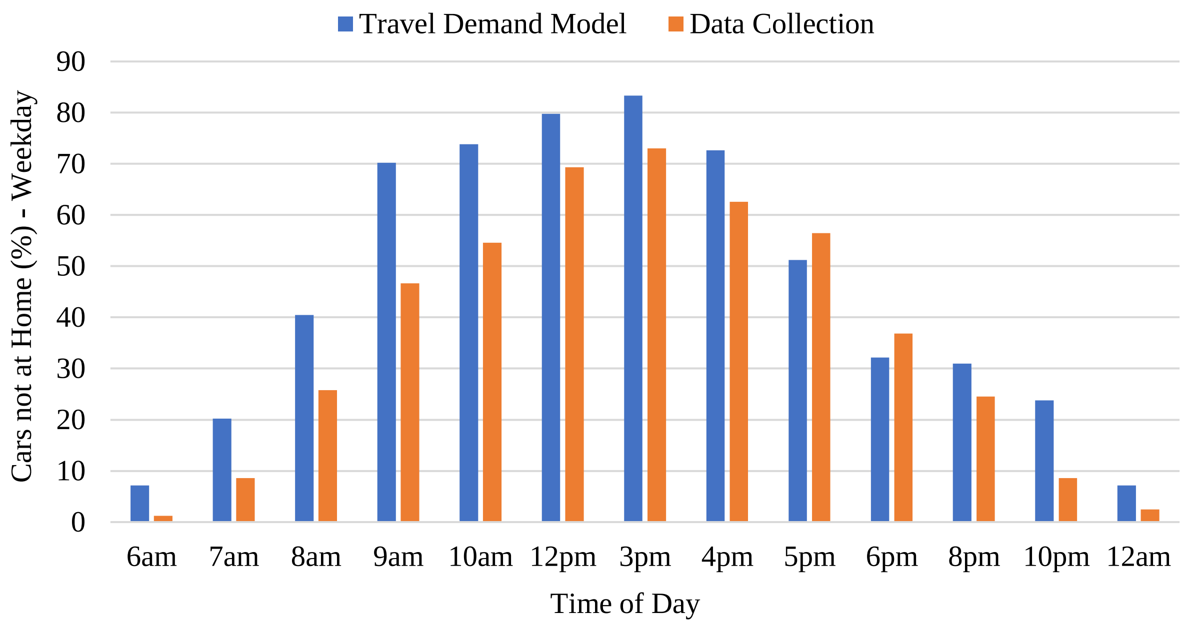


Figure 7.10: Cars not at Home – Weekday (Mon-Fri)

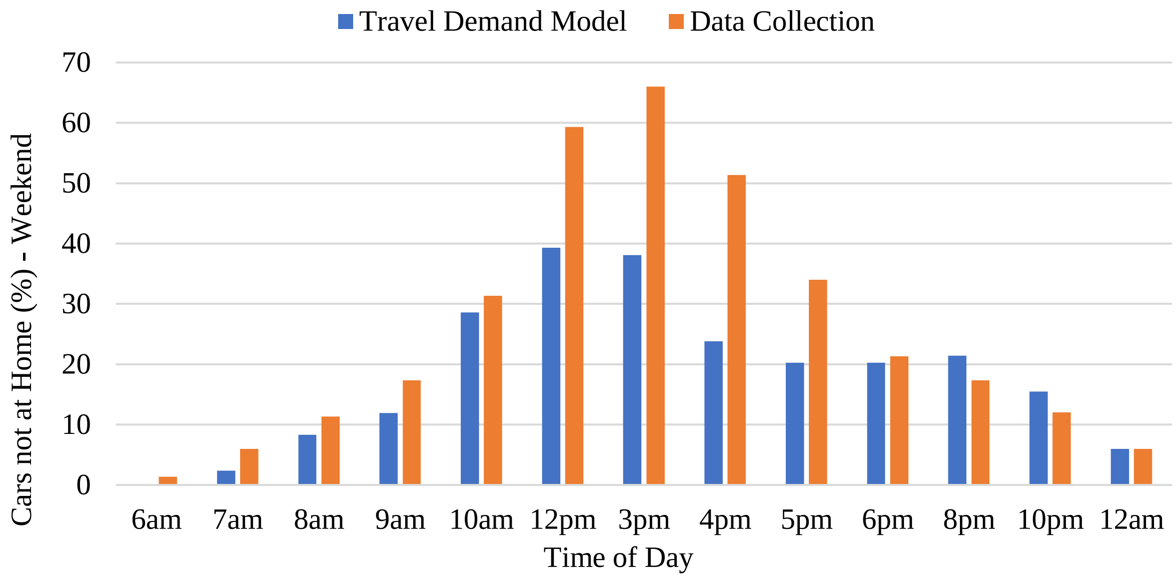


Figure 7.11: Cars not at Home – Weekend (Sat-Sun)

As shown by figure 7.10, the TDM slightly overestimated the early hour intervals. In contrast, with regards to the weekend, the TDM has instead underestimated vehicle usage, especially during peak hours of the day. This may be due to the hardcoded number of trips designated to occur at weekends and that number is slightly lower than what real life reflects. For instance, I've only assigned for one day trip per weekend per household, i.e. family day out. When in reality more may be going on. However, the general profile for both weekdays and weekends has been captured accurately by the TDM when compared to the results from the data collection.

7.2.3 Electric Vehicles

From the 'Electric Vehicles' section of the survey, over 91% of respondents report that they were aware of the EV transition. This question, and those prior, presented no information relating to the transition in order to understand participants baseline knowledge. The full results from enquiring about the awareness of the EV transition can be seen in figure 7.12.

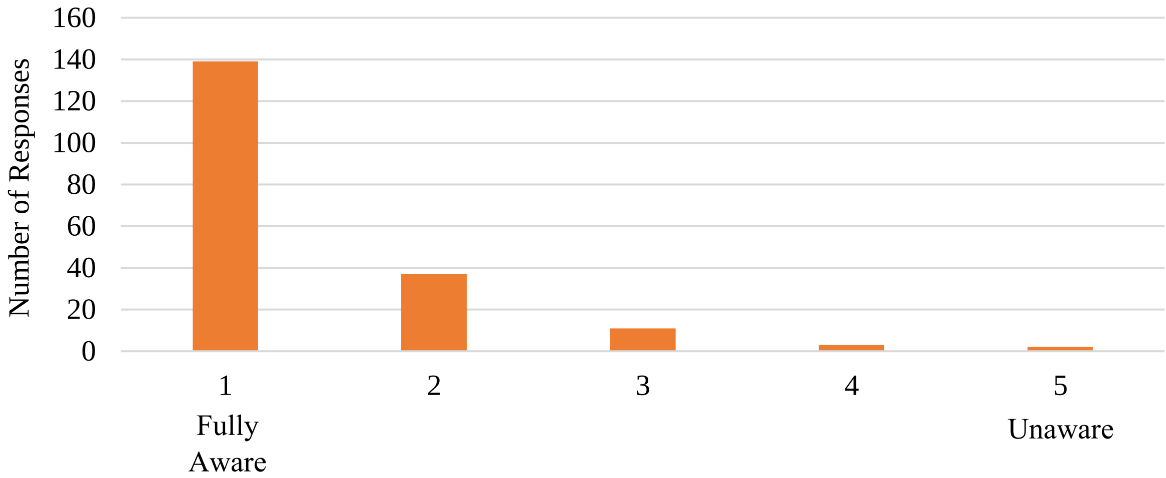


Figure 7.12: Awareness of the UK Governments push for Electric Vehicles to replace Diesel and Petrol cars

Although awareness of the transition is very high within the rural community (Figure 7.12), which is no surprise given the large media coverage EVs receive, this did not translate into much anticipation to own an EV in the future (Figure 7.13). With valid points on either side of the EV transition, as discussed in Chapter 2, this survey then sought to understand firstly the perception of EVs by this community, and then the opportunities for EVs in rural areas (discussed in the following section, Section 7.2.4). With this in mind, all participants were asked on the likelihood of their next vehicle being an EV, the answers for which are shown in figure 7.13.

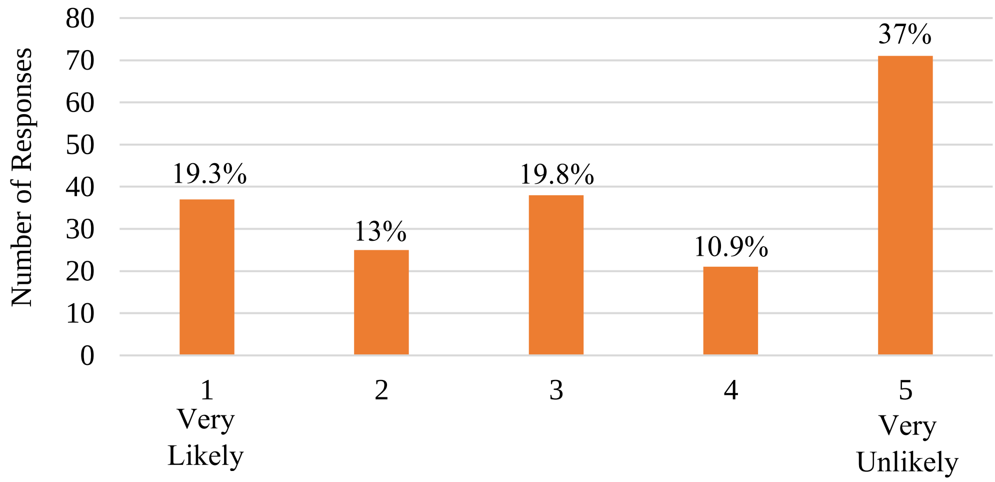


Figure 7.13: Likelihood of next vehicle being electric

Although 91% of households are aware of the EV transition and the UK Governments motives, only 19.3% of households anticipate their next vehicle to be an electric one. As reported previously, 17.2% of households do already own an EV, however this indicates a reluctance towards EVs, or at the very least a very slow paced transition. Price, range anxiety and distrust of the technology all rank highly as barriers for EV adoption (Tiwari et al., 2020; Steinhilber et al., 2013; Berkeley et al., 2017); however it is also prudent to note that the rural population is an aging population. Even more so than their urban counterparts (DEFRA, 2021). For this reason, and also due to simply lacking the need for a new vehicle in the future, respondents may not anticipate purchasing another vehicle, regardless of its propulsion system. Distrust of the technology also covers distrust of its capabilities, multiple individuals from the survey voiced concerns regarding towing capacities and its impact on battery life, as well as weather and temperature conditions. Both of which can be more severe in rural areas due to lack of infrastructure, for example, clearing roads during heavy snowfall. This is then no surprise given 37% reported that it would be 'Very Unlikely' that their next vehicle would be an EV. Although, when it came to replacing current vehicles with EVs, 56% reported that they do intend to, with a further 27% indicating that they will attempt to get by with fewer vehicles (see figure 7.14). This may be due to distrust of the technology, or a conscious attempt to reduce their environmental impact through reduction in the number of vehicles they own. However, it is very much apparent that everyone in rural areas requires their own private vehicle as 96% report a lack of local public transport, concurrent with the report from Better Transport (2018). This is in keeping with UK statistics which show much higher levels of household car ownership (Better Transport, 2018) and number of drivers licenses (Newman et al., 2014) in rural areas.

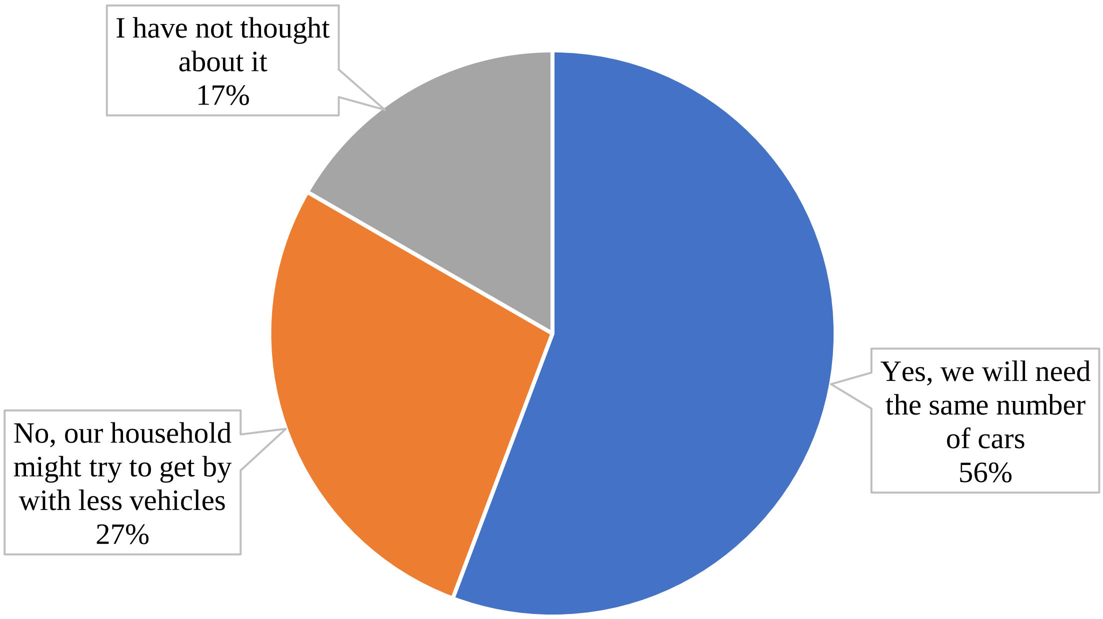


Figure 7.14: Intentions to replace current vehicles with EVs

7.2.4 Charging

With the understanding of the perception towards EVs in the rural community, this next section of the survey sought to unearth the opportunities for EVs in this environment. A large benefit for integrating EVs in rural areas is the larger space available, particularly when it comes to home charging (Newman et al., 2014). To confirm, respondents were asked what parking facilities were available at their homes, the results can be seen in figure 7.15 below.

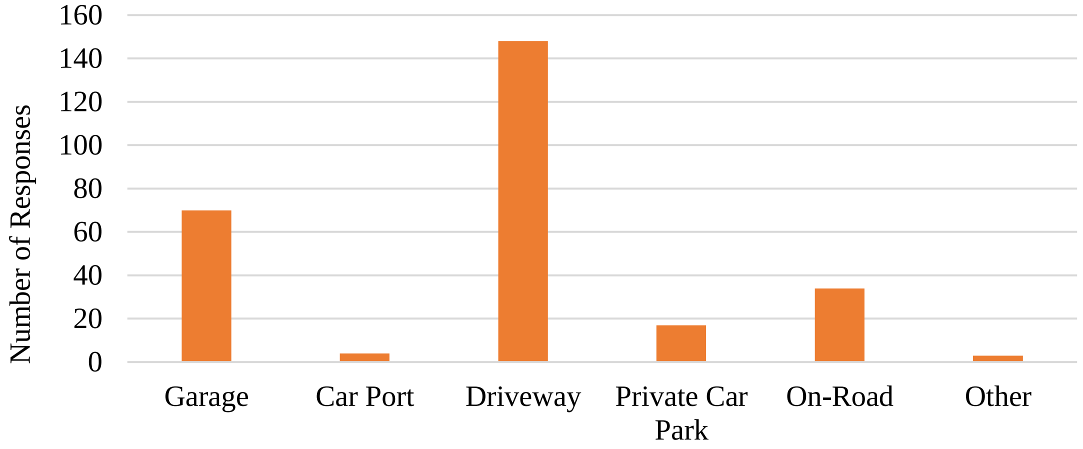


Figure 7.15: Parking facilities at home

As shown by figure 7.15, very few households have on-road parking, or private car parks away from their homes. These types of parking may prove difficult for EV ownership due to the inability to install a home charge point. Private parking solutions on the other hand, such as a garage or driveway are much more common in rural areas and are ideal for EV charging (Newman et al., 2014). When asked if individuals saw themselves charging EVs at home, 67% of respondents said that they likely would. This is in keeping with statistics published in previous literature, Hardman et al. (2018) showed that 50-80% of all charging events occur at home. The complete data collected on charging their potential future EVs at home is shown in figure 7.16 below.

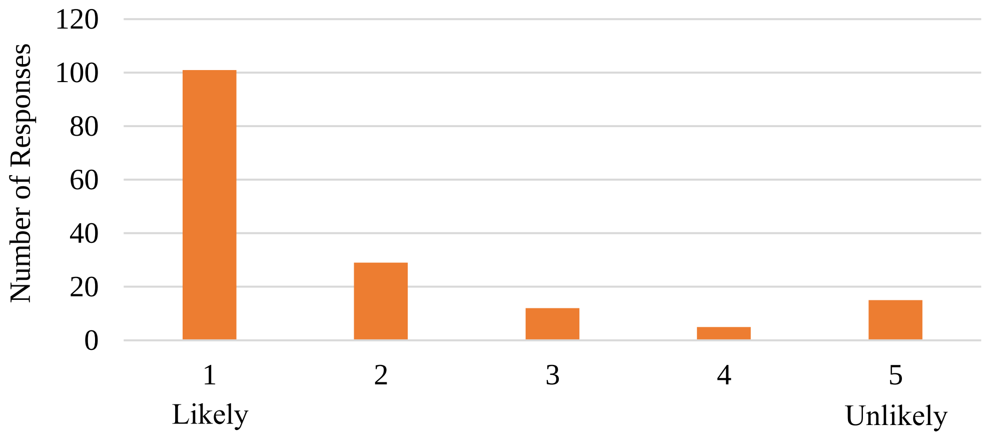


Figure 7.16: Will you charge your EV at home?

It should be noted that 30 households (15.6% of households/participants) failed to complete the above question (figure 7.16). This is likely due to their anticipation of never owning an EV in the future and thus this question did not relate to them, as well as including households who anticipate never switching to EVs. However, as shown by figure 7.13, the number of households anticipating not switching to EVs was significantly higher than 30.

The survey then proceeded to ask how many charge points respondents envisaged having. Typical UK households would be limited to two home charge points, assuming both are 7 kW, due to the 100A fused incomer. This raises concerns for if a household with a large number of vehicles expects to install multiple chargers. Figure 7.17 shows the number of home chargers respondents envisaged installing (orange), with the number of vehicles owned by each household for comparison (blue). The data presented here is for solely the households who expect to replace all their vehicles with EVs in the future, reported in the previous section (see figure 7.14).

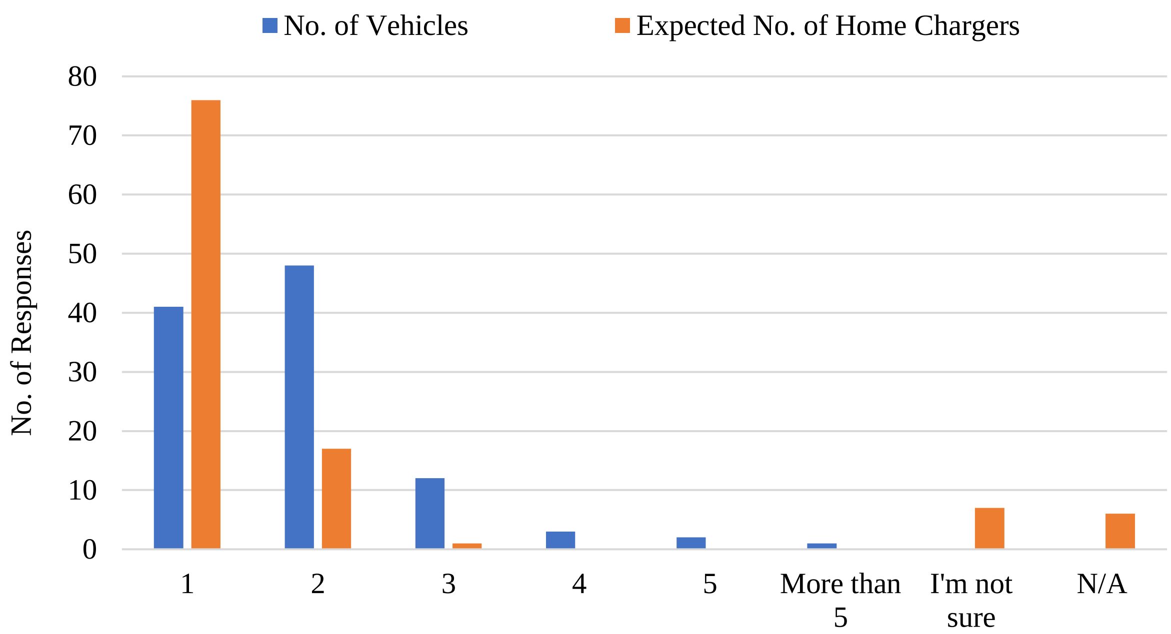


Figure 7.17: Number of home charge points (orange), number of vehicles owned (blue)

As shown by figure 7.17, survey responses show that households opt for fewer chargers than the number of vehicles they own. There is some indication of lack of knowledge with regards to home charge points with 11% responding with “I’m not sure”, but more importantly this question was used to uncover the individual consumer expectations. Only one household, out of the 192 which responded, owns 3 vehicles who also anticipate installing 3 home charge points, an unrealistic possibility due to infrastructure limitation as previously discussed but further investigation would be required. This also highlights the unrealistic nature of the assumption built into the EV Charging Model; one charge point per vehicle. Further discussion of this point and its implications for future work will be discussed in the following chapter, Chapter 8.

To investigate public charging opinions, the survey asked which public areas would be likely EV charging locations participants would utilise. The results of this question are shown below in figure 7.18.

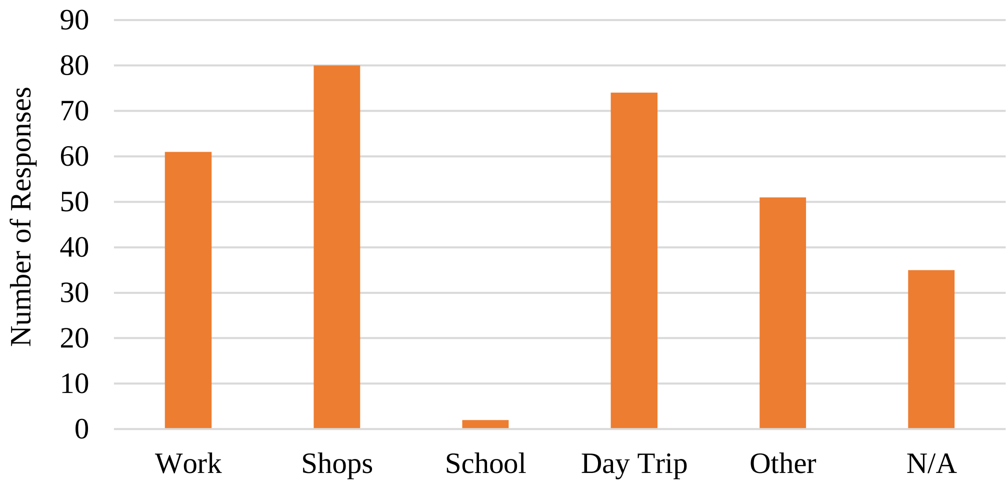


Figure 7.18: Public areas likely to charge at

Figure 7.18 shows all public areas are of high interest amongst the rural community for charging EVs, apart from “School”. This result requires further investigation to determine the reasoning for this low interest from consumers, but determination of employment statuses and occupations within a households would be of added benefit. This is most likely due to “School” largely being a pick-up/drop-off event, where one would not expect to be parked for a significant period of time, unless for instance the school was a participant’s workplace. In addition, an older demographic, as seen more so in rural areas (Age UK, 2018), are less likely to have school aged children and thus warrant visiting a school.

7.2.5 Electricity Tariffs

The final section of the survey, sought to understand the electricity meters and tariffs of respondents. These are highly entwined factors with the EV transition. The types of electricity meters reported for each household are shown in table 7.2.

Electricity Meter	Number of Responses (%)
Smart	38
Standard	28
Variable-rate (Economy 7 or Economy 10)	19
Digital	10
Dial	2
Prepayment	2
Other	1

Table 7.2: Responses for what type of electricity meter households have installed

EV tailored electricity tariffs are a new product offer by many electricity companies, which follow, more often than not, a similar pricing structure to economy electricity tariffs. They provide cheaper electricity rates during the early hours to encourage EV charging to occur during these times of lower electricity demand. When asked about the awareness of these tariffs 64% of respondents were unaware of their existence. The full results can be seen below in figure 7.19.

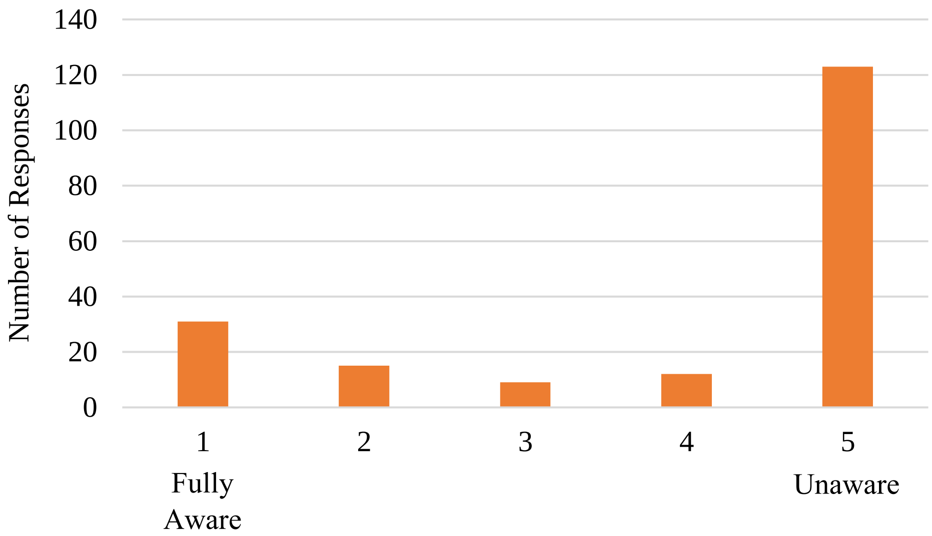


Figure 7.19: Awareness of EV tailored household electricity tariffs

EV tailored tariffs, in most cases, require a smart meter. For households to qualify for such would require the changing of their electricity meters to a smart meter, a controversial subject (The Telegraph, 2023). From the 192 households, 46% reported that they were open to having a different electricity meter installed, with a further 33% answering “maybe”. The remainder reported “No”. However, this population of households unwilling to change may comprise, in part, of households who already have smart meters installed.

7.3 Further Discussion of Survey Results

This survey presents a novel consideration to solely rural areas for surveying, to not just gather information relating to perceptions and attitudes towards EVs, as Graham-Rowe et al. (2012) focuses on, but also quantifiable information to aid the technical investigation of the EV transition in rural areas.

To further compare the results of this data collection with the models presented in this thesis previously, figure 7.20 combines the household occupancy and the number of vehicles, to compare directly with that of the NTS, first presented in figure 3.26 of Section 3.4.2.

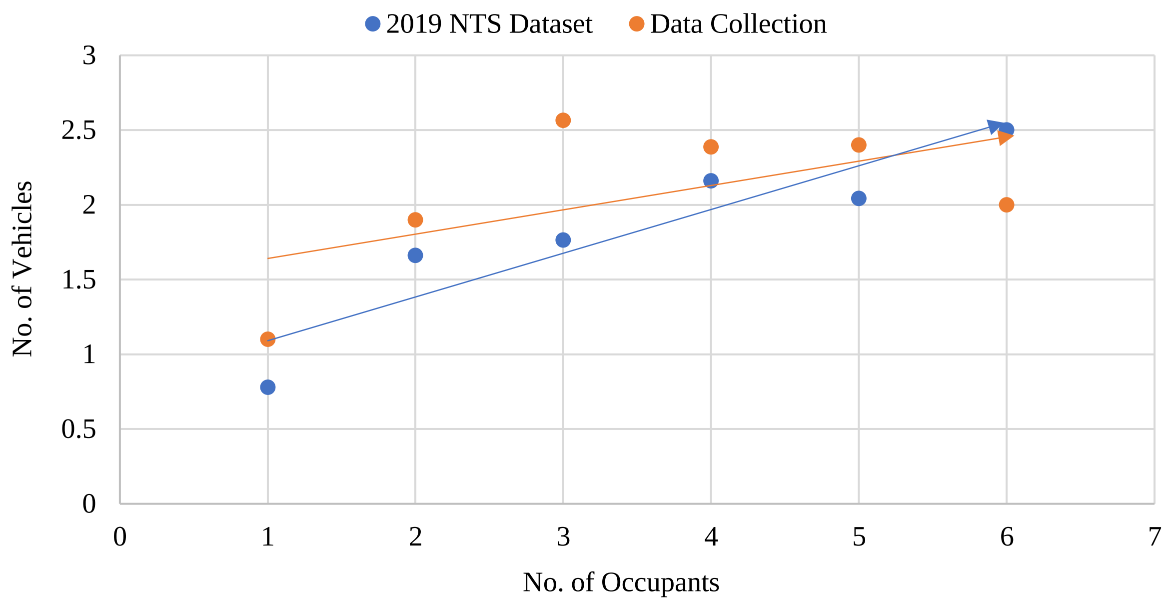


Figure 7.20: Comparison of household occupancies against number of vehicles available

Again, as highlighted previously, it is worth noting the applicability of the NTS dataset given it is over 10 years old at the time of writing. However, figure 7.20 does indicate a general increase, across each occupancy category, with the exception of 6 person households. This is to be expected due to the increase in car ownership levels over the last 10 years (GOV.UK, 2022e). Future considerations to household and vehicle distribution when modelling should account for the apparent plateau in the number of vehicles as the number of occupants increases. Although, the data collection results are drawn from a small sample, only 192 households in comparison to the 7,000 (2.74%) who take part in the NTS. For instance, only one household with 6 occupants was captured by the data collection and thus this point in figure 7.20 cannot be deemed as reliable.

Effort was also made to investigate the age profiles for the households with EVs already. Calculations included everyone within the household, regardless of ability to drive and own a vehicle. The average age of a household with an EV was 52.3. For all 192 households who participated in the survey, the average household age was 52.6. This suggests that age has very little influence in the determining factor for purchasing an EV. This is in line with reports from the Office for Low Emission

Vehicles, who found that most private EV owners are currently middle-aged, male, well educated, affluent individuals (OLEV, 2015). However, conclusions on gender, education cannot be drawn as these factors were not asked during the survey. Though, given these findings by the OLEV (2015) are 8 years old at the time or writing, and present day data collection suggests no change, efforts should be made to improve uptake of EVs for the wider community. Data gathered by from the latest UK Census, 2021, suggests more than half of motorists aged 16-49 years say they are likely to switch to all-electric vehicles within the next decade (ONS, 2021). This is also indicated by the results from this data collection. As shown by figure 7.13, 52.1% of participating households indicated between 1 and 3, with 1 being very likely, and 5 being very unlikely, that they're next vehicle would be electric.

7.4 Chapter Summary

This chapter presented a survey conducted across households in the Peak District, UK. This was done to provide real-life applicability, validation and further context to the work presented in this thesis previously. Over a period of 11 months, over 12,000 flyers were distributed amongst rural areas advertising and inviting households to complete the survey. A total of 192 households responded, capturing data from over 500 people and 376 vehicles.

Rural communities are aware of the EV transition, however much reluctance towards its implementation has been identified. Although responses have indicated their openness to new technology/change in general, this reluctance for EVs is warranted. This only further highlights the need for engagement of this crucial stakeholder to ensure a positive transition for all. Much of the assumptions and pre-existing knowledge, illustrated by past literature, has been reinforced with similar results found. In addition, evidence of EV uptake has been found with multiple households reporting that they already own such vehicles, and although awareness of EVs in general is high, it appears there is a lack of awareness for associated technologies, e.g. charge points, EV specific electricity tariffs etc. This may be inadvertently aiding the barriers to EV adoption.

Multiple validations of the Travel Demand Model (see Chapter 3) were presented, including comparisons between statistics from the 2011 UK Census. Statistics from this Census acted as inputs for many of the previous models discussed in this thesis, and so heavily influence the validity of their results. The material presented in this chapter fulfilled '*Objectives 4a and 4b*', and by extension achieved '*Research Aim 4*'.

The survey also provided insights into aspects of the EV Charging Model, presented in Chapter 4. Highlighting limitations, such as the number of chargers per household, whilst also highlighting the rural nuances in favour for the EV transition. Nuances such as available space and particular favoured charging locations, identifying multiple opportunities for EVs in rural areas.

With the findings from this survey, not only have multiple aspects of the work presented in this thesis been validated, providing integrity for the previous chapters findings and conclusions, but also potential improvements and considerations have been identified. Further discussion on these points will be the focus of the next chapter, the final chapter of this thesis.

CHAPTER 8: CONCLUSIONS AND FUTURE WORK

This thesis has presented the development of multiple novel models required to better understand the impact of EVs in rural areas. This has been supplemented further by the collection of real world data, enabling a comprehensive investigation into the feasibility of the EV transition for rural communities. This chapter will conclude the thesis, presenting summaries and final discussions for each chapter presented prior to. These discussions will also include the limitations which should sought to be overcome by future work, as well as other potential improvements and bodies of work which would complement this thesis.

Chapter 1 highlighted the justification for the work presented in this thesis; due to the ongoing climate change threat, the UK Government are implementing plans and strategies to reduce greenhouse gas emissions, especially carbon dioxide. The most viable option, currently available, is to electrify the current passenger vehicle transport mode. However, one aspect of the transition thus far neglected, is how this transition will be realised in rural areas.

Chapter 2 provided a comprehensive literature review covering topics such as the ongoing transition of electric vehicles replacing ICE vehicles, along with the factors facilitating and hindering this process. It also offered an in-depth examination of the rural environment, underscoring the existing gaps not only in academic research but also in political and industry perspectives. Chapter 2 also identified the methodology for which was utilised in this thesis for understanding the impact electric vehicles have, vis-à-vis their energy and power requirements, the simulation pathway. This highlighted the requirement for a travel demand model, to simulate the driving habits of vehicles, coupled with charging scenarios. The activity based travel demand model was identified through this literature review process to be most applicable for achieving the research aims set out. Additional topics such as EV charging in general, the electrical grid, with focuses on two key areas that were explored in depth in Chapter 6 (power outages and demand side management), and social theory, in particular examples of previous engagement of stakeholders and consumers in the EV transition, were also reviewed and presented. The literature review presented in Chapter 2 accomplished both 'Objectives 1a and 1b', and by extension satisfied 'Research Aim 1' as the review identified multiple important developments within the topic areas this thesis is situated. This not only provided an extensive background to the topic but highlighted shortcomings of previous examples in literature, shortcomings and gaps of consideration that this thesis has addressed. These key gaps, as well as important factors that were utilised in the development of the various models presented in this thesis, were extracted and listed in Section 2.9.1 as a summation for going into Chapter 3.

Chapter 3 presented the development of an activity based travel demand model for the small rural village of Bradbourne, located in the Peak District, UK. With a novel approach utilising readily available statistics for the rural area of Bradbourne, the TDM was developed with solely rural factors and inputs, previously not seen in other activity based TDMs. Utilising lifestyle scenarios also enabled the novel incorporation of rural demographics and their variance within the community. This TDM was shown to be capable of producing high fidelity results, including the 'location' and 'miles driven that day' every 30 minutes for each car over the course of a week (Mon – Sun). However, due to the dynamic nature of human behaviour and by extension vehicle usage, assumptions and simplifications were required. The limitations for the TDM will now be discussed.

Limitations within the TDM include the initial method for distributing vehicles to each household. This was done so following the 'the larger the household, the higher the number of vehicles that will be available' premise. In reality this may not be the case, although there is correlation between the number of people in a house and the number of vehicles a house has, car ownership levels for a household are determined more so by the travel necessities of the household. In addition, only 5 trip purposes were used, derived from the 14 categorised by the NTS (see section 3.3.2). This was done as a simplification step to reduce computational intensity of the model with effort to maintain and incorporate the most utilised and wide covering trip purposes. Adding additional trip purposes would have increased the variability of the model to reflect real-life situations more so. This is compounded by the blanket figure of 30 minutes utilised for all trip durations, and the single value utilised for the various trip purposes. To improve the models accuracy and real-life applicability, these factors would also vary. However, even with this in mind, the work presented in Chapter 3 achieves 'Objective 2a', for partial fulfilment of 'Research Aim 2'.

Continuing the simulation pathway, Chapter 4 built upon the results from the travel demand model of chapter 3 through simulating multiple charging scenarios. Assuming the vehicles of Bradbourne all to be electric, their energy requirements were first calculated. Then scenarios with varying parameters (including charging behaviour and electricity tariffs, influential factors highlighted by the literature review) for the recharging events were simulated. Additionally, key factors highlighted by the literature review were built into the EV charging model, for example, the simulations initialisation stage which involved the 'Day 0' approach. Through repeating the results from the TDM, a simulation period of 4 weeks for the EV charging model was achieved. With many previous studies into charging demands for EVs only lasting a day or two, the novel EV Charging Model presented in this thesis enables the monitoring of EV impact over a much longer duration.

There are several improvements which could be made to the EV Charging model, most notably overcoming the limitations of one charge point per vehicle. As highlighted during Chapter 4, this is a large overestimation for the number of private charge points which would ever be installed. Due to limiting factors in infrastructure, a household would only allow one of two charge points installed. Investigating how fewer charge points would impact the transition could bring about notable differences to the results presented in this thesis.

The EV Charging model also lacks consideration into the effect a non-homogenous EV fleet. To reflect reality more so, multiple brands and models of EV would be present in a community, each with varying energy consumption rates. These energy consumption rates would also vary not just between vehicles, but also continuously along a journey depending on factors such as driving style, weather, and temperature. Although, as discussed in Chapter 4, this design of the EV Charging Model and parameter setting does actually reflect solely a consumption rate, not the Nissan Leaf specifically. I.e. the fleet of EVs simulated could all be different makes and models but each with an average consumption rate of 26.5 kWh/100mile. This key aspect of the EV Charging Model increases its utility and applicability drastically. Although, to build upon this further, it would be beneficial to modify the model to account for multiple consumption rates, so a true non-homogenous EV fleet could be simulated which would be a truer reflection of real life.

In addition, this model solely focused on 7 kW chargers, whereas a more accurate avenue of investigation would have simulated a wide range of different power levels for charge points. Furthermore, as stated during the model parameters of the EV Charging Model (Section 4.1.1), both the charger and EV batteries simulated have been assumed to operate at 100% efficiency. To further increase the accuracy of this model, consideration of efficiencies and their variation over time should be included.

Finally, it would be beneficial to understand the impact when varying the SOC limits for discharging and recharging (i.e. the 20% and 80% SOC limits that were in place for various scenarios). As previously discussed, human behaviour is dynamic in nature which should also be reflected in discharge/recharge cycles. Incorporating this into the EV charging model would improve accuracy. Chapter 4, along with Chapter 3, achieve ‘Objectives 2a and 2b’ and complete ‘Research Aim 2’; to examine the energy and power requirements of EVs in rural areas. This novel EV Charging Model presented in this thesis addressed the main gap identified within previous examples, which was the duration for which the previous models would simulate. Focusing on obtaining a longer period of time for the simulation, only further improves the applicability of the results presented in this thesis when compared to others. This duration factor will prove vital to a wide range of parties, including grid planners, EV manufacturers and consumers for multiple reasons. Namely to remove uncertainty when it comes to the EV transition and what impact it will have from a grid perspective to a usability of consumers POV.

Chapter 5 presented the multiple sets of results from the EV Charging Model combined with real-world data from a substation local to Bradbourne. It was shown that the impact of EVs on rural grid infrastructure is largely determined by the local communities recharging schedule and behaviour. These two factors presented themselves through the electricity tariff and charging behaviour variables. The combination of the results from the EV Charging Model and the pre-existing grid load required scaling of the results. A simplified method for this scaling step was chosen to meet time and resource constraints of the thesis. However, the scalability of the models which have been developed and presented in this thesis should be noted: given the required inputs for the TDM (number of houses, occupancy etc…), these models have the possibility to capture and simulate any sized population. Although, computational requirements would increase and become the hindering factor.

Chapter 5 also conducted further investigation into the worst performing EV charging scenario from Chapter 4, assessing its impact individually, which revealed large causes for concern. Grid operators are currently pushing EV tailored electricity tariffs which follow pricing structures similar to Economy tariffs. These tariffs encourage individuals to charge in the early hours of the day during the grids pre-existing demands natural trough. For the small number of EVs currently in circulation, findings showed this does not pose any threat. However, this thesis has shown should larger market penetrations of EVs occur in the future, this behaviour becomes unstable. A significant number of voltage violations throughout the year were witnessed in this examination. Chapter 5 also presented a simple timeline model that was developed to forecast when this high number of EV charge points is likely to be reached. The work presented in Chapter 5 achieved ‘Objective 3a’ of ‘Research Aim 3’.

In an effort to expand the focus of this thesis and understand the wider picture for electric vehicles in rural areas, Chapter 6 examined the impact of both unplanned and planned power outages, as well as demand side management techniques to alleviate the added pressures on grid infrastructure due to the EV transition. Unplanned power outages for durations ranging from 12 to 48hrs and planned power outages following the protocols laid out in the ESEC were simulated following the development of additional novel models. Regarding demand side management, three strategies were investigated, including two that have not been found in past literature (First come, first serve and lowest battery charge has priority). Chapter 6 demonstrates that the existing electrical grid offers considerable flexibility without requiring significant investment. Additionally, building on the key findings from the literature review (Section 2.9.1), which highlighted specific considerations for rural communities during the transition to EVs, the findings in this thesis indicate that rural residents can confidently own and operate EVs. It has been established that EVs in rural areas are fully capable of meeting the daily travel needs of their inhabitants, even in the face of challenges such as power outages. By adopting EVs, rural communities may reduce their reliance on traditional power grids, potentially shifting local power dynamics towards more communities-centred energy management practices. The work presented in this chapter achieved ‘Objective 3b & 3c’ and by extension with Chapter 5, ‘Research Aim 3’ has been fulfilled.

In Chapter 7, the development and results of an online survey, distributed to households within the Peak District, was presented. This chapter provided a social approach to enrich the technical findings previous. Engaging the rural community in relation to the EV transition, not only gave this previously neglected stakeholder a voice for their concerns, but also identify and highlight any other nuances not found during the literature review presented in Chapter 2. In addition, the results from this survey were utilised to validate the findings from the TDM and the EV charging model. The models presented in this thesis were shown to have been accurate compared to the real-world data collected via this survey. Conducting this survey and the results obtained from such fulfilled ‘Objectives 4a and 4b’, achieving

‘Research Aim 4’. By incorporating stakeholder and consumer engagement findings into this EV transition analysis, the thesis broadens its considerations to explore wider concepts such as how these communities reliance on external energy resources shape their transition to EVs. Examining how these communities can alter their resource dependencies can enhance local energy autonomy and reduce environmental impact.

Upon reflection, the survey conducted as part of the work presented in this thesis did lack some considerations. For instance, as highlighted in Section 7.2.2, one question regarding the respondents vehicles lacked the ability to differentiate the types of EVs reported. This may have led to inaccuracies with regards to the true number of EVs, in particular BEVs, in rural areas. The over-arching themes of the survey itself were also very high level in nature, which presented a slight disconnect in the attempts for validating the aforementioned models. As previously discussed, this decision was made to offset the potential drop-off rate of responses should more detailed questions be asked, however, in order to thoroughly validate the models presented in this thesis, a deeper level of questioning would be required.

In addition, as discussed in section 7.2.3, the responses from this survey included the nearby town of Ashbourne. This area is classed as an urban area, especially in comparison to the areas of interested presented throughout this thesis and so will have some impact on the results presented. Work should be conducted to remove these urbanised results so as to understand any impact or bias these results are inflicting.

As discussed, all objectives set out in Chapter 1 have been fulfilled, and so, by extension, the research aims of the thesis have been achieved. Broadly speaking, this thesis provides a thorough understanding of the EV transition in rural areas of the UK. However, there are multiple opportunities to build upon the work presented in this thesis further. Suggested future work on this topic will now be discussed.

8.1 Future Work

As well as addressing the limitations highlighted previously, there are also other bodies of work which if conducted would provide beneficial findings to further support the transition to EVs in rural areas. One such body of work would be to incorporate vehicle-to-grid (V2G) technology.

V2G offers multiple opportunities building upon two key areas investigated within this thesis. Firstly, building upon the DSM, presented in Chapter 6, V2G would allow vehicles to reduce the pre-existing voltage spikes and demand on the grid already, including those created by a large influx of EVs on the grid. This could instil more flexibility and stability into the system, a huge benefit for rural infrastructure. Secondly, as highlighted in the literature review, V2G technology could also alleviate the pressures created by power outages. With V2G technology, EVs could provide power to the household during grid power outages. Vehicles would be unable to move during this transfer process however, rendering the vehicles useless for transport purposes. Although it is highly likely, for the periods that they are parked at home when the power is out, consumers would choose to use some of their vehicles to power their homes basic necessities. Investigation into how this would impact the vehicles SOC profile over time, and by extension its impact on the vehicles usability travel wise would be useful insights from consumer perspectives.

Additionally, research into public charging should be considered. The maintenance of an EVs battery SOC will be a result of both private, at home, and public charging. The latter of which has not been considered by this thesis. Research into public charging for rural areas should also include optimising locations for installations, which may yield different results to those conducted in urban areas if rural community nuances are incorporated. In addition, a business case for public charge point installation should be investigated. As highlighted by this thesis, the transition is largely industry led, which is determined by good business cases. Work to not only understand the business case for rural areas but identify potential opportunities to improve the business case would aid the transition of EVs in these areas. Public charge points would not only impact the findings from this thesis, but also the finances of owning and operating an EV in rural areas, which in turn will impact uptake for rural consumers.

Building upon this, work into the impact of including solar panels and an Energy Storage System would be beneficial as these technologies are proving to be more and more popular with consumers and so a likely future scenario. This in turn would also impact any emission or financial analysis conducted. With this in mind, future work should also seek to analyse the impact on emissions generated by this transition for the work conducted in this thesis. Understanding the fundamental change to emissions is imperative for validating the transitions necessity in the first place. Thus, validating the effort which is currently being placed in pushing this transition. From a consumer perspective to couple with the emission analysis, a financial analysis would also contribute to the facilitation of EVs in rural areas. This would be especially important considering the findings regarding the DSM strategies and power outages and understanding the financial impact of choosing when to charge your vehicle would, as previous literature has suggested, largely influence this behaviour.

8.2 Final Thoughts

The work presented in this thesis offers key insights into the EV transition for rural areas. Under current legislations, EVs are an inevitability for everyone in the UK. For rural areas whereby private vehicles are a necessity, it is imperative work, like that conducted in this thesis, is continued, to ensure these areas are not left behind. This transition requires a multi-faceted approach that considers the unique characteristics and needs of rural communities. To conclude this thesis, the findings presented expose multiple recommendations for implementing rural EV infrastructure which have been presented below in Table 8.1 below.

Recommendations	Details
Existing Infrastructure	Determine the state of existing infrastructure and timelines – understanding how long current infrastructure will last during this transition is imperative to understanding the level of need for a rural location. This extends into improving and on-going monitoring at locations to understand the usage profiles and changing demand profiles that have been shown in the results presented in this thesis due to the EV transition
Leveraging Existing Infrastructure	Explore the opportunities for mitigating the increase in demand (power and energy) that EVs pose for local infrastructure, as highlighted by the work presented on Demand Side Management
Education and Awareness	Implement education and outreach programs to raise awareness about the benefits of EVs. Including trials to test EVs and impart knowledge on how this new transport system operates (requirements and understanding for installing home charge points etc.). This can then be extended further down the line to awareness and instructions on using and operating local public charging infrastructure Offer training programs for local technicians on the installation and maintenance of EV charging stations to build local expertise
Pilot Projects	Launch pilot projects for rural residents to be able to easily test drive EVs and interact with EV charging solutions in rural settings (fast chargers, solar-powered chargers etc.)
Incentives	Implemented targeted incentives for developing EV infrastructure in rural areas, such as tax credits, low-interest loans, and grants. Additionally, partner with local businesses and community gatekeepers (parish councils etc.) to install charging stations.
Stakeholder Engagement	Engage with a range of stakeholders, including local governments, utility companies, EV manufacturers, and most importantly rural residents. This will ensure the infrastructure meets rural community needs and preferences

Table 8.1: Future Recommendations for the EV transition in rural areas

In summary, this thesis bridges significant gaps in our understanding of rural EV adoption, providing robust empirical data, innovative methodologies and a solid theoretical framework. These themes, by extension, touch upon resource dependency theory; by examining the potential shifts in resource dependencies through strategic EV adoption, the thesis not only contributes to academic theory but also provides a blueprint for enhancing local energy autonomy and reducing environmental impacts.

This is complemented by an exploration of social dynamics, where stakeholder and consumer engagements are integrated into the analysis, thereby providing a holistic view of the transition process and its implications for rural communities. These contributions are pivotal not only for academics circles but also for informing policy and practical implementations, paving the way for more sustainable and inclusive transportation solutions in rural areas. Henceforth, may the findings and insights derived from this thesis inspire further exploration and meaningful action.

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APPENDICES

Appendix A - NTS Summary Table NTS0403

Purpose	Trips Per Person Per Year (Including short walks)	Trips Per Person Per Year (Excluding short walks)	Miles Per Person Per Year (including Short Walks)	Miles Per Person Per Year (Excluding Short Walks)	Average Trip Length (Miles)	Average Trip Duration (minutes)
Commuting	144.4485	132.913515	1276.80724	1271.372896	8.839184	30.125167
Business	29.550397	27.543372	566.974062	566.163911	19.186669	40.990979
Education	66.124574	44.753795	212.820724	203.181811	3.218481	21.069655
Escort education	59.902447	37.293656	128.293703	118.591074	2.141709	13.329609
Shopping	187.794619	145.188888	743.518694	726.831756	3.959211	17.012627
Other escort	88.967577	79.419648	457.711772	453.594068	5.1447	17.474692
Personal business	92.137063	74.90495	449.869708	443.306012	4.882612	19.005025
Visiting friends at private home	84.084301	71.750063	893.015128	888.006351	10.620472	26.867765
Visiting friends elsewhere	52.605975	41.147063	317.949668	312.938492	6.043982	21.872258
Entertainment / public activity	59.816468	52.7418	430.664199	427.480479	7.199757	23.048694
Sport: participate	14.155749	13.089903	95.806989	95.340023	6.76804	20.377694
Holiday: base	11.971709	10.585306	520.989762	520.45246	43.518274	77.018415
Day trip	32.676972	32.676972	378.269235	378.269235	11.576015	31.694572
Other including just walk	62.02491	23.419776	57.405827	39.208863	0.925528	21.313999
All purposes	986.261261	787.428707	6530.096711	6444.737431	6.621059351	22.92679369
Unweighted sample size:						
individuals	14150	14150	14150	14150	14150	14150
trips ('000s)	256.262	202.712	256.262	202.712	256.262	256.262

Appendix B – Vehicle and Household Compositions

Vehicle and household composition statistics for census output areas served by the primary substation 890067.

Village (Area)	Census Output Area	Household Data		Vehicle Data	
		No. of Occupants	**No. of Households**	**No. of Vehicles**	**No. of Households**
Bradbourne	**E00099163**	*1 Person*	*15*	*No Cars*	*4*
		2 People	*14*	*1 Car*	*17*
		3 People	*13*	*2 Car*	*18*
		4 People	*3*	*3 Car*	*9*
		5 People	*2*	*4 Car*	*1*
		6 People	*1*		
		7 People	*1*		
		8 People	*0*		
		TOTAL	**49**	**TOTAL**	**84**
Parwich	**E00099209**	*1 Person*	*37*	*No Cars*	*0*
		2 People	*64*	*1 Car*	*53*
		3 People	*18*	*2 Car*	*58*
		4 People	*25*	*3 Car*	*22*
		5 People	*7*	*4 Car*	*10*
		6 People	*1*		
		7 People	*0*		
		8 People	*0*		
		TOTAL	**152**	**TOTAL**	**275**
	E00099210	*1 Person*	*14*	*No Cars*	*6*
		2 People	*17*	*1 Car*	*18*
		3 People	*6*	*2 Car*	*16*
		4 People	*5*	*3 Car*	*5*
		5 People	*4*	*4 Car*	*2*
		6 People	*1*		
		7 People	*0*		
		8 People	*0*		
		TOTAL	**47**	**TOTAL**	**73**
Ballidon (& Aldwark)	**E00099162**	*1 Person*	*21*	*No Cars*	*2*
		2 People	*22*	*1 Car*	*19*
		3 People	*8*	*2 Car*	*25*
		4 People	*11*	*3 Car*	*9*
		5 People	*7*	*4 Car*	*6*
		6 People	*2*		
		7 People	*0*		
		8 People	*0*		
		TOTAL	**71**	**TOTAL**	**120**

Brassington	**E00099164**	*1 Person*	*32*	*No Cars*	*9*
		2 People	*53*	*1 Car*	*46*
		3 People	*16*	*2 Car*	*46*
		4 People	*21*	*3 Car*	*17*
		5 People	*6*	*4 Car*	*11*
		6 People	*0*		
		7 People	*1*		
		8 People	*0*		
		TOTAL	**129**	**TOTAL**	**233**
	E00099165	*1 Person*	*27*	*No Cars*	*9*
		2 People	*43*	*1 Car*	*49*
		3 People	*15*	*2 Car*	*39*
		4 People	*19*	*3 Car*	*12*
		5 People	*4*	*4 Car*	*1*
		6 People	*2*		
		7 People	*0*		
		8 People	*0*		
		TOTAL	**110**	**TOTAL**	**167**
Tissington (and Lea Hall)	**E00099212**	*1 Person*	*17*	*No Cars*	*6*
		2 People	*25*	*1 Car*	*18*
		3 People	*9*	*2 Car*	*28*
		4 People	*11*	*3 Car*	*8*
		5 People	*3*	*4 Car*	*6*
		6 People	*1*		
		7 People	*0*		
		8 People	*0*		
		TOTAL	**66**	**TOTAL**	**122**
Newton Grange	**E00099205**	*1 Person*	*7*	*No Cars*	*1*
		2 People	*13*	*1 Car*	*16*
		3 People	*7*	*2 Car*	*16*
		4 People	*12*	*3 Car*	*7*
		5 People	*8*	*4 Car*	*9*
		6 People	*1*		
		7 People	*1*		
		8 People	*0*		
		TOTAL	**49**	**TOTAL**	**105**
Carsington	**E00099166**	*1 Person*	*23*	*No Cars*	*2*
		2 People	*49*	*1 Car*	*31*
		3 People	*17*	*2 Car*	*59*
		4 People	*14*	*3 Car*	*8*
		5 People	*3*	*4 Car*	*7*
		6 People	*1*		
		7 People	*0*		
		8 People	*0*		
		TOTAL	**107**	**TOTAL**	**201**

Appendix C – ESEC Disconnection Levels

Government Planned Blackouts schedule

Level 1 Disconnection

Each period is of nominal 3 hours duration. Detailed timings of disconnections and reconnections will be confirmed by an Activation Schedule issued by the NGESO otherwise this is the default rota disconnection plan.

DAY	MONDAY								TUESDAY								WEDNESDAY								THURSDAY								FRIDAY								SATURDAY								SUNDAY							
PERIOD	1	2	3	4	5	6	7	8	1	2	3	4	5	6	7	8	1	2	3	4	5	6	7	8	1	2	3	4	5	6	7	8	1	2	3	4	5	6	7	8	1	2	3	4	5	6	7	8	1	2	3	4	5	6	7	8
A	■																					■																											■							
B			■				■											■																																						
C					■			■												■																																				
D		■											■																																					■						■
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Level 2 Disconnection

Each period is of nominal 3 hours duration. Detailed timings of disconnections and reconnections will be confirmed by an Activation Schedule issued by the NGESO otherwise this is the default rota disconnection plan.

DAY	MONDAY								TUESDAY								WEDNESDAY								THURSDAY							
PERIOD	1	2	3	4	5	6	7	8	1	2	3	4	5	6	7	8	1	2	3	4	5	6	7	8	1	2	3	4	5	6	7	8
A	■				■										■					■		■										
B	■		■				■									■		■				■										
C			■		■			■										■		■												
D		■				■					■		■										■									
E		■		■					■				■		■									■								
G				■		■			■		■					■																
H							■			■				■					■		■		■									
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DAY	FRIDAY								SATURDAY								SUNDAY							
PERIOD	1	2	3	4	5	6	7	8	1	2	3	4	5	6	7	8	1	2	3	4	5	6	7	8
A																	■							
B																	■							
C																								
D																		■						■
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T		■		■					■				■									■		
U				■		■			■		■					■								

Level 3 Disconnection

Each period is of nominal 3 hours duration. Detailed timings of disconnections and reconnections will be confirmed by an Activation Schedule issued by the NGESO otherwise this is the default rota disconnection plan.

DAY	MONDAY								TUESDAY								WEDNESDAY								THURSDAY								FRIDAY								SATURDAY								SUNDAY							
PERIOD	1	2	3	4	5	6	7	8	1	2	3	4	5	6	7	8	1	2	3	4	5	6	7	8	1	2	3	4	5	6	7	8	1	2	3	4	5	6	7	8	1	2	3	4	5	6	7	8	1	2	3	4	5	6	7	8
A	■		■		■										■			■		■		■																											■							
B	■		■		■		■									■		■		■		■																			■									■							
C	■		■		■			■										■		■		■																	■										■							
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Level 4 Disconnection

Each period is of nominal 3 hours duration. Detailed timings of disconnections and reconnections will be confirmed by an Activation Schedule issued by the NESO otherwise this is the default rota disconnection plan.

DAY	MONDAY							
PERIOD	1	2	3	4	5	6	7	8
A	■		■		■			
B	■		■		■		■	
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N								■
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Q								
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T							■	
U								■

DAY	TUESDAY							
PERIOD	1	2	3	4	5	6	7	8
A	■			■			■	
B		■			■			■
C			■			■		
D	■		■		■			
E	■		■		■		■	
G	■		■		■			■
H		■		■		■		
J		■		■		■		
K		■		■		■		
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M								■
N							■	
P							■	
Q								
R								■
S								
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U								

DAY	WEDNESDAY							
PERIOD	1	2	3	4	5	6	7	8
A		■		■		■		
B		■		■		■		
C		■		■		■		
D	■			■			■	
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DAY	THURSDAY							
PERIOD	1	2	3	4	5	6	7	8
A							■	
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C								■
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J							■	
K								■
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M	■		■		■		■	
N	■		■		■			■
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Q		■		■		■		
R		■		■		■		
S	■			■			■	
T		■			■			■
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DAY	FRIDAY							
PERIOD	1	2	3	4	5	6	7	8
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B								■
C							■	
D							■	
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P	■		■		■			
Q	■		■		■		■	
R	■		■		■			■
S		■		■		■		
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DAY	SATURDAY							
PERIOD	1	2	3	4	5	6	7	8
A								
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E								■
G							■	
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J								■
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DAY	SUNDAY							
PERIOD	1	2	3	4	5	6	7	8
A	■			■				
B	■							
C	■						■	
D		■			■			■
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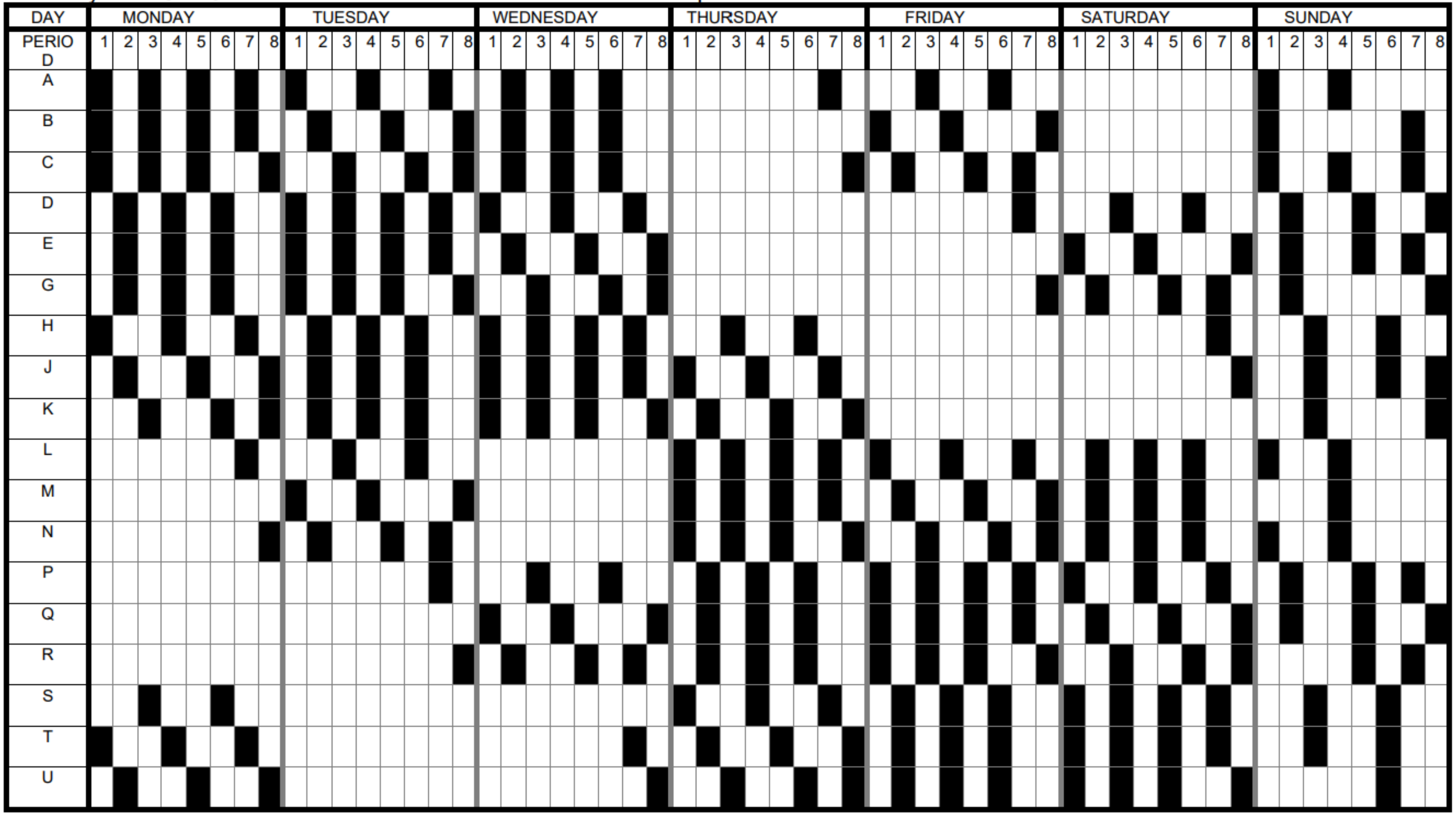
Level 5 Disconnection

Each period is of nominal 3 hours duration. Detailed timings of disconnections and reconnections will be confirmed by an Activation Schedule issued by the NGESO otherwise this is the default rota disconnection plan.



Level 6 Disconnection

Each period is of nominal 3 hours duration. Detailed timings of disconnections and reconnections will be confirmed by an Activation Schedule issued by the NGESO otherwise this is the default rota disconnection plan.

DAY	MONDAY							
PERIOD	1	2	3	4	5	6	7	8
A	■		■		■		■	
B	■		■		■		■	
C	■		■		■			■
D		■		■		■		
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DAY	TUESDAY							
PERIOD	1	2	3	4	5	6	7	8
A	■			■			■	
B		■			■			■
C			■			■		■
D	■		■		■		■	
E	■		■		■		■	
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J		■		■		■		
K		■		■		■		
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R					■			■
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DAY	WEDNESDAY							
PERIOD	1	2	3	4	5	6	7	8
A		■		■		■		
B		■		■		■		
C		■		■		■		
D	■			■			■	
E		■			■			■
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H	■		■		■		■	
J	■		■		■		■	
K	■		■		■			■
L		■						
M				■				
N						■		
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DAY	THURSDAY							
PERIOD	1	2	3	4	5	6	7	8
A			■				■	
B					■		■	
C	■							■
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E						■		
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R		■		■		■		
S	■			■			■	
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DAY	FRIDAY							
PERIOD	1	2	3	4	5	6	7	8
A			■			■		■
B	■			■				■
C		■			■		■	
D	■						■	
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DAY	SATURDAY							
PERIOD	1	2	3	4	5	6	7	8
A		■						
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DAY	SUNDAY							
PERIOD	1	2	3	4	5	6	7	8
A	■			■			■	
B	■			■			■	
C	■			■			■	
D		■			■			■
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Level 7 Disconnection

Each period is of nominal 3 hours duration. Detailed timings of disconnections and reconnections will be confirmed by an Activation Schedule issued by the NGESO otherwise this is the default rota disconnection plan.

DAY	MONDAY								TUESDAY								WEDNESDAY								THURSDAY								FRIDAY								SATURDAY								SUNDAY							
PERIOD	1	2	3	4	5	6	7	8	1	2	3	4	5	6	7	8	1	2	3	4	5	6	7	8	1	2	3	4	5	6	7	8	1	2	3	4	5	6	7	8	1	2	3	4	5	6	7	8	1	2	3	4	5	6	7	8
A	■		■		■		■		■			■			■			■		■		■			■		■				■				■			■		■		■				■			■			■			■	
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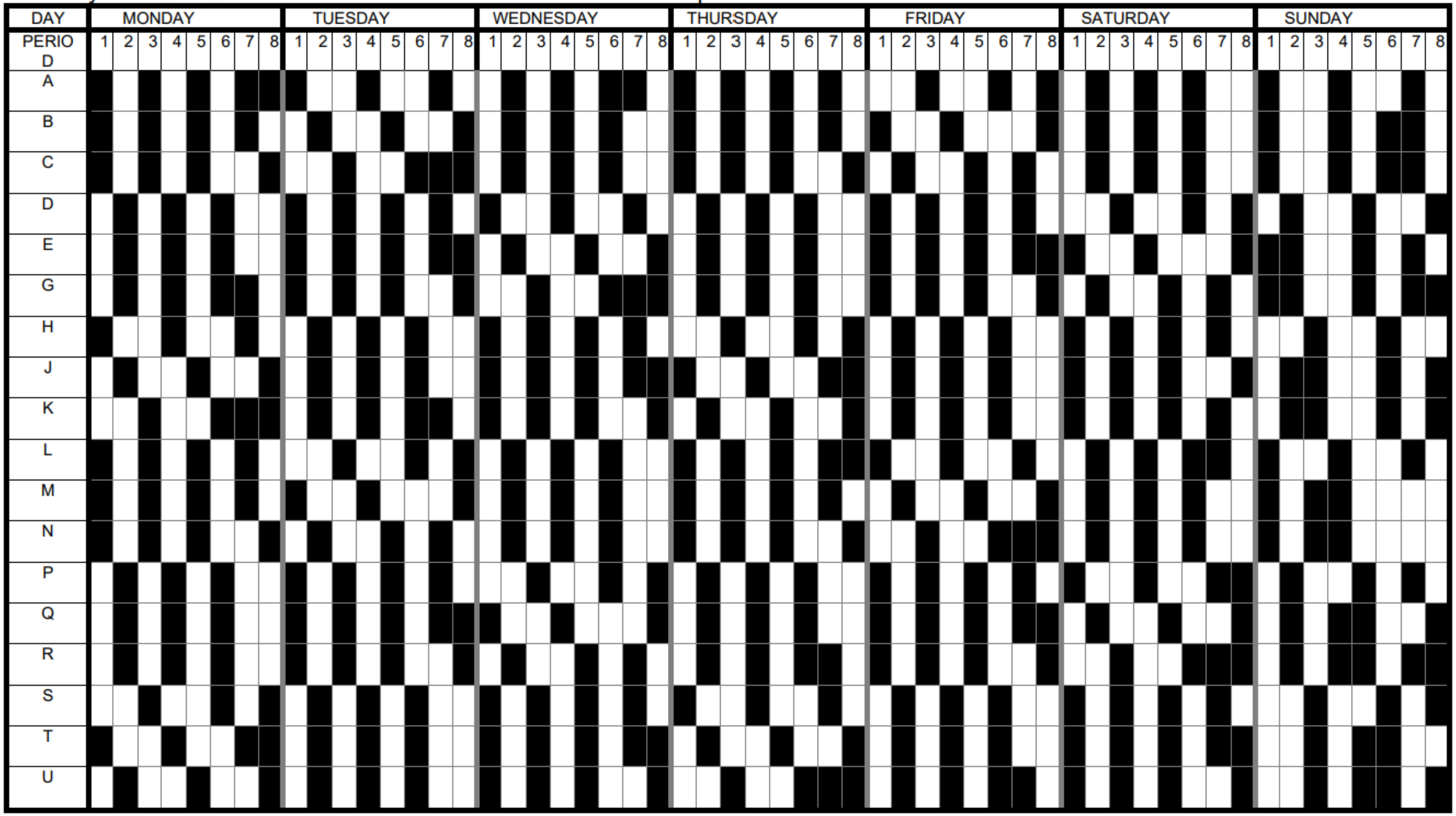
Level 8 Disconnection

Each period is of nominal 3 hours duration. Detailed timings of disconnections and reconnections will be confirmed by an Activation Schedule issued by the NGESO otherwise this is the default rota disconnection plan.

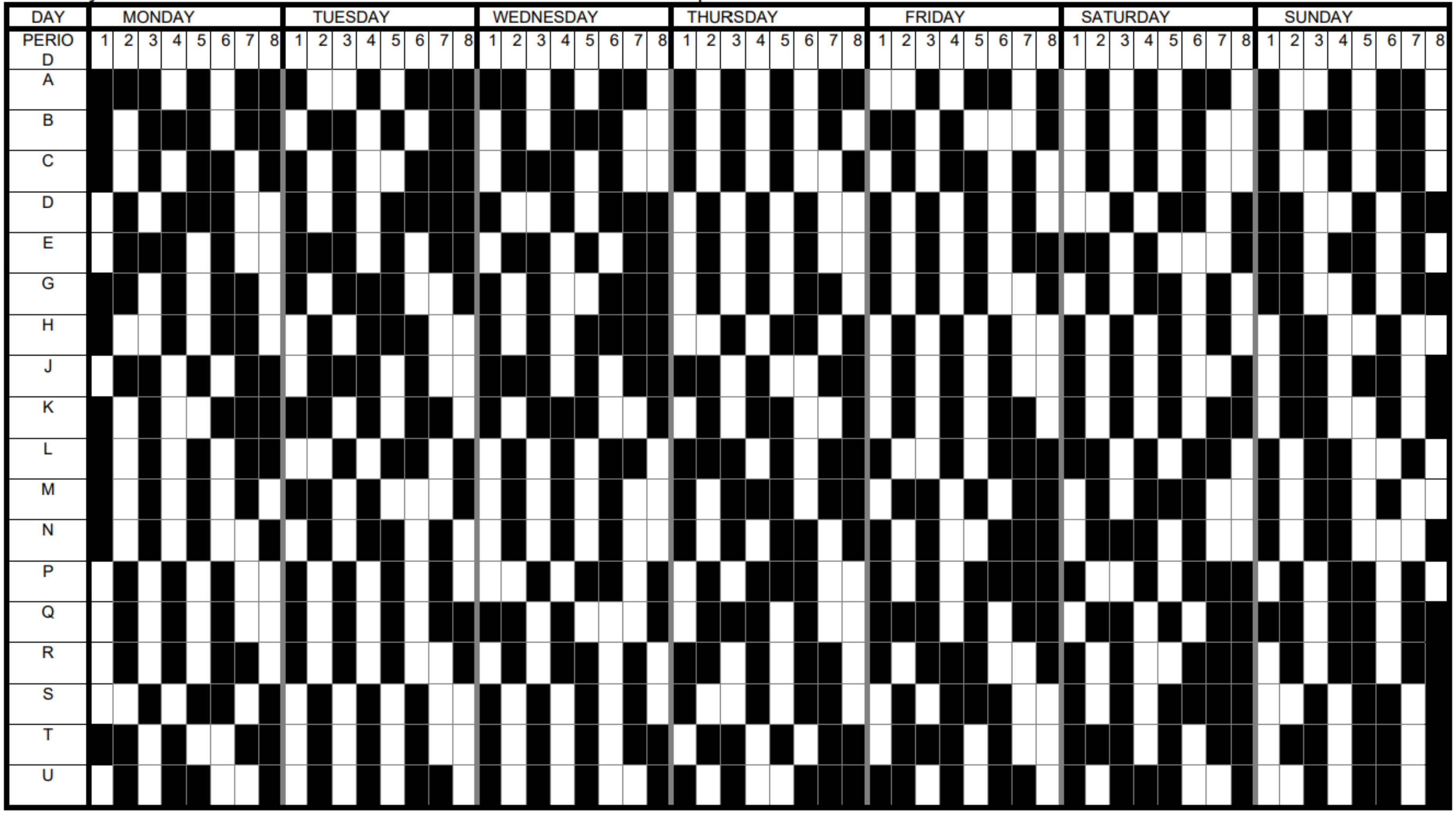


Level 9 Disconnection

Each period is of nominal 3 hours duration. Detailed timings of disconnections and reconnections will be confirmed by an Activation Schedule issued by the NGESO otherwise this is the default rota disconnection plan.

Level 10 Disconnection

Each period is of nominal 3 hours duration. Detailed timings of disconnections and reconnections will be confirmed by an Activation Schedule issued by the NGESO otherwise this is the default rota disconnection plan.



Level 11 Disconnection

Each period is of nominal 3 hours duration. Detailed timings of disconnections and reconnections will be confirmed by an Activation Schedule issued by the NGESO otherwise this is the default rota disconnection plan.

DAY	MONDAY								TUESDAY								WEDNESDAY								THURSDAY								FRIDAY								SATURDAY								SUNDAY							
PERIOD	1	2	3	4	5	6	7	8	1	2	3	4	5	6	7	8	1	2	3	4	5	6	7	8	1	2	3	4	5	6	7	8	1	2	3	4	5	6	7	8	1	2	3	4	5	6	7	8	1	2	3	4	5	6	7	8
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Level 12 Disconnection

Each period is of nominal 3 hours duration. Detailed timings of disconnections and reconnections will be confirmed by an Activation Schedule issued by the NGESO otherwise this is the default rota disconnection plan.

DAY	MONDAY								TUESDAY								WEDNESDAY								THURSDAY								FRIDAY								SATURDAY								SUNDAY							
PERIOD	1	2	3	4	5	6	7	8	1	2	3	4	5	6	7	8	1	2	3	4	5	6	7	8	1	2	3	4	5	6	7	8	1	2	3	4	5	6	7	8	1	2	3	4	5	6	7	8	1	2	3	4	5	6	7	8
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Level 13 Disconnection

Each period is of nominal 3 hours duration. Detailed timings of disconnections and reconnections will be confirmed by an Activation Schedule issued by the NGESO otherwise this is the default rota disconnection plan.

DAY	MONDAY								TUESDAY								WEDNESDAY								THURSDAY								FRIDAY								SATURDAY								SUNDAY							
PERIOD	1	2	3	4	5	6	7	8	1	2	3	4	5	6	7	8	1	2	3	4	5	6	7	8	1	2	3	4	5	6	7	8	1	2	3	4	5	6	7	8	1	2	3	4	5	6	7	8	1	2	3	4	5	6	7	8
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Level 14 Disconnection

Each period is of nominal 3 hours duration. Detailed timings of disconnections and reconnections will be confirmed by an Activation Schedule issued by the NGESO otherwise this is the default rota disconnection plan.

DAY	MONDAY								TUESDAY								WEDNESDAY								THURSDAY								FRIDAY								SATURDAY								SUNDAY							
PERIOD	1	2	3	4	5	6	7	8	1	2	3	4	5	6	7	8	1	2	3	4	5	6	7	8	1	2	3	4	5	6	7	8	1	2	3	4	5	6	7	8	1	2	3	4	5	6	7	8	1	2	3	4	5	6	7	8
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Level 15 Disconnection

Each period is of nominal 3 hours duration. Detailed timings of disconnections and reconnections will be confirmed by an Activation Schedule issued by the NGESO otherwise this is the default rota disconnection plan.

DAY	MONDAY								TUESDAY								WEDNESDAY								THURSDAY								FRIDAY								SATURDAY								SUNDAY							
PERIOD	1	2	3	4	5	6	7	8	1	2	3	4	5	6	7	8	1	2	3	4	5	6	7	8	1	2	3	4	5	6	7	8	1	2	3	4	5	6	7	8	1	2	3	4	5	6	7	8	1	2	3	4	5	6	7	8
A	■	■	■		■	■	■	■	■	■		■	■	■	■	■	■	■	■	■		■	■	■	■	■	■		■	■	■	■	■		■	■	■	■	■	■	■	■		■	■	■	■		■		■	■	■	■	■	■
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C	■		■	■	■	■		■	■	■	■		■	■	■	■		■	■	■	■	■	■	■	■		■	■	■	■		■		■	■	■	■	■	■	■		■	■	■	■	■	■		■		■	■	■	■	■	■
D	■	■		■	■	■	■		■		■	■	■	■	■	■	■	■		■	■	■	■	■	■	■	■	■		■	■	■	■		■	■	■	■	■	■	■		■	■	■	■	■	■	■	■		■	■	■	■	■
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Level 16 Disconnection

Each period is of nominal 3 hours duration. Detailed timings of disconnections and reconnections will be confirmed by an Activation Schedule issued by the NGESO otherwise this is the default rota disconnection plan.

DAY	MONDAY								TUESDAY								WEDNESDAY								THURSDAY								FRIDAY								SATURDAY								SUNDAY							
PERIOD	1	2	3	4	5	6	7	8	1	2	3	4	5	6	7	8	1	2	3	4	5	6	7	8	1	2	3	4	5	6	7	8	1	2	3	4	5	6	7	8	1	2	3	4	5	6	7	8	1	2	3	4	5	6	7	8
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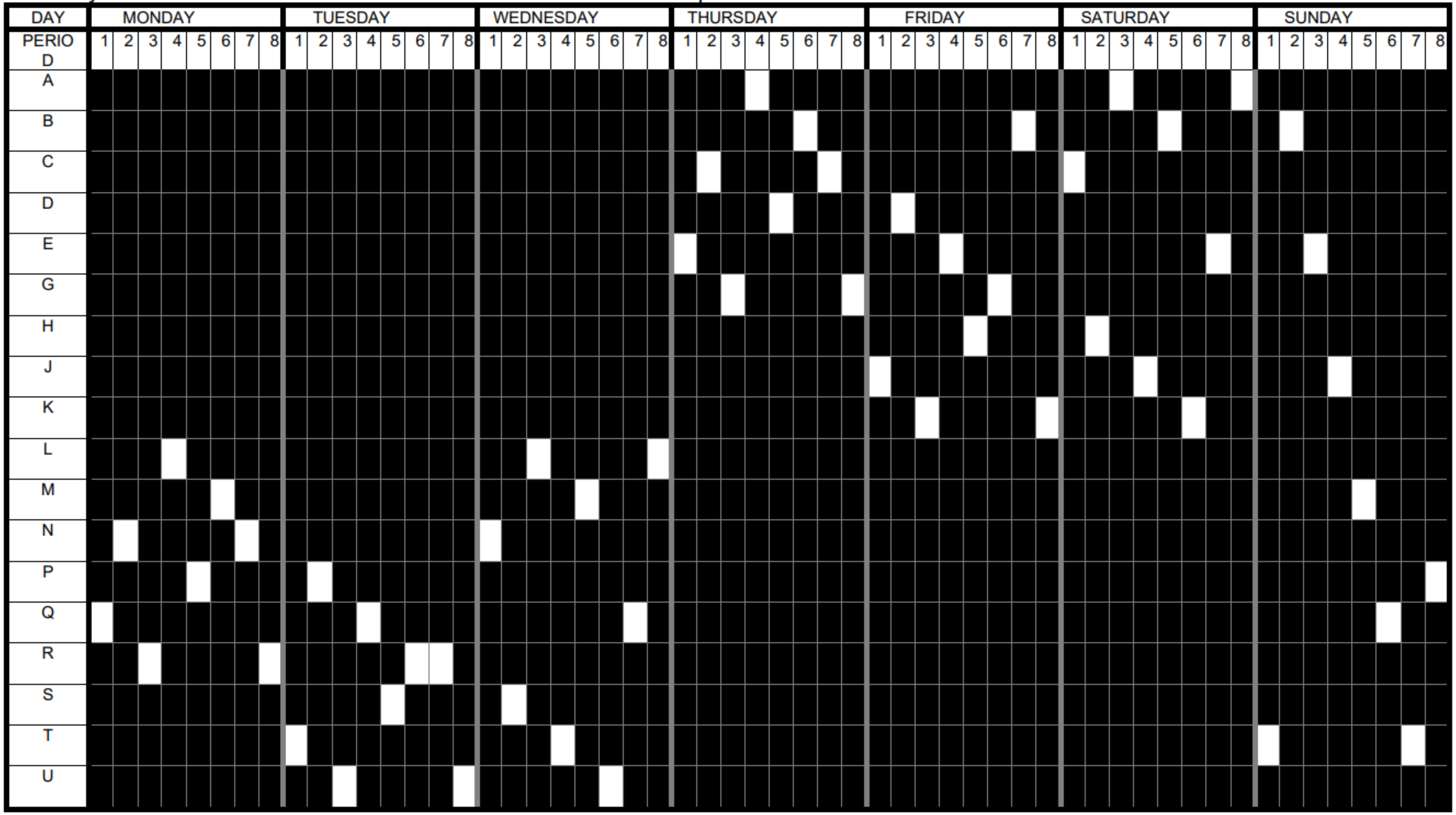
Level 17 Disconnection

Each period is of nominal 3 hours duration. Detailed timings of disconnections and reconnections will be confirmed by an Activation Schedule issued by the NGESO otherwise this is the default rota disconnection plan.



Level 18 Disconnection

Each period is of nominal 3 hours duration. Detailed timings of disconnections and reconnections will be confirmed by an Activation Schedule issued by the NGESO otherwise this is the default rota disconnection plan.

DAY	MONDAY								TUESDAY								WEDNESDAY								THURSDAY								FRIDAY								SATURDAY								SUNDAY							
PERIOD	1	2	3	4	5	6	7	8	1	2	3	4	5	6	7	8	1	2	3	4	5	6	7	8	1	2	3	4	5	6	7	8	1	2	3	4	5	6	7	8	1	2	3	4	5	6	7	8	1	2	3	4	5	6	7	8
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Appendix D – Copy of Survey

Copy of Survey

University of Sheffield - Electric Vehicles Questionnaire

This questionnaire forms part of research being conducted by Thomas McKinney (University of Sheffield, PhD Student), Dr Erica Ballantyne (University of Sheffield, Management School) and Prof David Stone (University of Sheffield, Department of Electronic and Electrical Engineering).

Completing this survey will help us to investigate the transition from petrol/diesel to electric cars for rural communities. Through collecting information on travel patterns, how you use your cars and your energy tariffs, we hope to understand how electric vehicles might cope with these requirements and develop solutions to any potential problems to ensure this transition is as smooth as possible for everyone.

NOTE: Only one response per household is required, so please check if anyone in your household has already completed this questionnaire or not before proceeding.

This questionnaire should take no more than 10 minutes to complete. At the end of which will be an opportunity for you to provide an email address so we may send you our findings from this research and a breakdown of the results, including more general information you may find helpful regarding this Electric Vehicle transition. Thank you for your time.

* Indicates required question

Consent to participate

You are being asked to participate in our research as you currently live in the Peak District, the main focus area of this research project. By doing so, you may benefit from information regarding new legislations, timelines, electric vehicle specific electricity tariffs and at the very least alert you to this transition and its possible implications.

This questionnaire is carried out with accordance to data protection legislation and the legal basis we are applying in order to process your personal data is that 'processing is necessary for the performance of a task carried out in the public interest' (Article 6(1)(e)). Further information can be found in the University's Privacy Notice https://www.sheffield.ac.uk/govern/data-protection/privacy/general

All responses to our questionnaire will remain annoymous throughout. All information gathered will be kept strictly confidential and will be stored on the University of Sheffield Server, where it wil be password protected with only the research team having access. The research has recieved ethical approval from the University of Sheffield (Ethic Review ID: 044759).

It is completly up to you whether or not you wish to take part. Should you choose to discontinue or withdraw from the research you can exit the questionnaire at any time without providing any reason - simply close down this internet browsing tab and all of the answers you provided will be deleted if you have not already submitted them at the end of the questionnaire. If you do wish to take part, please read the following 'Participant Information Sheet' linked below:

https://docs.google.com/document/d/1EaG5CI83HI5oJlqeZBIZ-zi58TA3szL-/edit?usp=sharing&ouid=116775477501286660074&rtpof=true&sd=true

Then please read the following statements and indicate your agreement to participate by checking the box after each statement:

1. I have read and understood the project information presented on the previous page of this questionnaire. *

Tick all that apply.

☐ Yes

2. I agree to take part in the project. I understand that taking part in the project will include the completion of this questionnaire. *

Tick all that apply.

☐ Yes

3. I understand that by choosing to participate as a volunteer in this research, this does not create a legally binding agreement nor is it intended to create an employment relationship with The University of Sheffield. *

Tick all that apply.

☐ Yes

4. I understand that my taking part is voluntary and that I can withdraw from the study at any time; I do not have to give reasons for why I no longer want to take part and there will be no adverse consequences if I choose to withdraw. *

Tick all that apply.

☐ Yes

5. I understand and agree that other authorised researchers will have access to this data only if they agree to preserve the confidentiality of the information as requested in this form. *

Tick all that apply.

☐ Yes

6. I understand and agree that other authorised researchers may use my data in publications, reports, web pages, and other research outputs, only if they agree to preserve the confidentiality of the information as requested in this form. *

Tick all that apply.

☐ Yes

7. I give permission for my answers to this questionnaire to be deposited in EV Logistics Research Group storage server at The University of Sheffield. *

Tick all that apply.

☐ Yes

8. I agree to assign the copyright I hold in any materials generated as part of this project to The University of Sheffield. *

Tick all that apply.

☐ Yes

Contact Information

Thomas R. McKinney	Dr. Erica E.F. Ballantyne	Prof. David A. Stone
Sheffield University Management School The University of Sheffield Conduit Road, Sheffield S10 1FL, UK Email: trmckinney1@sheffield.ac.uk	Sheffield University Management School The University of Sheffield Conduit Road, Sheffield S10 1FL, UK Email: e.e.ballantyne@sheffield.ac.uk	Department of Electronic and Electrical Engineering The University of Sheffield Sir Frederick Mappin Building, Mappin Street, Sheffield S1 3JD, UK Email: d.a.stone@sheffield.ac.uk
Sheffield University Management School The University of Sheffield Conduit Road Sheffield S10 1FL United Kingdom Tel (General enquiries): +44 (0)114 222 3232		

Section 1 - Demographic

Now that you have provided your consent to complete this questionnaire, please answer all 19 questions, which have been split into 5 sections. Once completed, you will be taken to the final page to submit your answers and finish the questionnaire.

9. 1. Please select your local area: *
(If your area is not listed below, please select your closest other settlement)

Mark only one oval.

- ○ Alsop
- ○ Alstonefield
- ○ Ashbourne
- ○ Atlow
- ○ Ballidon
- ○ Biggin
- ○ Bradbourne
- ○ Bradley
- ○ Brassington
- ○ Brund
- ○ Carsington
- ○ Clifton
- ○ Coldeaton
- ○ Dale End
- ○ Eaton
- ○ Ecton
- ○ Elton
- ○ Friden
- ○ Glutton Bridge
- ○ Gratton
- ○ Hartington
- ○ Heathcote
- ○ Hope
- ○ Hopton
- ○ Hulme End
- ○ Hurdlow
- ○ Hognaston
- ○ Ible
- ○ Kniveton

- Knockerdown
- Lea
- Longcliffe
- Longnor
- Milldale
- Monyash
- Newhaven
- Newton Grange
- Osmaston
- Parwich
- Pikehall
- Rowfields
- Sheen
- Sturston
- Tissington
- Warslow
- Wetton
- Winster
- Yeldersley
- Youlgreave
- Other

10. 2. How many people live in your household? *

Mark only one oval.

- 1
- 2
- 3
- 4
- 5
- 6
- More than 6

11. 3. What ages are the people in your household? *

Please list the ages of everyone that lives in your household, separated by commas

Section 2 - Your Cars and Travel

This section will ask you questions on the vehicles you own and how you use them

12. 4. How many vehicles do you have at your household? *

This questionnaire is focused on private passenger vehicles, which can include vans if they are used for non-work related trips regularly. Please do not include motorbikes in your vehicle count.

Mark only one oval.

- 0
- 1
- 2
- 3
- 4
- 5
- More than 5

13. 5. Do you own an Electric Vehicle, if so how many?

This includes battery electric vehicles (BEVs), plug-in hybrid electric vehicles (PHEVs) and hybrid electric vehicles.

Mark only one oval.

- 0
- 1
- 2
- 3
- 4
- 5
- More than 5

14. 6. Roughly how many miles a week, in total, do all the vehicles at your household drive? *

For example, if your household has 2 cars:

Car 1 drives 20 miles/week

Car 2 drives 50 miles/week

The total would be 70 miles for this household.

15. 7. Thinking about your average WEEKDAY, what time is your car NOT at home?

Thinking about how your car(s) are used on any average WEEKDAY, please select all the time periods (or those which are closest) for when your car(s) are NOT at home.

Tick all that apply.

- 00:00 - 06:00
- 06:00 - 07:00
- 07:00 - 08:00
- 08:00 - 09:00
- 09:00 - 10:00
- 10:00 - 12:00
- 12:00 - 15:00
- 15:00 - 16:00
- 16:00 - 17:00
- 17:00 - 18:00
- 18:00 - 20:00
- 20:00 - 22:00
- 22:00 - 00:00
- N/A

16. 8. Thinking about your average WEEKEND, what time is your car NOT at home?

Thinking about how your car(s) are used on any average WEEKEND, please select all the time periods (or those which are closest) for when your car(s) are NOT at home.

Tick all that apply.

- [ ] 00:00 - 06:00
- [ ] 06:00 - 07:00
- [ ] 07:00 - 08:00
- [ ] 08:00 - 09:00
- [ ] 09:00 - 10:00
- [ ] 10:00 - 12:00
- [ ] 12:00 - 15:00
- [ ] 15:00 - 16:00
- [ ] 16:00 - 17:00
- [ ] 17:00 - 18:00
- [ ] 18:00 - 20:00
- [ ] 20:00 - 22:00
- [ ] 22:00 - 00:00
- [ ] N/A

Section 3 - Electric Vehicles

17. 9. How aware are you of Electric Vehicles and the UK Governments push for them to replace diesel and petrol cars?

Mark only one oval.

Fully Aware

1 ◯

2 ◯

3 ◯

4 ◯

5 ◯

Unaware

18. 10. How likely will you purchase an Electric Vehicle as your next car?

Mark only one oval.

Very Likely

1 ◯

2 ◯

3 ◯

4 ◯

5 ◯

Very Unlikely

19. 11. Do you think you will end up replacing ALL of your vehicles with electric ones or would you own less/no cars in the future? *

Mark only one oval.

◯ Yes, we will need the same number of cars

◯ No, our household might try to get by with less vehicles

◯ I have not thought about it

20. 12. Is public transport sufficient in your area for your day-to-day needs or do you require your own personal vehicle(s)? *

Mark only one oval.

◯ I can/could get by with just my local public transport

◯ We require our own personal cars to get around

Section 4 - Charging

21. 13. What are the parking facilities at your home? *

Tick all that apply.

- [ ] Garage
- [ ] Car Port
- [ ] Driveway
- [ ] Private Car Park
- [ ] On-Road
- [ ] Other

22. 14. Will you charge your EV at home?

If you already have an EV, do you have a charger at your household? If you do not own an EV, but will likely in the future, would you considered buying a home charger? The alternative would be charging at public charge points at places of work, supermarkets etc. If you are unlikely to ever own an EV, please leave this question blank.

Mark only one oval.

Likely

1 ⬭
2 ⬭
3 ⬭
4 ⬭
5 ⬭

23. 15. If you were to install home chargers, how many would you have? *

Mark only one oval.

- ⬭ I'm not sure
- ⬭ 1
- ⬭ 2
- ⬭ 3
- ⬭ 4
- ⬭ 5
- ⬭ More than 5
- ⬭ N/A

24. 16. Please select from the following list, which public areas you would be likely * to charge your electric vehicle, if not at home.

Tick all that apply.

- ☐ Work
- ☐ Shops
- ☐ School
- ☐ Day Trip (i.e. public car parks at day trip destinations)
- ☐ Other (i.e. visiting friends, sports/activities, when conducting personal errands)
- ☐ N/A

Section 5 - Electricity Tariffs

This is the final section of questions before submitting and completion the questionnaire

25. 17. What kind of electricity meter do you have? *

Mark only one oval.

- ⬭ Standard meter
- ⬭ Dial meter
- ⬭ Digital meter
- ⬭ Variable-rate meter (Economy 7 or Economy 10)
- ⬭ Prepayment meter
- ⬭ Smart meter
- ⬭ Other

26. 18. Are you aware of Household Electricity tariffs tailored to Electric Vehicle owners?

Mark only one oval.

Fully aware

1 ◯

2 ◯

3 ◯

4 ◯

5 ◯

Unaware

27. 19. Would you have a different electricity meter installed? *

In order to obtain an Electric Vehicle electricity tariff, in most cases you are required to have a Smart Meter. If you do not have one already, would you consider installing one to access electric vehicle specific tariffs.

Mark only one oval.

◯ Yes

◯ No

◯ Maybe

Questionnaire Completed

Thank you for completing our questionnaire. The answers you have provided here today will really help us achieve our goal of understanding and aiding the rural communities of the UK and their transition to electric vehicles.

If you would like to recieve a copy of the final report from this research, including a breakdown and the findings from this questionnaire, please feel free to provide an email address below and a copy will be sent to you when ready. The email address you provide will in no way be associated with your answers to the questionnaire to maintain your complete anonymity.

Yours Sincerely,

Thomas McKinney, Dr. Erica Ballantyne & Prof. David Stone

28. Email Address:

Appendix E – Participant Information Sheet

Participant Information Sheet

Research Project Title

Facilitating the Uptake of Electric Vehicles in Rural Communities

Invitation Paragraph

You are being invited to take part in a research project. Before you decide whether or not to participate, it is important for you to understand why the research is being done and what it will involve. Please take time to read the following information carefully and discuss it with others if you wish. If there is anything that is not clear or if you would like more information, please contact us via any of the emails below. Take time to decide whether or not you wish to take part and thank you for reading this.

What is the project's purpose?

You might have already noticed the increased push for electric vehicles in recent years, with many major car manufacturers bringing out electric versions of their cars, government incentives and new legislation phasing out petrol and diesel vehicles. Electric vehicle charge points have also already started appearing at public car parks, supermarkets, and places of work but the majority of investment and research so far has been based on urban areas. This project aims to facilitate the electric vehicle transition for the more rural areas, and this survey hopes to collect real-world data to help achieve this. Through collecting information on travel patterns, car usage requirements, electricity tariffs and charging behaviours we hope to understand what effect electric vehicles will have in rural areas and as a result help aid a smooth transition to electric vehicles for your community.

Why have I been chosen?

You have been chosen for the simple reason that you currently live in a rural area of the UK. More specifically, this research project has been focused on the Peak District. So as to align with this, Parish/Town Councillors of the Peak District area were contacted to inform them of the project and bring them onboard so that they may distribute this survey to their respective communities, of which you are a part of.

Do I have to take part?

It is up to you to decide whether or not to take part. If you do decide to take part, you will be given this information sheet to keep (and be asked to provide consent at the start of the survey) and you can still withdraw at any time without any negative consequences. You do not have to give a reason. If you wish to withdraw from the research, please contact us using any of the emails provided at the end of this document. If you wish to withdraw mid-way through the survey, all you have to do is exit the browser, no information is saved or processed until you submit your responses on the very last page of the survey. Please not that by choosing to participate in this research, this will not create a legally binding agreement, nor is it intended to create an employment relationship between you and the University of Sheffield.

What will happen to me if I take part? What do I have to do?

Taking part in this research project involves two surveys. A link to the first has been emailed to you from your Parish/Town Councillor. In this first survey, you will be asked questions regarding the current cars you own, your travelling habits electricity tariffs, as well as potential electric cars that might interest you and charging behaviour. Once you have completed and submitted the first survey, these answers will be used to model how electric vehicles would fair compared to your current cars, as well as providing insights into the possible financial impact of the transition. These results will be emailed back to you, so that you may review them yourselves. This second email will also include a link to a second survey which will ask similar questions again, to look at possible attitude and answer changes from you, having now learnt the results from the first survey.

What are the possible disadvantages and risks of taking part?

No identifiable information is collected, apart from your email address, name, and the local area where you live. There are questions which relate to when your car is in use and not in use, but this is of no concern as no information relating to your address is collected. The results report may be cause for concern if, for some reason, an electric vehicle is found to not be practical for your driving habits, but there is absolutely no rush to switch as of yet. Electric vehicle technology and infrastructure is constantly improving, so will only become less of a concern as time goes on, but all of this will be fully explained during the survey and results report.

What are the possible benefits of taking part?

You may or may not be aware of the electric vehicle transition, but by taking part in this research, you will be sure to afterwards as the surveys contain a lot of information regarding new legislations, timelines, electric vehicle specific electricity tariffs and more. Furthermore, for those wondering if electric vehicles will have a long enough range for their driving needs, or are worried about the costs associated with them, the results that will be emailed back to you after the completion of the first survey will help provide insight into these questions and more.

Will my taking part in this project be kept confidential?

All the information that we collect about you during the course of the research will be kept strictly confidential and will only be accessible to members of the research team. You will not be able to be identified in any reports of publications, if you agree to us sharing the information you provide with other researchers (e.g. by making it available in a data archive) then your personal details will not be included unless you explicitly request this.

What is the legal basis for processing my personal data?

According to data protection legislation, we are required to inform you that the legal basis we are applying in order to process your personal data is that 'processing is necessary for the performance of a task carried out in the public interest' (Article 6(1)(e)). Further information can be found in the University's Privacy Notice https://www.sheffield.ac.uk/govern/data-protection/privacy/general

What will happen to the data collected, and the results of the research project?

As well as the response above to the question '*What will happen to me if I take part? What do I have to do?*' which talked about the results report you will be emailed with following the completion of the first survey, once the data collection has finished and the surveys taken off-line following a few months being available for participants, the data will be collated and used to develop some more general findings, rather than the personalised, individual nature of the results reports. These results are likely to be published in an academic journal and within the thesis submission for the PhD that is this research project. No personal information of any kind will be published.

An anonymised version of the data will be stored on the University of Sheffield Server following the completion of the project. There is no planned future use for the data and should it be deemed no required following completion of the project, will be deleted entirely. However, due to the nature of this research it is likely that other researchers may find the data collected to be useful in answering their research questions, in which case, only the anonymised versions will be available for their use, which can in no way be traced back to you.

Who is organising and funding the research?

The University of Sheffield

Who is the Data Controller?

No Personal data is collected in this research project. The University of Sheffield will act as the data controlled for the data that will be collected, which means that the University is responsible for looking after your information and using it properly.

Who has ethically reviewed the project?

This project has been ethically approved via the University of Sheffield's Ethics Review Procedure, as administered by the Sheffield Management School Department.

What if something goes wrong and I wish to complain about the research or report a concern or incident?

If you are dissatisfied with any aspect of the research and wish to make a complaint or report a concern of incident, please contact any of the individuals listed at the end of this document.

Contact for further information

Thomas McKinney (PhD Research Student) – trmckinney1@sheffield.ac.uk

Dr. Erica Ballantyne - e.e.ballantyne@sheffield.ac.uk

Prof. David Stone - d.a.stone@sheffield.ac.uk

Appendix F – Contacts for Survey Distribution

Contacts for Survey Distribution

Parish Councils
Wetton
Hartington
Brassington
Tissington & Lea Hall
Tissington and Lea Hall
Ballidon and Bradbourne
Kniveton
Carsington & Hopton
Hartington (Nether & Town)
Elton
Alstonefield
Ible Parish Council
Parwich
Eaton & Alsop & Newton Grange

Schools
Parwich Primary
Brassington Primary
Carsington and Hopton Church Primary
Tissington Kindergarden
Hartington Primary

Hand Delivery
Bradbourne
Brassington
Parwich

Royal Mail Door-to-Door Service (Postcode Areas)
DE6 1
SK17 0
DE4 2

Appendix G – Survey Results Report

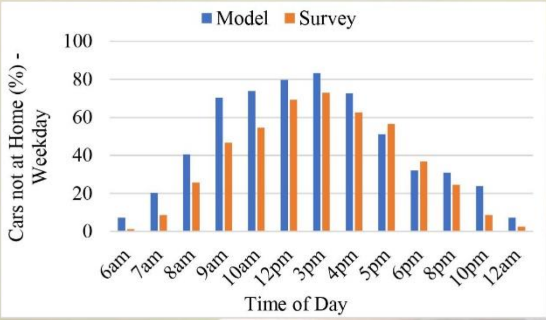
Results Report

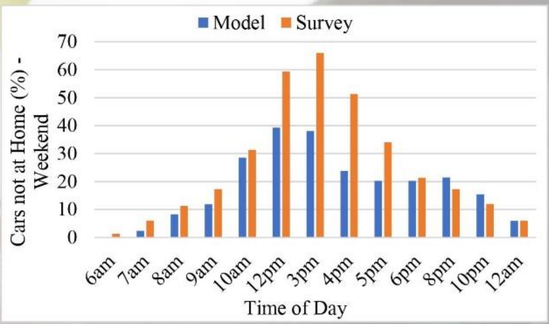
Sheffield University Research on Car Usage in Rural Areas

Just over a year ago marks the start date of our data collection, looking at how cars are used in rural areas and the transition to electric vehicles. Thank you to everyone who took the time to complete our survey, your answers have been invaluable to our project, and we are now in a place to share some of the results with you.

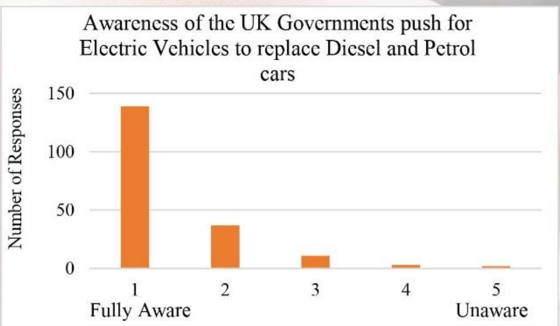
Mr. Thomas McKinney, Dr. Erica Ballantyne & Prof. David Stone

We had responses from households of all sizes, representing ages from 14 weeks to 87 years old. Collectively, you provided important data on 376 vehicles, each averaging 110 miles per week. A large part of your contribution went towards verifying models we have built to simulate how vehicles are used in rural areas.





It's important to know when cars are in use and not in use, as well as how many miles they are driving so that we can accurately understand what the corresponding energy consumption would be if they were electric vehicles. From there, we are then able to calculate when they would be able to charge and by extension the impact on the electrical grid if we all had electric vehicles.



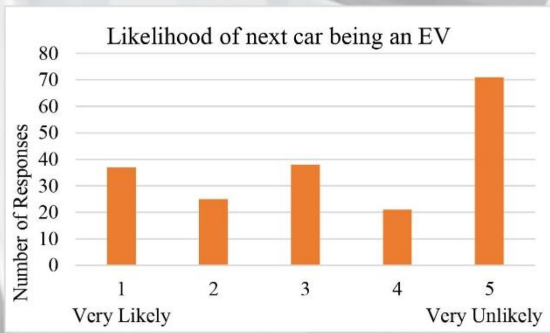
96.7% of respondents require their vehicles to get around, stating public transport in the area is not sufficient

- The UK Governments latest plans ban the sale of **NEW** petrol and diesel cars by 2030. Bear in mind though, that there will still be the second hand marketplace for some years after.
- However, it is inevitable that we will all need to change our vehicles at some point in the future and that's what our project is looking into.

We also asked about the chances of your next car being an EV with many of you stating no, reasons include:

- Price
- Range Anxiety
- Distrust of Technology

Battery Technology is constantly improving and with that not only are the prices of an EV decreasing, but their range increasing. When considering lifetime costs, although there is the higher upfront cost, servicing, running, and charging an EV comes out considerably cheaper than a petrol or diesel vehicle.



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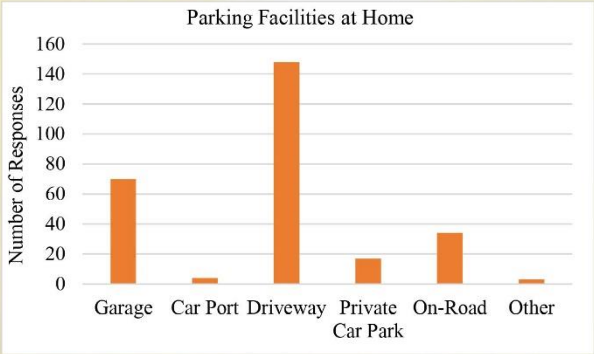
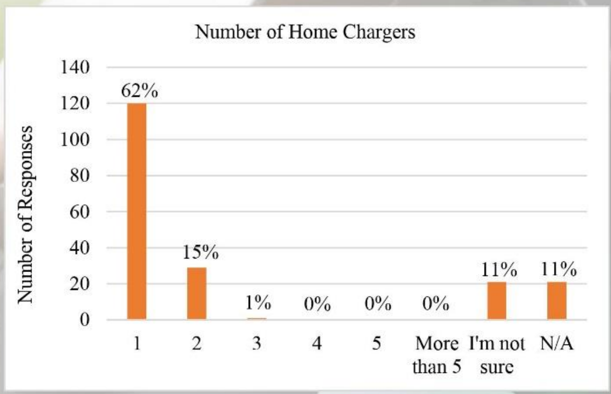


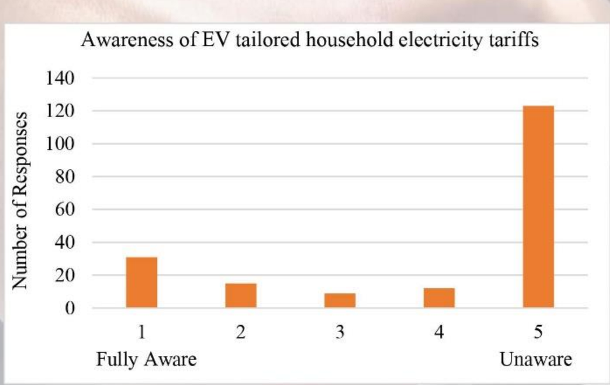
- Rural areas also solve one of the most difficult issues with EVs in cities and that is home charging. With typically more space and off-street parking options, rural households are perfect for the installation of home chargers.
- With the longer distances of trips in rural areas this means bigger savings in your transport costs over time.
- With Vehicle-to-Grid (V2G) technology around the corner, they also provide the possibility of a large battery to power your house during events such as a power cut.

When considering home charging and the number of chargers you wish to have, it is important to understand the potential limits you may encounter:

- A typical house fuse is 100A
- A typical EV Charger requires 32A

Realistically most homes will only be able to tolerate one or two chargers. However, many EV chargers these days not only have delay functions for when to start charging, but also can have two plug-ins and able to switch between the two.





EV Tariffs are similar to Economy tariffs and offer cheaper rates at night-time. The idea being to encourage you to charge your vehicle overnight when rates are cheaper. EV specific electricity tariffs can be found with Octopus, EDF, British Gas.

- British Gas' EV tariff offers electricity at just 9.4p per kWh between 12am-5am.
- For a 40kWh Nissan Leaf this would only cost £3.76 for a full charge which would get you around 168 miles.

If you are interested at all at looking into Electric Vehicles further, here are some useful links:
https://rightcharge.co.uk/
https://www.zap-map.com/
https://energysavingtrust.org.uk/advice/electric-vehicles/

Thank you again to all that took the time to respond.

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