An Integrated Approach to Planning Charging Infrastructure for Battery Electric Vehicles

This thesis is submitted for the degree of Doctor of Philosophy

School of Engineering

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March 2018

Declaration

I hereby declare that this thesis is a record of work undertaken by myself, that it has not been the subject of any previous application for a degree, and that all sources of information have been duly acknowledged.

For the avoidance of doubt, it must be noted that unless explicitly stated, all the work in this thesis is carried out by the author.

Parts of this work, have been the subject of previous publications:

Journal Papers:

Neaimeh M, Hill GA, Hübner Y, Blythe PT. "Routing systems to extend the driving range of electric vehicles." *IET Intelligent Transport Systems* 2013, 7(3), 327-336.

Neaimeh M, Wardle R, Jenkins A, Hill GA, Lyons P, Yi J, Huebner Y, Blythe PT, Taylor P. "A probabilistic approach to combining smart meter and electric vehicle charging data to investigate distribution network impacts." *Applied Energy* 2015, 157, 688-698.

Neaimeh M, Salisbury SD, Hill GA, Blythe PT, Scoffield DR, Francfort JE. "Analysing the usage and evidencing the importance of fast chargers for the adoption of battery electric vehicles." *Energy Policy* 2017**,** 108**,** 474-486.

Conference Papers:

Neaimeh M, Higgins C, Hill GA, Hübner Y, Blythe PT. "Investigating the Effects of Topology on the Driving Efficiency of Electric Vehicles to Better Inform Smart Navigation." *In: Road Traffic Information and Control (RTIC)*. 2012, London: The Institution of Engineering and Technology (IET).

Neaimeh M, Hill GA, Blythe P, Wardle R, Yi J, Taylor PC. "Integrating Smart Meter and Electric Vehicle Charging Data to Predict Distribution Network Impacts." *In: 4th European Innovative Smart Grid Technologies (ISGT) Conference*. 2013, Copenhagen, Denmark: IEEE.

Neaimeh M, Hill GA, Guo W, Wardle J, Bramich A, Blythe PT. "Understanding the role of a rapid charging infrastructure on urban and interurban mobility patterns." *In: Electric Vehicle Symposium (EVS29)*. 2016, Montréal, Québec, Canada.

Project Reports:

Neaimeh M, Blythe P, Serradilla J, Pinna C, Hill G, Guo A, "Rapid Charge Network Activity 6 Study Final Report". 2015. http://rapidchargenetwork.com/resources.php

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Acknowledgments

I would like to thank Prof. Phil Taylor for guiding me through this challenging and rewarding PhD journey. Also, thank you Phil for creating an inclusive and supportive work environment where people can thrive.

I would like to thank my colleagues and papers' co-authors who provided invaluable insight and support. Namely Graeme Hill, Neal Wade, Padraig Lyons, Jialiang Yi, Robin Wardle, Andrew Jenkins, Simon Blake, Amy Guo, Neil Thorpe, Yvonne Huebner, Stefano Utili, Laura Brown, Peter Bach Andersen, Francisco Carranza, Shawn Salisbury and Don Scofield.

I would like to thank Josey Wardle and Phil Blythe for funding my PhD through the RCN and LC Transforms projects.

I couldn't have done it without the support of my family and friends. Namely Charlotte, Sarah, Imane, Adrian, Nadine, Ben, Oliver, Kevin, Rony, Carla, Marwan, Ghassan, Samira and Michel. Antoinette, I'm where I am because of you!

I would also like to thank my examiners Prof. Ghanim Putris and Dr. Roberto Palacin for taking the time to examine my thesis and critically appraise it. Your comments made valuable points of note and the thesis has been strengthened with your suggested amendments.

Last and not least, I would like to thank the R and OpenDSS community who believe in the power of open source software.

Abstract

Battery electric vehicles (BEVs) could break our dependence on fossil fuels by facilitating the transition to low carbon and efficient transport and power systems. Yet, BEV market share is under 1% and there are several barriers to adoption including the lack of charging infrastructure.

This work revealed insights that could inform planning an appropriate charging infrastructure to support the transition towards BEVs. The insights were based on analysis of a comprehensive dataset collected from three early, real world demonstrators in the UK on BEVs and smart grids. The BEV participants had access and used home, work and public charging infrastructure including fast chargers (50 kW). Probabilistic methods were used to combine and analyse the datasets to ensure robustness of findings.

The findings confirm that it is essential to consider a new refuelling paradigm for BEV charging infrastructure and not replicate the liquid-fuel infrastructure where all demand is met at public fuelling stations in a very short period of time. BEVs could be charged where they are routinely parked for long periods of time (i.e. home, work) and meet most of the charging needs of drivers. Installing slow charging infrastructure at home and work would be less expensive and less complicated than rolling-out a ubiquitous fast charging infrastructure to meet all charging needs. In addition, ensuring that cars are connected most of the time to the electricity network allows proper management of BEV charging demand. This could support reliable and efficient operation of the power system to minimise network upgrade costs. Finally, when slow charging infrastructure is neither available nor practical to meet charging needs, fast chargers can be used to fill in this gap. Analysing data of BEV drivers with access to private charging locations, the findings show that fast chargers become more important than slow chargers for daily journeys above 240km and could help overcome perceived and actual range barriers.

An appropriate infrastructure takes an integrated approach encompassing BEV drivers' requirements and the characteristics of the distribution networks where BEV charging infrastructure is connected. A non-integrated approach to delivering a charging infrastructure could impede the transition towards BEVs. The findings of this work could support on-going policy development in the UK and are crucial to planning national charging infrastructure to support the adoption of BEVs in a cost-optimal manner.

Highlights

- Analysis of a comprehensive dataset collected from three early, real world demonstrators in the UK on BEVs and smart grids.
- Data was collected from BEVs of several users, different types of charging infrastructure, at different locations, and for an extended period of time. Data was also collected from different types of electricity distribution networks.
- Analysis of 121,000 BEV trips and associated 25,000 charging events.
- Analysis of BEV usage patterns from users residing in urban areas and rural areas.
- Charging events collected from home, workplace, and public charge infrastructure including fast chargers (50kW). This resulted in charging profiles that are spatially and temporally diverse.
- The diverse charging profiles were considered in a probabilistic study examining electricity distribution impacts of BEV adoption. This diverse demand reduces the estimated impacts on distribution networks.
- For all 3 networks studied and for all BEV penetration levels considered (up to 60% penetration), voltage magnitude did not drop below statutory limit. In contrast to voltage, transformer loading issues were detected. For the case study urban network, load data (97^{th} percentile) for 60% BEV penetration, loading limits (500 kVA) of the transformer were approached. Loading limits were exceeded at 30% BEV penetration for the urban generic network, and at 15% BEV penetration for the case study rural network.
- Weather and real driving conditions affect the BEV achievable range, which is less than the advertised range determined in laboratory conditions.
- Over 95% of daily driving is under 150 km and most of driving days can be met with an existing BEV model on one charge.
- Fast chargers start to become more important than slow chargers for journeys that are above 240km per day.
- Fast chargers enabled using BEVs on journeys above their single-charge range that would have been impractical using slow chargers.
- Fast chargers could help overcome perceived and actual range barriers, making BEVs more attractive to future users.
- Empirical evidence can be used to support on-going policy development in the UK, including the new Automated and Electric Vehicles Bill.

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Chapter 1. Introduction

1.1 Background

It is essential to decarbonise and improve the efficiency of the main sectors of the economy, namely the industry, buildings, transport and power sectors [1]. While decarbonisation is defined as displacing the use of fossil fuels by low carbon technologies, efficiency is making the most effective use of resources.

Battery electric vehicles (BEVs)[1] for road transport are a disruptive new technology with the potential to support the transition of both the transport and power sectors to low carbon and more efficient systems. Compared to a conventional liquid-fuel vehicle, a BEV uses an electric motor and electricity stored in an on-board battery, instead of an internal combustion engine (ICE) and fossil fuel to transport people and light goods around.

From the perspective of transport, BEVs recharge using electricity that has the potential to be produced from low-carbon renewable sources such as wind and solar; in contrast to conventional vehicles that use carbon intensive and non-renewable fossil fuels. In addition, an electric motor transforms electric energy into mechanical energy more efficiently than an internal combustion engine converts thermal energy into mechanical energy. The efficiency of internal combustion engines range between 15 and 30 percent while the efficiency of electric motors can range between 75 and 98 percent [2]. Consequently, driving a BEV uses energy much more efficiently than driving a conventional vehicle [3].

From the perspective of the electric power system, a large number of BEVs have the potential to become a source of flexibility that would facilitate efficient operation of a power system with a high share of low carbon generation [4]–[7]. Flexibility in power systems refers to the ability to quickly respond to changes in electricity demand and generation to maintain the balance that is necessary for reliable operation of the power system [8], [9]. Flexibility is particularly important for power systems that integrate high levels of renewable energy such as solar and wind. This is because the power output of renewable energy can be variable and uncertain, creating a fluctuating power supply. This fluctuating supply increases the complexity and the cost of operating a reliable power system [10]. The decarbonisation of

[1] In this work, the term "electric vehicles" (EVs) encompasses hybrid, plug-in hybrid, hydrogen fuel cell and battery electric vehicles (BEVs).

the UK power system is underway with high levels of renewable energy already on the system comprising 34% of the installed generating capacity in 2016 [11]. While the 2016 generation emission intensity was 286gCO2/kWh, further low-carbon generation growth is needed to meet the 100gCO2/kWh 2030 target set by the UK Committee for Climate Change [1]. Flexibility resources, such as BEVs, can support reliable and cost effective operation of the UK power system containing a high share of renewable energy [5]–[7], [12], [13].

As well as meeting transportation needs, BEVs have an untapped potential to support the operation of the electric power system. Automobiles are an asset with a low level of utilisation [14]. This applies particularly to private passenger cars, which are the focus of this thesis. A car is typically used for no more than a couple of hours in a day and parked for the majority of the time. A US study analysing one year of driving data from a sample of representative ICE passenger cars found that even during the weekday rush hour, on average, approximately 85% of the vehicles are parked [15]. Similarly, a UK study analysing the National Travel Survey (NTS) dataset, which monitors household personal travel, found that cars are stationary more than 80% of the day, and during travel peak hours (morning and afternoon commuting hours) non-stationary cars only occasionally exceed 20% [6]. Furthermore, these studies show that the majority of daily driving is under 50 miles (80 kilometres). This indicates that daily driving requirements would not exceed half of the vehicle battery capacity, which is advertised at 200 km for typical BEV models currently available on the market (circa 2017). These findings on daily distance and energy requirements have been corroborated using data collected from real world demonstrators of BEVs in the UK and the US [16], [17]. As such, the long parking time of the car, and the surplus battery capacity could allow flexibility in the time, duration and rate of charging and discharging of the car that could support the operation of the power system while still respecting the transportation needs of the drivers [18]–[23].

Customers could potentially offer their BEVs to support the power system in exchange for lower bills. For example, flexible BEV load can reduce the need to curtail available wind output by shifting demand towards periods of surplus energy [5]. The flexible BEV demand can also be shifted out of peak demand periods to avoid congestion on transmission and distribution electricity networks. Furthermore, BEVs can provide grid balancing services (e.g. frequency regulation) and reduce the need for carbon intensive conventional generators to provide these services. This results in cost savings given that balancing services using conventional generators reduce the operational efficiency of these generators due to part-loaded operation [6].

As described above, BEVs would facilitate the transition to low carbon and efficient transport and power systems. To further emphasise the importance of transport electrification, the next paragraphs describe how this transition could boost the economy, improve air quality and mitigate anthropogenic climate change.

The following examples illustrate some of the potential savings to the UK economy from moving away from fossil fuels. Fossil fuels remain the dominant source of the energy supply in the UK, accounting for 82% in 2016. 19% of this energy supply was dissipated in conversion losses in coal and gas power stations [24], [25]. A transition to renewable energy sources, facilitated by a flexible power system, could reduce the reliance on carbon intensive fossil fuels, and consequently minimise the waste of resources. Moreover, the transport sector remains the largest consumer of energy since 1988. Of the total final expenditure on energy in 2016 (£111 billion), the transport sector, which is almost entirely fuelled by petroleum products, accounted for the biggest share at 50 per cent [25]. Approximately half (48%) of the final energy consumption in the transport sector was for road passenger vehicles [26]. So, a shift towards BEVs will see demand for traditional road transport fossil fuels replaced with demand for electricity, which could be met with renewable energy sources and could decrease the energy bill of the UK [27], [28].

Poor air quality is the largest environmental risk to public health in the UK and could reduce life expectancy by increasing deaths from lung, heart and circulatory conditions [29]. The most immediate action required to improve air quality is reducing the Nitrogen Dioxide (NO_2) concentrations- the only statutory air quality limit that the UK currently fails to meet [29]. The latest (2015) DEFRA national statistics of air pollutants' emissions by source in the UK show that road transport and the energy industries (combustion in power plants and energy production) are responsible for the majority of national nitrogen oxides (NOx) emissions, with road transport accounting for 34% and the energy industries 29% of NOx emissions [30]. BEVs could improve air quality by minimising the use of fossil fuels in the transport sector by displacing it with electricity; and in the power sector by supporting the integration of renewable energy sources.

As with air pollution, BEVs could help reduce Greenhouse Gas (GHG) emissions from the combustion of fossil fuels in both transport and power sectors and help meet the UK's emission reduction targets. The latest figures for the UK show that the transport sector is the largest GHG emitter with 27% of total UK GHG emissions (in $MtCO_2e$), with passenger cars and light vans accounting for the largest share of these emissions (Figure 1) [31]. Following the transport sector, the power sector accounted for 26% of total UK GHG emissions (Figure 1) [31].

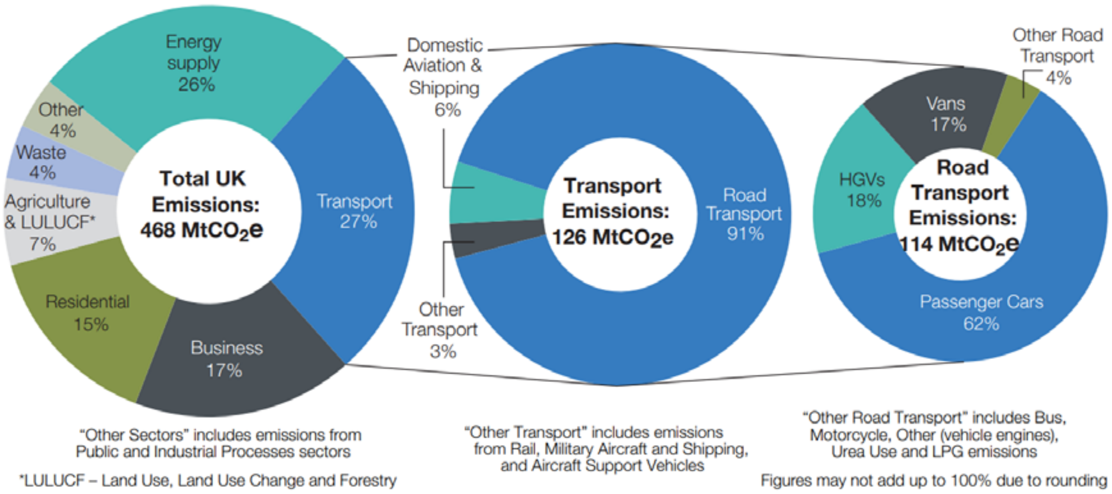

Figure 1: Breakdown of UK's Green House Gas Emissions in 2016 [31].

The UK government recognises the significant benefits of a transition to low carbon and efficient power and transport sectors to the environment and the economy. The UK is developing its modern industrial strategy to improve the country's living standards and economic growth. At the core of the strategy is upgrading the UK's infrastructure such as the electric power system, and supporting businesses such as the automotive industry to position the UK as a global leader in the transition to cleaner and more efficient technologies [32]. An important part of the industrial strategy is the plan to upgrade the electric power system by increasing its flexibility to integrate a high share of low carbon generation. The plan highlights the role of energy storage, such as from BEVs, to achieve this aim [33]. To help realise the strategy and its plans, the government announced the Industrial Strategy Challenge Fund investments- for example the £246m Faraday Challenge fund is focusing on the design and manufacture of improved (i.e. cost effective, high performing and recyclable) batteries for electric vehicles [34], [35].

In parallel, the government made available £600m between 2015 and 2020 supplemented by a further £270m announced at the 2016 Autumn Statement to support electric vehicles. These funds helped launch the national Go Ultra Low (GUL) campaign to raise awareness on EVs, provided funding for research and development projects, grants for car subsidies and support for the infrastructure needed for EVs [28], [36], [37]. The 2017 Autumn Statement included the announcement of a new £400m EV Charging Infrastructure Investment Fund (CIIF), with £200m investment from the government to be matched by private investors. In 2018, the government published "The Road to Zero" strategy laying out government support and actions required (including from industry) to deliver zero emission road transport [31].

These efforts could help overcome the barriers to adoption of electric vehicles and achieve the government target of having all new cars zero emission by 2040 with BEVs playing an important role in meeting this target. This is an ambitious increase from a total of 90,000 EVs and a market share of 1.4% in 2016 (Figure 2) [28], [38], [39].

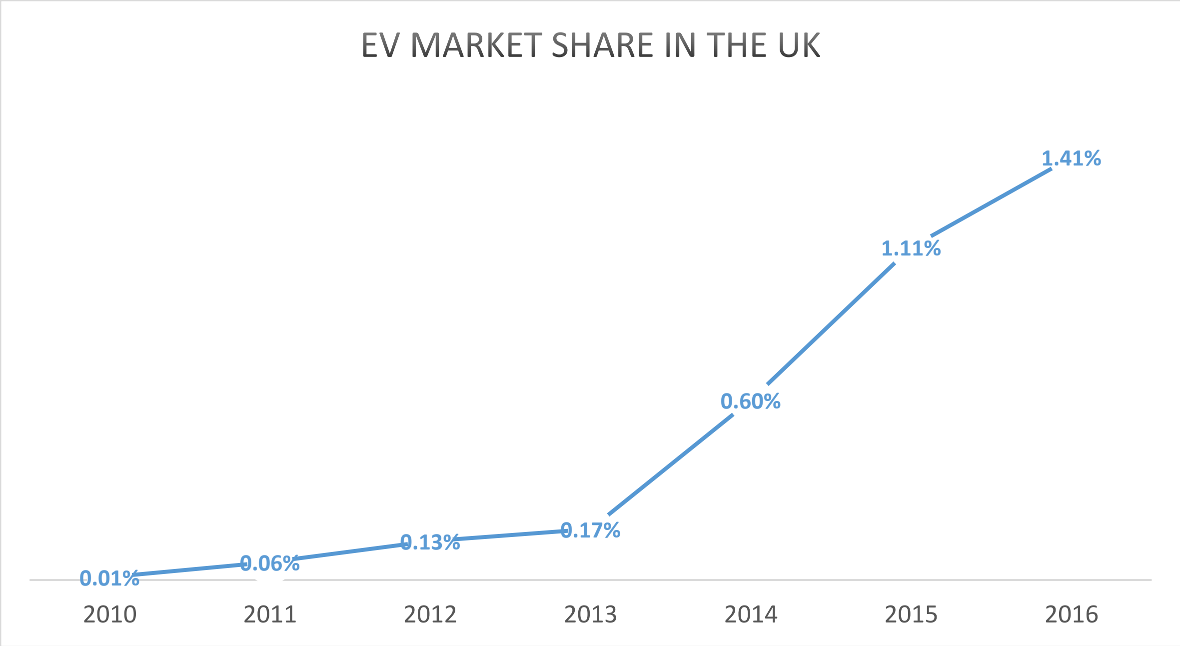

Figure 2: Electric vehicles' market share in the UK between 2010 and 2016 [39].

This low market share could be explained by several barriers to adoption such as high purchasing cost compared to an equivalent liquid-fuel vehicle, limited driving range and the lack of an appropriate charging infrastructure to support the adoption of BEVs [40]–[43]. For example, the results on public attitudes to electric vehicles from the Office for National Statistics Opinions and Lifestyle survey in 2016 showed that the most important factor deterring people from buying an electric vehicle was the lack of a charging infrastructure [40].

If the number of BEVs increase to millions to meet the government's target, the charging demand of these vehicles could create detrimental effects on the power system. The charging infrastructure of BEVs will be mainly connected to low voltage (LV) electricity distribution networks, therefore, it is likely that this part of the power system would face the first impacts of a large scale introduction of electric vehicles, namely voltage and thermal constraints [44], [45].

The average daily electricity use of a BEV is around 8kWh [17], [46], [47], which could almost double the average daily electricity consumption of a household-currently at around 10.8kWh [48]. Problems are more likely to arise if charging of cars coincide with each other or coincide with the existing peak electricity demand, which is at late afternoon until early evening in the UK [44], [49], [50]. The constraints from charging a large number of BEVs at the same time can create the need for costly grid reinforcement to allow the electricity network to host a large number of BEVs and their charging infrastructure.

1.2 Justification Of This Work

While the market share of BEVs is low and before electric cars enter the mass market, there is a window of opportunity to shape the charging infrastructure, norms and regulations so that BEVs can meet the needs of both the consumer and the power system. An integrated approach to shaping the BEV charging infrastructure that takes into account both the transport requirements and the power system characteristics is essential. A non-integrated approach to delivering a charging infrastructure could impede the transition towards electric cars.

An appropriate charging infrastructure would meet the charging demand of BEV users so that they can use the electric car for all their journeys. To design an appropriate charging infrastructure for BEVs, it is necessary to take into account the BEV characteristics that are different to conventional liquid-fuel cars. Unlike conventional cars, BEVs can be charged at locations where cars are naturally parked for long periods of time (e.g. home, work) and most of the charging demand could be met at these locations [15], [51]. Consequently, rolling-out a BEV infrastructure should not mimic the existing refuelling infrastructure of conventional cars where all the refuelling demand of a car is met quickly at public fuelling stations. The benefits of considering a new refuelling paradigm for BEVs charging infrastructure are two-fold. First, installing low power-rate (slow) charging infrastructure at locations where cars are parked for long periods of time is less expensive and less complicated than developing a ubiquitous public high-power rate (fast) charging infrastructure to meet all charging needs [52]. Second, relying solely on public fast charging infrastructure to meet all charging demand would lock away the charging flexibility potential of BEVs, which can support the power system [4], [19].

Furthermore, an appropriate BEV charging infrastructure would minimise its impact on the electricity network and the subsequent costly reinforcement that could slow down the transition to mass BEV adoption. It is essential to take into account actual BEV driving and charging requirements to robustly investigate their impact on the electricity networks. Previous studies using simulated data and assumptions of charging behaviour overestimated the impacts on distribution networks and the requirements for grid reinforcement [45], [53]–[60]. One of the studies that focused on British distribution networks found that a 12.5% uptake would cause severe impacts on the transformer and the LV underground cable supplying the households [44]. While that previous study used a probabilistic approach to address uncertainties associated with residential loads and BEV user behaviour, it noted that real-world data of BEV usage could improve the probabilistic methods used [44]. When actual BEV usage patterns were used, the impact studies revealed that networks have a greater capability than previously suggested to accommodate a larger number of BEVs [16], [61].

Therefore, it is clear that we must take an integrated approach to planning an appropriate charging infrastructure to support BEV adoption and minimise the impact on electricity networks. This work is focusing on private passenger cars. The analysis and recommendations apply to charging infrastructure installed at locations where cars are parked for long periods of time (i.e. slow chargers at home and work), complemented by a network of public fast chargers (referred as rapid chargers in the UK).

1.3 Thesis' Aim and Objectives

The aim of this thesis is to propose charging infrastructure, integrating both transport requirements and power system characteristics, to ensure successful and cost effective BEV transition. At the heart of the integrated approach is the need to understand the characteristics and actual usage patterns of BEVs, and similarly grid characteristics and existing electricity usage patterns.

To meet the aim of the thesis, the following research questions and objectives are investigated:

Research Question 1 (RQ1): What are the learnings from existing projects and initiatives that could support future charging infrastructure roll-out and what are the gaps in current knowledge?

- **Objective 1:** Establish current state of the art on the provision of BEV charging infrastructure.

RQ2: How do people use battery electric vehicles? i.e. driving behaviour and charging behaviour such as energy transferred at charging events at different times and locations.

- **Objective 2**: Design a real-world BEV demonstrator and collect BEV usage data from the demonstrator
- **Objective 3:** Analyse charging and driving patterns of BEVs using data from two real world BEV demonstrators.

RQ3: What is the impact of BEV charging, using low power-rate chargers (i.e. 3.8 kW), on LV electricity distribution networks? And do realistic charging and driving patterns change the expected impact on these networks?

- **Objective 4:** Investigate the impact of residential BEV charging using low-rate power chargers (i.e. 3.8 kW) and actual charging data on LV electricity distribution networks.

RQ4: How does BEV usage impact the requirement for charging infrastructure (i.e. low power-rate (slow) and high power-rate (fast) charge infrastructure)?

- **Objective 5:** Investigate the role and importance of fast chargers (i.e. 50 kW) for the adoption of BEVs.

1.4 Overall Methodology

The overall method to meet the objectives of this work involves the following steps:

- Review UK Government policy to support the roll-out of charging infrastructure; and international and national projects and initiatives on BEV charging infrastructure.
- Collect data from existing and new BEV demonstrators, national travel survey data and existing smart grid project.
- Conduct graphical exploration and descriptive statistics analysis of driving and charging usage data.
- Produce insights on actual BEV usage behaviour.
- Couple BEV data with smart meter data using Monte Carlo Simulation, then undertake power flow analysis to assess the impact of slow charge (3.8kW) on LV residential electricity distribution networks.
- Couple driving and charging data using multiple linear regression to assess the importance of fast chargers (50 kW) for the adoption of BEVs.

1.5 Overview of Datasets Used in This Work

To gather evidence that can help shape the roll-out of the required BEV charging infrastructure, the government and the private sector funded several real world demonstrators measuring actual usage of BEVs, charging infrastructure and their impact on the electricity networks [62]–[68].

The work in this thesis is based on data collected from three early, real world demonstrators in the UK on electric vehicles and smart grids, namely SwitchEV, RCN and CLNR projects [47], [63], [69]. More detail on the SwitchEV and RCN projects can be found in chapter 3, while detail on the CLNR project can be found in chapter 5.

The BEV charging data on these trials was collected from 3.8 kW and 50 kW unidirectional chargers. These are typical and commonly used charging posts (circa 2018) and consequently the focus of this work. Low power-rate (slow) charging stations (e.g. 3.8 kW charging station) could take hours to recharge a vehicle and high-power rate (fast) chargers (e.g. 50kW charging station) can recharge a BEV from an empty battery to about 80% of full state of charge (SoC) in approximately 30 minutes [70].

Figure 3 shows an overview of the data collection and analysis on the aforementioned 3 projects. The design of the BEV trial on the RCN project was carried out by the author.

For SwitchEV and RCN BEV trials, data loggers allowing detailed monitoring of vehicles' usage were installed in the participating BEVs. Data loggers collected up to minute-by-minute data during charging events and second-by-second data during driving events. This high resolution dataset required cleaning and subsequently pre-processing into event-based logs. Unlike raw data (e.g. minute-by-minute charging information), the event-based logs contained summary measures of an event (for example, total energy used during a charge event or total energy used during a driving event).

Some of the cleaning and pre-processing steps included ensuring that the data was chronological; separating mixed driving data and charging data into two separate datasets; ensuring that the loggers are continuously collecting data; creating an automated notification when a logger had not sent data in 48 hours; liaising with participant to troubleshoot the logger, etc. For the SwitchEV project, as indicated in Figure 3, a colleague carried out the data cleaning and pre-processing steps described above. For the RCN project, the company providing the data logging solution carried out the data cleaning and pre-processing activities. As part of the RCN BEV demonstrator design, the author assessed several data loggers' manufacturers and prepared technical specifications to tender for loggers. This exercise was carried out to identify companies who developed data logging solutions that minimised data loss, data errors and provided data cleaning and pre-processing as part of their product. The event-based logs (i.e. event-based summaries) for both the SwitchEV and RCN projects were used for this work. Additional detail on data loggers and data management are presented in chapter 3.

For Customer Led Network Revolution, network monitoring equipment was installed in selected case-studies networks to collect network data (e.g. voltage). In addition, network characteristics' information (e.g. number of customer per LV feeder on the case-study networks) required for network modelling were obtained directly from Northern Powergrid (electricity distribution network operator involved in the smart grid project). In addition to the CLNR urban and rural network models, the characteristics of a commonly used UK generic urban network are publicly available and were used to model a generic network. Smart meters were installed in thousands of selected households as part of CLNR. The data collection and processing of the smart meter dataset was carried out by a colleague (Figure 3). The processing of the smart meter data included separating it into datasets following socio-economic characteristics (e.g. annual income). More detail on the smart meter data can be found in chapter 5. For this work, the processed smart meter datasets were used by the author for further analysis as detailed in chapter 5.

To summarise, the datasets used for this work are event-based charging and driving data collected from the SwitchEV and RCN BEV trials. To compare daily driving distance of BEVs and ICE vehicles, publicly available UK National Travel Survey data was used. CLNR smart meter datasets, network data and case-study urban and rural network models were used. Finally, publicly available generic network characteristics were used to model the network and compare it to the CLNR urban and rural case study networks.

Figure 3: Projects and datasets used in this work.

1.6 Thesis Structure

The background to the research (section 1.1), justification of this work (section 1.2), aim and objectives (section 1.3), overall method (section 1.4), datasets used (section 1.5), thesis' structure (section 1.6, Figure 4), and original contribution to knowledge (section 1.7) are presented in chapter 1.

A literature review on national and international charging infrastructure projects and initiatives, and a review of UK government policy is presented in chapter 2. Further, specific literature reviews on BEV network impact studies and fast charging research are conducted at the beginning of chapters 5 and 6 respectively.

The description of the BEV demonstrators with a focus on the RCN BEV trial design that was carried out by the author, as well as data collection and management is presented in chapter 3.

The analysis of SwitchEV and RCN datasets on BEV driving and charging usage is presented in chapter 4. The analysis revealed usage patterns' insights that informed the input into studies in the following chapters. Some of the findings are also published in [1]–[3] and [7]. Data from the UK National Travel Survey was analysed to compare daily driving distances between BEVs and ICE vehicles (chapter 4).

In chapter 5, the SwitchEV BEV dataset, CLNR smart meter data, CLNR network models and a UK generic network model were used to investigate the impact of BEVs on residential LV electricity distribution networks. A probabilistic method based on a Monte Carlo Simulation (carried out in the R programming language) was used to combine BEV charging patterns and smart meter data to provide load input to generic, urban and rural power (load) flow studies. The generic network modelling and power flow analysis were carried out in OpenDSS, an open source electric power distribution system simulation (DSS). The urban and rural case-study networks were previously modelled as part of the CLNR project and the power flow studies were carried out in IPSA2 by a colleague using the input load data obtained by the probabilistic method developed by the author. The probabilistic method, results, discussion and conclusions of chapter 5 are published in [2] and [5].

The comprehensive RCN dataset of BEVs and fast chargers usage is used in chapter 6 to investigate the role and importance of fast chargers for the adoption of BEVs. This investigation was undertaken by developing a statistical model using multiple regression analysis and determining relative importance of predictors. The modelling was carried out in R and the work is published in [17] and [72].

The overall discussion of the findings and the conclusion are presented in chapter 7 and 8 respectively. The Monte Carlo Simulation model is presented in Appendix A. Descriptions of power flow analysis, distribution network modelling and power flow simulation in OpenDSS are presented in Appendices B and C. The list of awards obtained for presenting parts of this work is shown in Appendix D. Parts of this work have been published in peer-reviewed journal papers, which are included in Appendix E.

This work is based on UK projects and used private passenger vehicles data; however, the methods developed can be applied to other geographical locations and to the analysis of commercial vehicles (e.g. fleet and company cars).

1.7 Original Contribution to Knowledge

- Reveal insights on BEV usage patterns by analysing data collected from real world trials.
- Develop a probabilistic method combining real BEV, smart meter and network data, to investigate LV distribution network impacts of BEV uptake.
- Provide recommendations to Distribution Network Operators (DNOs) for preliminary demand management strategy of BEV demand.
- Develop a statistical method combining real driving and charging data including fast charge events to examine the impact of fast chargers on driving patterns and investigate their role for the adoption of BEVs.
- Provide recommendations to private and public stakeholders planning the roll-out of BEV charging infrastructure.

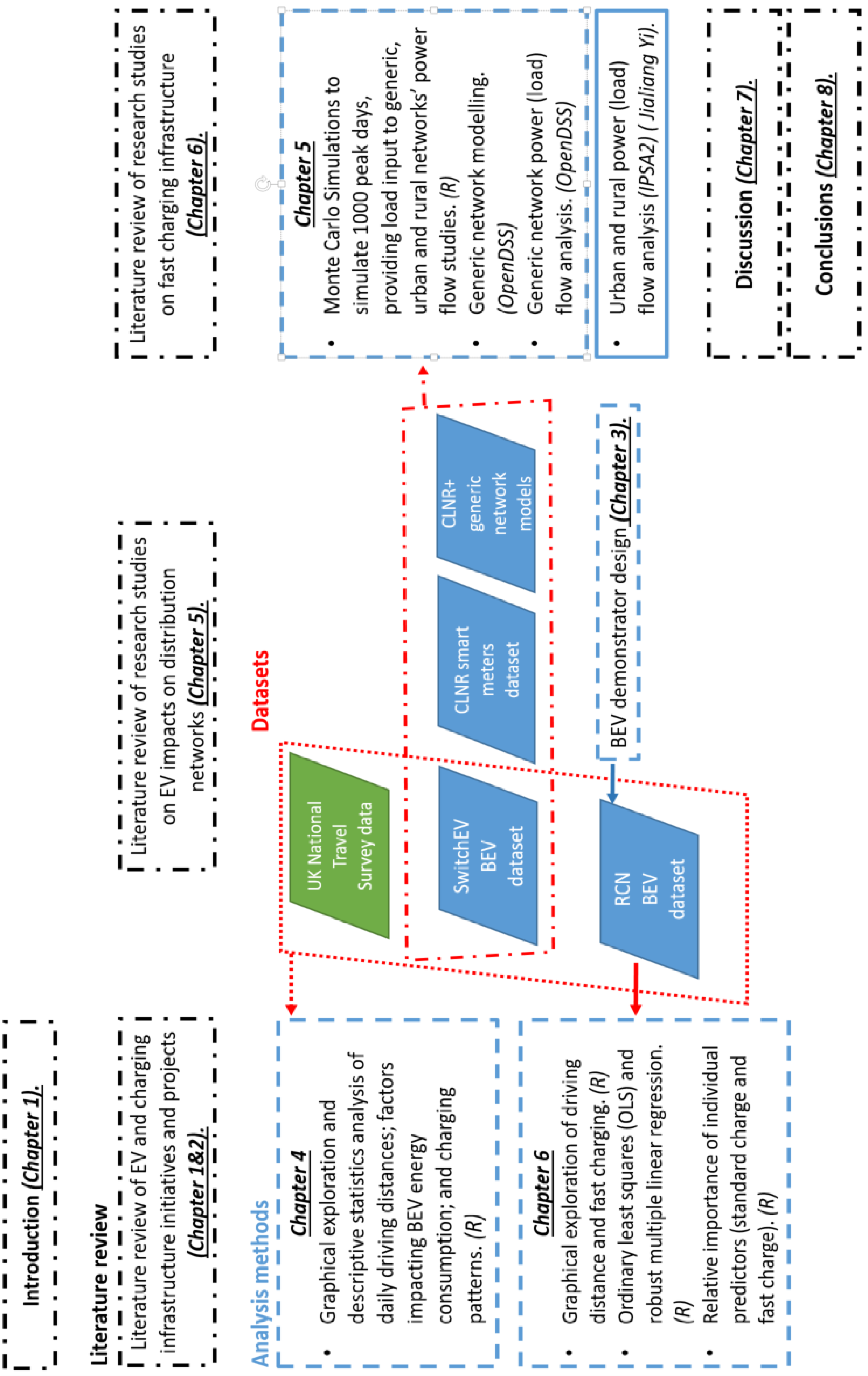

Figure 4: Thesis Overview.

Chapter 2. Review of Electric Vehicle and Charging Infrastructure Initiatives

A brief overview of BEV and charging infrastructure technology is presented in section 2.1. This is followed by a description of the latest UK policy and initiatives to support EV uptake, including support for charging infrastructure in section 2.2. A review of international and national projects and studies are described in section 2.3. Section 2.4 identifies a research gap and the contribution of this work to support the development of EV policy and charging infrastructure roll-out in the UK.

2.1 BEV and Charging Infrastructure Technology Overview

Battery electric vehicles (BEVs) were introduced to the mass market in 2010 [42]. A BEV does not have an internal combustion engine and it is propelled using an electric motor and electricity stored in an on-board battery. A common BEV model in the UK (circa 2010- 2016) has a 24 kilowatt-hour (kWh) Lithium-ion battery[2] capacity and an advertised driving range of 200 km. A selected number of BEV models available in the UK are shown in Table 1. The typical cost of a BEV is at least £20,000 after government purchase subsidy. BEV high purchasing cost, mainly due to the expensive battery pack, is one of the main barriers to adoption [40], [41]. However, battery cost is falling [74]. While the purchasing cost of BEVs has remained steady for the past 6 years since their introduction, it can be noticed from Table 1 that battery capacity is increasing. For example, the Nissan LEAF was first introduced with a 24 kWh battery in 2010 and the new 2018 model has a 40 kWh battery for a similar price range. Car manufacturers are introducing bigger battery capacities to make BEVs more attractive by increasing their limited driving range compared to liquid-fuel vehicles.

[2] A lithium-ion battery is a family of rechargeable battery types in which lithium ions move from the negative electrode to the positive electrode during discharge and back when charging. Lithium-ion battery technology have high energy and power densities making it suitable for automotive applications. Current BEV models almost exclusively use lithium-ion traction batteries [73].

Make	Model	Country of Origin	Year Introduced	Battery Capacity	Advertised Range
BMW	i3	Germany	2014	22 kWh	190 km
Mitsubishi	iMiev[3]	Japan	2010	16 kWh	160 km
Nissan	LEAF	Japan	2010	24 kWh	200 km
Nissan	LEAF	Japan	2016	30 kWh	250 km
Nissan	(new) LEAF	Japan	2018	40 kWh	375 km
Nissan	e-NV200	Japan	2012	24 kWh	170 km
Renault	ZOE	France	2013	22 kWh	240 km
Renault	ZOE	France	2016	41 kWh	400 km
Tesla	Model 3	US	2019	50-75 kWh	350-500 km

Table 1: Information on selected BEV models available in the UK [75]–[78].

There are 3 options for charging a BEV: conductive, inductive (also called wireless) and battery swapping methods.

Battery swapping could take few minutes which is comparable to refuelling a conventional ICE vehicle; however, the early initiatives for battery-swapping have failed. Better Place was the main commercial company providing battery swapping. With approximately $1 billion in funding and partnerships with major BEV manufacturers, Better Place constructed battery-swapping stations and partnered with a major BEV manufacturer to develop battery swap-capable cars. The company launched in 2007 and declared bankruptcy in 2013. The capital cost for BEVs was still high and consequently the demand was low, which is one of the main reasons for the failure of the company [79].

With inductive charging, no wires are used and energy is transferred to the vehicle using an electromagnetic field. Prototype inductive charging pads have been showcased by Qualcomm Technologies [80]; however, BEV capable of inductive charging and inductive chargers are not yet commercially available. While there are still barriers to commercialisation, inductive charging could increase the availability of BEVs to support the power system by overcoming the requirement to make sure the cars are always plugged when parked. To support the development of inductive charging, the UK government announced in 2018 a multi-million R&D programme to develop and trial low cost wireless charging [31].Conductive charging (i.e. wired) is currently the de facto charging method and conducive charging equipment is commercially available.

[3] The Mitsubishi iMiev was also introduced as Peugeot iOn and Citroen C-zero.

Alternating current (AC) and direct current (DC) are used for wired charging. AC charging is typically used with low-rate power chargers (e.g. 3.8 kW, 7.7 kW) and these chargers are typically installed at home, work and in public parking places. Charging a BEV battery from empty to full state of charge using these low-rate power chargers would take several hours. BEV batteries require DC power to be charged and the electricity network delivers AC power. Consequently, an AC/DC converter is installed on-board of the vehicle to allow battery charging. While 23kW AC chargers exist, the on-board charger of most current EV models don't accept this charging rate. For example, the Nissan LEAF is fitted with a 3.3 kW on-board charger and it could be fitted with an optional 6.6 kW. This means that a LEAF plugged to a 22kW AC charger would be charging at a maximum rate of 6.6 kW. The BMW i3 is fitted with a 11kW on-board charger, Tesla model S is fitted with a 23kW on-board charger and the Renault ZOE is fitted with a 43kW on-board charger [81].

Charging at higher rates (e.g. 50kW, 120 kW) is typically carried out using publicly available DC charging stations. With these higher power levels, the converter is bigger and more expensive and consequently it is installed in the charging station instead of the car [75], [82], [83]. Charging a 24kWh/30kWh BEV battery from empty to 80% of full state of charge using 50kW chargers would take approximately 30 minutes.

Different charging standards and connectors for conductive charging have emerged since the introduction of BEVs to mass market. The different standards could be contributed to industrial competition and diverging interests. For AC, the most common plug is the type 2 connector [83]–[85]. The 2014/94/EU Directive stated that charge points should adopt at least the Type 2 "Mennekes" connector (EN 62196-2) [86]. The UK adopted this requirement as stated in the Alternative Fuels Infrastructure Regulations 2017 [87]. For DC, there are 3 main charging standards and associated connectors. The Combined Charging System (CCS) standard is supported mainly by European and US automakers. The CCS connector on DC charge points is required by the EU Directive EN 62196-3 and UK regulation [86], [87]. The CHAdeMO standard is supported by the Japanese automakers, and TESLA developed its own proprietary DC Supercharger network (120 kW) [75]. In the UK, multi-standard DC fast chargers with both CHAdeMO and CCS plugs are common [64].

Typical charging points power rating (circa 2010- 2018) and locations are summarised in Table 2.

Typical charging power rating (kW)	Typical location	AC/DC
Up to 3.8 kW	Home, work, public	AC
>3.8kW to <= 22kW	Work, public	AC
50 kW, 120kW (for TESLAs)	Public (e.g. at motorway service stations)	DC

Table 2: Information on typical charging points used by light duty BEVs (circa 2018).

Several companies developed low power charge points that can be readily installed at home and work locations. The starting cost of a home charge point is approximately £300 after government subsidy (circa 2018) [88]. There were approximately over 14,000 public charging points in the UK at the beginning of 2018, funded by the government and the private sector (e.g. car companies, charge network operators) [89], [90]. These charging points form a fragmented public charge network, which is run by over 20 charging network operators. Some operators provide national coverage (e.g. Charge Your Car, Ecotricity) while others provide regional coverage (e.g. Plugged-In Midlands, Greater Manchester EV). Some charge points can be accessed with a Radio-frequency identification (RFID) card; phone application or simply using a contactless bank card. RFID and a phone application are still specific to individual network operators meaning that several identification and access cards might be required to access more than one charge network. Moreover, some charge points are free to use while other points are accessible with fees such as price per time, price per energy used or a combination. There are several websites that provide information on charge points such as location, power rating, and access and payment methods [90], [91].

2.1.1 Emerging EV Charging Technology (ultra-fast chargers and bidirectional chargers)

With the continuous growth of the EV market new charging technology is being developed, namely ultra-fast chargers and bidirectional chargers.

The associated charging time using a common 50kW fast charger is approximately 30 minutes. In contrast, higher power-rate charging (150-350 kW) called extreme-fast chargers in the US and ultra-fast chargers in Europe are being developed to reduce EV charging time significantly, making it comparable to refuelling a conventional vehicle. This could become particularly relevant with the increase in vehicles' battery size. Currently (circa 2018), no BEV on the market can charge using a 350 kW charger [92], [93].

There are many technological and economic barriers facing the deployment of ultra-fast chargers. The US DOE assigned a team of researchers from Idaho National Lab, Argonne National Laboratory and the National Renewable Energy Laboratory to assess the feasibility of high rate charging up to 350 kW. The study, published in a series of papers, identified barriers preventing the implementation of extreme-fast charging with regards to battery technology; battery cell and pack design and thermal considerations; vehicle design considerations including progress in power electronics design; infrastructure and economic feasibility. For example, the EV battery pack must be able to accommodate the electrochemical and thermal demands of extreme-fast charging and the on-board electronics must be capable of handling high charging power. Power electronics would need to handle up to 1200V, up from 600V or less in most of current vehicle models, and this would add cost and complexity to vehicles' development. The study also identified potential research, development and deployment activities to address the gaps [94], [95]. Some examples of early deployment of ultra-fast chargers are mentioned in section 2.3.1.

Bidirectional chargers allow vehicles to be charged and discharged in response to a control signal. The control of charging rate and the reverse power flow aim to optimise the operation of the power system [7], [96], [97]. In the case of discharging (i.e. reverse power flow), the car is considered as a generator and the charger or the car (depending on where the export inverter is installed) would need to comply with relevant distribution grid codes to ensure the bidirectional system meets safety and power quality standards. Bidirectional chargers are an emerging new technology with very few models currently available for purchase (circa 2018). In addition, only few EV models allow bidirectional charging (i.e. Nissan LEAF, Nissan eNV200 and the Mitsubishi Outlander PHEV). Many technical, economic and regulatory barriers still face mass deployment of bidirectional chargers. The UK government has recently invested £30M in 21 projects including large scale real world demonstrators to support the development of bidirectional chargers, also referred as vehicle-to-grid (V2G) chargers. Most of the announced projects are developing bidirectional DC chargers with power ratings ranging between 6 and 15 kW. For these DC chargers, the export inverter (i.e. DC to AC inverter) would be installed inside the charger. In contrast, for an AC charger the export inverter would be installed in the vehicle.

2.2 UK Government Support for Electric Vehicles

The UK government's ambition is that by 2050 almost every car and van will be zero-emission, with BEVs playing a key role in achieving this target. Replacing liquid-fuel vehicles by EVs could improve air quality, reduce GHG emissions and deliver economic benefits to the UK. For example, one in five BEVs sold in Europe in 2016 was made in the UK [98].

Recognising the benefits of electric transport, the government is investing over £1 billion between 2015 and 2021 to boost the number of EVs on UK roads. The funding is used to launch awareness campaigns, support vehicle demonstrator trials, provide car-subsidies grants, invest in R&D projects such as the latest Faraday Challenge Fund to improve the design and manufacture of batteries for the automotive sector, and deploy charging infrastructure [35], [37], [99]–[104].

2.2.1 UK Government charging infrastructure strategy

The UK government acknowledges that having adequate charging infrastructure is fundamental to adoption of EVs. In 2011, the government's Office for Low Emission Vehicles (OLEV) published its initial vision for the development of charging infrastructure to support EV adoption in the UK. The Strategy included the steps needed to be undertaken by the government and industry to ensure a successful provision of national charging infrastructure. The Strategy identified home charging as the primary charging location, followed by workplace for whom charging at home is not practical or sufficient. In addition, the charging infrastructure would be complemented with a targeted amount of public infrastructure, including on-street chargers and fast chargers [105].

To this end, grant schemes were put in place to support the installation of charge points at private and public locations.

OLEV implemented the Plugged-in Places (PiP) scheme between 2010 and 2013 that accelerated the roll-out of charging infrastructure in the UK. The scheme made available up to £30 million to eight regions to install charging infrastructure. OLEV offered match-funding to businesses and public sector organisations and over 5,500 charging points were installed by June 2013 [106]. Additionally, OLEV offered funding to install charge points at public sector estate (e.g. city councils). It also made available funding to train operating companies to cover up to 75% of the capital costs of procuring and installing charging infrastructure at train station parking spaces between 2013 and 2015 [107].

OLEV's EV HomeCharge and Worplace Charging schemes currently provide support towards the up-front costs of the purchase and installation of charging points. Up to £500 including VAT is granted towards the total capital costs of a domestic charge point. For the workplace, the contribution is limited to £300 for each socket up to a maximum of 20 across all sites for each application. In addition, OLEV currently provides grants to local authorities to install on-street residential charge points. The funding covers 75% of the capital costs of procuring and installation charge points and associated dedicated parking bay (where applicable) [100].

The ‘Go Ultra Low (GUL) cities’ is a joint partnership between the government and several car manufacturers. Four cities were granted £35 million in 2016 to raise awareness on EVs and the funding included grants to install charging infrastructure. For example, car-charging street lighting would be installed in Hackney-London; Bristol would install up to 80 charge points across the city including fast chargers (50+kW); 230 charge points would be installed in Nottinghamshire and Derby. An additional £5 million of development funding was awarded at the same time for specific initiatives in Dundee, Oxford, York and the north east regions. For example, Newcastle is installing a fast charger filling station in the middle of the city including up to 8 chargers [37].

Highways England (known as Highways Agency before April 2015) is a government owned company which manages the Strategic Road Network (SRN) in the UK (motorway and major A roads). Highways England presented to Parliament its road investment strategy for the 2015-2020 period. The company stated that it is committed to installing charging points every 20 miles on the SRN; and that wherever it is possible, these charge points would be typically fast chargers that would allow the car to be charged in less than 30 minutes [108]. The Clean Growth Strategy published by the Department for Business, Energy and Industrial Strategy in 2017 mentioned that the Highways England allocated £15 million for the roll-out of fast charge points [109].

The 2017 Autumn Budget- an economic statement made by the government every year identifying spending- announced further measures to support EVs including investing £200 million, to be matched by private investment into a new £400 million Charging Investment Infrastructure Fund to further develop and expand the UK’s EV charging infrastructure [110].

2.2.2 Automated and Electric Vehicles Bill

A key enabler in delivering the charging infrastructure to support the anticipated uptake of EVs is the government’s new “Automated and Electric Vehicles Bill”[98].

At the time of writing of this thesis, the government is currently legislating the "Automated and Electric Vehicles Bill". This Bill proposes a regulatory framework to prepare for the expected increase in the presence of automated and electric vehicles in the UK. The Bill would empower the government to set standards and to regulate some aspects of the EV industry if necessary in future years. This Bill supplements existing legislation on electric charging points in the UK (i.e. EU Directive 2014/94/EU, known as the 'Alternative Fuels Infrastructure Directive') [98].

A consultation process was put in place to seek views on what measures should be included in the Bill to support the uptake of EVs. The consultation ran for one month in 2016 and collected input from car manufacturers, charging infrastructure manufacturers and operators, associations, public bodies, electricity network operators, etc. Answers and summaries are published online [28].

Based on the answers receiving from the consultation process, the government made a decision on what to include in the Bill, which is proposing regulatory change to expand and improve the network of charge points in the UK. This include improving consumer experience when locating, accessing and paying for the usage of public charging. The Bill also includes powers to mandate the provision of sufficient infrastructure at strategic sites to cater for longer journeys, including motorway service areas. In addition, the Bill provides powers to require future charge points to be responsive and enable demand management to support the electricity network [98].

There are several stages that a proposed bill needs to pass before it becomes law. A proposed bill needs to complete all the parliamentary stages in both the House of Commons and the House of Lords. The parliamentary stages include several readings of the proposed bill and the invitation of experts and stakeholders to share their insights to explore how the bill could be improved to make a greater impact. Once these stages are completed in both Houses, the bill is ready to receive royal asset, which is when the Queen formally agrees to make the bill into an Act of Parliament (law). The practical implementation of an Act is the responsibility of the appropriate government department, not Parliament [111].

The Bill was introduced to the House of Commons in October 2017 and has already received cross-party support during its passage. At the end of January 2018, the Bill was introduced to the House of Lords [112]. Several clauses in the Bill are not final and are still debated. For example, there were some criticism from the Chairman of the Petrol Retailers Association against mandating the addition of chargers on large fuel retailers [98].

The provisions in the EV Bill will give broad powers but would require secondary legislation to introduce any requirements for new mandatory provision. The current proposed measures will place no requirements on any parties. Government will monitor market developments and will assess the requirements of secondary legislation or direct government support in the case of market failure to provide appropriate charging infrastructure. For example, as per current progress on the EV Bill, there will be no requirements for charge point or car manufacturers to include smart charging capabilities in their products. If there are proposals to bring some measures into effect through secondary legislation, then these measures would be subject to a further consultation process and would require a detailed impact assessment [28].

Findings from this work and previous studies and real world demonstrators on BEVs can be used to provide empirical evidence to support additional EV legislation.

2.2.3 Government support for efficient integration of EVs into the power system

The Office of Gas and Electricity Markets (Ofgem), the energy regulator in the UK, and the government published a joint 'Plan for a Smart, flexible energy system' mentioning that the government is seeking powers in the upcoming EV Bill to set standards for charge points. These standards would ensure that the flexibility potential of EVs can be used to support an efficient operation of the power system to lower overall power system costs. Ofgem mentions that they will work with different stakeholders to develop an integrated approach to accommodating EVs into the energy system, reflecting the costs and benefits to customers and the energy system. In addition, Ofgem "will assess any regulatory, network and tariff implications that EVs represent so that risks can be mitigated and the benefits of EVs to the energy system can be optimised" [33].

A working paper from Ofgem, "Reform of electricity network access and forward-looking charges", sets out options for how to accommodate increased demands on the networks most efficiently from new technologies such as EVs. The paper mentions that if a household has specific access requirements such as rapidly charging an EV at peak times, then a suggested approach could be "to offer the users options to pay for this additional access, with choices over whether that is peak or off-peak, or interruptible or not". The paper mentions that "access which would trigger less incremental cost on the networks would be cheaper, with the aim of allowing users to meet their needs while providing them with an incentive to adjust their behaviour to reduce network costs, so that costs to consumers as a whole are no more than necessary [113]."

2.2.4 National Infrastructure Commission

The government has set up a new National Infrastructure Commission (NIC) in 2016 to identify the UK's future infrastructure requirement across transport, energy, water and sewage, flood risk, digital communications and waste and the potential interactions and interdependencies between these sectors. The Commission will establish the infrastructure development priorities and needs for the UK for the coming decades. The Commission states that it will consider how to encourage uptake of EVs to meet the government targets and recognise that key to this will be ensuring that the charging infrastructure is in place to allow widespread uptake of EVs, while managing the challenges that this would present for the energy system. Furthermore, the Commission emphasises the need for the government to start planning for an EV charging infrastructure that would reduce the cost of electricity network upgrades [114], [115]. The Commission seeks to engage with a range of stakeholders and experts, who would provide evidence to support the commission's work.

In summary, findings and evidence from this work and previous studies and real world demonstrators on BEVs can be used to support the new EV Bill, Ofgem and NIC in assessing and developing a strategy for the UK's infrastructure requirements to accommodate BEVs.

2.3 Review of Projects and Initiatives Providing Evidence to Support the Planning of National Charging Infrastructure

In the last decade (2008-2018), electric vehicle research and demonstration has received exponential attention from governments, research institutions and industry worldwide. Battery electric vehicles (BEVs) are a new and evolving technology and several projects were funded worldwide to gather evidence on the actual usage and suitability of this new technology. Some of the findings were made publicly available in forms of project reports and academic publications. Some of these projects and studies will be described in the literature review sections of this work (chapter 2, chapter 5 and chapter 6).

The “Research Councils UK Gateway” website provides access to the database of publicly funded projects in the UK including research and innovation on EVs [116]. The Energy Networks Association website includes a repository for publicly funded projects focusing on gas and electricity networks in the UK, and this is increasingly including projects on EVs [117]. In addition, the European Commission (EC) provides several public portals providing access to information and data on European Union (EU) funded projects including EVs and charging infrastructure. These platforms include CORDIS, “Community Research and Development Information Service” and the EV-Radar tool, which provides information on over 320 EU-wide electro-mobility projects funded by Commission [118]–[121].

Relevant evidence from these studies and projects could inform policies and legislations on low carbon transport in the UK, including shaping the roll-out of the required BEV charging infrastructure. Specifically, these findings could support the development of the UK EV Bill and following legislations.

Early projects developed models and roadmaps in anticipation of the introduction of BEVs to the market. With the increase in the availability of mass-produced EVs and charging infrastructure, the desktop-based studies were followed by real world demonstrators of the new technologies to measure the usage of BEVs outside labs, in a real world setting with actual drivers. Indeed, early projects recommended that the developed methods and models should be tested in real-life conditions so that these existing models are refined using monitored data [122].

Focusing on BEV charging infrastructure and electricity network impact, selected UK-based and international projects are described in the following section. While not all findings from international projects might be applicable to the UK, some of the methods and thinking developed could constitute a valuable input to on-going and future projects.

2.3.1 International projects, initiatives and studies on BEVs and charging infrastructure

This section describes selected international projects, studies, and best practices on BEVs and charging infrastructure.

The EU recognises the need to adapt its road infrastructure to encourage EV uptake and meet the current and forecasted e-mobility requirements. The EU directed its member states to ensure the availability of publicly accessible charging stations with adequate coverage (clause 23 of the EU directive on the deployment of alternative fuels infrastructure [86]). In addition, the EU co-financed several EV charging infrastructure projects as part of the Trans-European Transport Network (TEN-T) plan to improve the connectivity between member states. Rapid Charge Network (RCN), described in the following chapters, is a TEN-T funded project that deployed fast chargers (50kW) on major roads in England and Ireland and constitutes one of the key projects supporting the work in this thesis [123]. ULTRA-E is another TEN-T project, which runs between 2016 and the end of 2018 and will deploy 25 ultra-fast chargers (150-300 kW) on transport corridors connecting the Netherlands, Belgium, Germany and Austria. The NEXT-E project is co-funded by the Connecting Europe Facility (CEF) and will install 30 ultra-fast chargers (150-350 kW) along TEN-T core corridors across 6 countries [124].

The EU- funded project North Sea Region (NSR)[4] Electric Mobility Network (E-Mobility NSR) ran for 3 years between 2011 and 2014. One of the main objectives of the project was to raise awareness on e-mobility in the NSR region, synchronise and share strategies to support further development and growth of EVs across the North Sea region. E-Mobility NSR provided recommendations for charging infrastructure development. The project also emphasised the need for a coordinated approach between automotive and energy stakeholders and developed smart grid models for the grid integration of EVs, including battery degradation models [96], [122], [125], [126].

Green eMotion was one of the largest European electro-mobility projects (€42 million). Green eMotion included real world demonstrators and collected data from 11

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[4] The North Sea Region is connected by the North Sea. The 7 North Sea Region Programme countries are Sweden, Denmark, Germany, the Netherlands, the Flemish Region of Belgium, the UK and Norway.

demonstration regions throughout 8 countries in Europe (excluding the UK) between May 2011 and December 2013. 78,000 charging events and 95,000 trip events were collected from approximately 2,700 charging points and 700 vehicles [127]. Green eMotion developed and demonstrated a framework to support the adoption of EVs and the framework took into account the requirements for public charging infrastructure and its optimised integration into the grid [127].

With regards to learnings on standardisation, both Green Emotion and E-mobility NSR found that several charging plugs have been deployed and there is a wide variety of access and payment methods that are not always interoperable across different charging networks in Europe. The projects recommended that it is vital to harmonise standards and technologies to allow BEV drivers convenient access and roaming between charging networks [83], [84], [126]. For example, open standards for vehicle-charge point communication and payment can enable interoperability between charging networks [128]. Following EU-wide standardisation research efforts, EU standards were announced and were adopted by the UK. UK regulation specified that, as of November 2017, an infrastructure operator must provide charging point access to any person without the need to enter into a pre-existing contract, implying that operators might need to allow access and payment directly using a bank card [86], [87].

A study based on Green eMotion data assessed EV charging infrastructure business models. The study found that private home charging is the cheaper option if using lower cost off-peak electricity tariffs and it is likely to be the preferred option for drivers who can charge at home. The Green eMotion study also found that a profitable business case for fast charging requires more intensive infrastructure usage [129]. One study analysed the EV charging behaviour from charging points installed across the whole island of Ireland to inform future infrastructure roll-out plans. Data was analysed from a total of 711 charge points mainly in public locations including 83 fast chargers. The dataset also contained data from 43 chargers installed in private residential locations. The study found that EV users preferred charging at home in the evening during peak demand. In contrast to the Green Emotion study, the Irish study demonstrated that fast chargers recorded high usage frequencies and indicated that public fast charging infrastructure is most likely to become commercially viable in the short to medium term [130].

A recent study by the International Council on Clean Transportation assessed charging infrastructure deployment practices in major EV markets. One of the findings is that charging infrastructure availability currently varies greatly at a local level and that there is no universal benchmark for the number of EVs per public charge point. Different housing and population density characteristics could explain this variation. For example, in California where people have access to home and work charging, there is one public charger per 25 to 30 EVs typically. This is in contrast to the Netherlands where private parking and charging are rare and there is one public charger per 2 to 7 EVs typically. For the UK, the study found that there is one public charger per 15 to 25 EVs [128]. The EU indicated that at least one public charger per 10 cars would be appropriate but the total number of charging points should be established taking into account member states' individualities [86].

The EU is also promoting smart charging to minimise the impact on the electricity network and the use of BEVs to support the integration of renewable energy [86]. This support followed evidence from several EU projects, with selected ones described below.

Several EU projects focused on electricity network impact and integration of EVs. The MERGE project, "Mobile Energy Resources for Grids of Electricity", started in 2010 and ran for 24 month, was financed by the EU with academic and industrial partners from across Europe including the UK. The research project examined the impact of EVs on the EU power system including planning and operation and investigated potential solutions. In parallel and similarly, G4V project, "Grid-for-Vehicles", was another EU funded project that started in 2010 and ran for 18 month, with academic and industrial partners across Europe including the UK. G4V looked at grid integration challenges and opportunities of mass introduction of EVs on the electricity networks in Europe. Similarly, the EU-funded PlanGridEV project ran for 33 month between 2013 and 2016. The main objective of PlanGridEV was to design new tools and methods that could be used by distribution network operators to facilitate mass roll-out of EVs while enabling distribution renewable energy integration [131].

In addition to projects across several EU countries, some projects had a national focus and selected initiatives will be described below.

Several innovative projects were funded in Denmark to examine the network integration of EVs, which are seen as a key technology to support the country's integration of the significant wind energy supply. 40% of Denmark's energy supply comes from wind power with plans to reach 100% fossil fuel free in 2050 [132]. The EDISON project, "Electric vehicles in a Distributed and Integrated market using Sustainable energy and Open Networks", ran between 2008 and 2013 and was co-funded by the Danish transmission system operator (Energinet.dk) and industrial partners. EDISON was a research project that examined the challenges and potential solutions to integrate EVs into electricity networks [133]. The Nikola project followed EDISON and ran between 2013 and 2016. Nikola identified several grid services that could be provided by EVs to support the power system and explored the required technologies that would enable them through simulations and in-field testing [134]. The Parker project started in 2016 and will run until 2018. Parker builds on EDISON and Nikola projects, which have laid the foundation for understanding the EV's potential in balancing the Danish power system. Parker applies the balancing services that were identified in the previous project to an actual fleet of electric vehicles [135]. In parallel, the ACES project runs between 2017 and 2020, and will deploy 50 EVs and controllable charging infrastructure on the island of Bornholm in Denmark. ACES will also examine the potential of EVs to provide services and participate in the Danish electricity market [136].

The Netherlands is a leading EV market with one of the most developed charging infrastructure in the world [128], [137]. ElaadNL, a partnership started in 2009 consisting of the united electricity network operators in the Netherlands, established a network of more than 3,000 public charging stations across the country. ElaadNL initiated the development of open and interoperable communication protocols for the EV charging infrastructure (i.e Open Charge Point Protocol). The open protocols are enforced through the public charge network in the Netherlands. In addition, ElaadNL monitors the charging infrastructure and coordinate the connections between public charging stations and the electricity network. ElaadNL states that smart charging allows optimal use of the existing network and mitigate the need for expensive alterations to the electricity network; and its mission is to simulate innovation in smart charging and the use of sustainable energy to charge EVs. The organisation is also developing the Open Smart Charging Protocol to support an efficiency operation of the electricity network [137].

Germany is one of the major global car manufacturers in the world; it established the National Platform for Electric Mobility in 2010. The platform is an advisory body to the German government and includes key stakeholders for electro-mobility such as car manufacturers, energy companies, associations and research institutions [138]. The e-Mobility Berlin project was an early demonstrator of EVs and charging infrastructure run by the car manufacturer Daimler between 2008 and 2010. The project leased 100 Daimler EVs and installed 500 chargers at home and public locations. The project contributed towards charging infrastructure standardisation in Europe [139], [140]. The German government established the Modellregionen Elektromobilität' programme in 2009 that supported several projects in eight model regions. The funding was used to showcase EVs, charging infrastructure and fund research projects to provide insights to help build the charging infrastructure [141]. More recently, the government increased its support to build the public charging infrastructure and announced a nationwide program that includes €100 million to support the deployment of 10,000 slow chargers and €200 million for 5,000 DC fast charging stations [128]. In parallel, initiatives by the private sector are also supporting the roll-out of public charging infrastructure. Ionity, a joint venture of BMW Group, Daimler AG, Ford Motor Company, the Volkswagen Group, Audi and Porsche, was established in 2017. The aim of the venture is to build a pan-European high-power charging network for EVs. Ionity's headquarters are in Munich and they plan to implement and operate about 400 fast charging stations, rated at up to 350kW, installed across 18 European countries by 2020 [142].

Another roll-out of public fast chargers, including ultra-fast chargers deployment, led by a car company is underway in the United States. The Electrify America initiative funded by Volkswagen would roll-out up to 1,800 fast chargers including 350kW chargers [92], [143].

The US Department for Energy (DOE) launched the largest demonstrator in the world on EVs and charging infrastructure. The EV Project, ran by Idaho National Lab, started in January 2011 for 3 years and deployed and collected data from 17,000 public and residential charging stations and over 7,800 privately owned electric cars (including plug-in hybrids and BEVs). The project captured 6 million charging events and 200 million kilometres of driving.

The project examined the usage of different types of charging infrastructure and the driving patterns of EV drivers in a real world environment. The analysis showed that despite the installation of extensive public charging infrastructure, the majority of charging was done at home and at work; public slow chargers usage was low overall and some fast chargers experience heavy use [52], [144].

More recently (2017), the US DOE, through the National Renewable Energy Lab, conducted a study to analyse the national non-residential plug-in EV (PEV)[5] infrastructure requirements. The study categorised PEV charging infrastructure requirements by area served (cities, towns, rural areas, and Interstate corridors) and the results were quantitative estimates for the required number of public and workplace charge points in the US to support plug-in EV adoption. The estimates were presented for different scenarios of plug-in EV adoption rates and battery capacities. For their central scenario (15 million PEVs in 2030), and under a home-dominant charging assumption, the study found that 3.4 fast charger plugs (150 kW) are required to support 1,000 PEVs and 40 non-residential type 2 plugs (6.2 kW) per 1,000 PEVs are required at work and public. The mix of the 15 million PEVs is as follows: 10% PHEV20; 35% PHEV50; 15% BEV100; 30% BEV250; 5% PHEV20-SUV; 5% BEV250-SUV. SUV stands for Sport Utility Vehicle. The range of the cars in miles is indicated by the number after the type; for example BEV250 stands for BEV with a range of 250 miles [145].

Moreover, the U.S. DOE is promoting the installation of workplace charging by inviting employers to sign up to the Workplace Charging Challenge pledge. The benefits to employers from taking the Challenge include gaining access to informational resources, technical assistance and recognition of workplace charging efforts. For example, employers could receive support and information on how to install solar power to supplement workplace charging and how to include charging station credit for Green Building certifications. The U.S. DOE aims to partners with 500 employers across the country by 2018 and have already reached 400 employers in 2016 [146].

[5] Plug-in EV (PEV) refers to plug-in hybrid and battery electric vehicles and excludes hybrid EVs and hydrogen fuel cell EVs.

The California Public Utilities Commission (CPUC) regulates services and utilities in California. The state regulator approved several charging infrastructure programs proposed by investor-owned utilities in California. This approval means the regulator allowed these companies to invest customers' money to install EV charging infrastructure. Initial projects include installing up to 12,500 charging stations with a total budget of $197 million [147].

2.3.2 UK studies and projects on BEVs and charging infrastructure

The UK government, through the Technology Strategy Board (predecessor of Innovate UK) and OLEV (the UK's office for low emission vehicles), launched the £25 million Ultra-Low Carbon Vehicle Demonstrator Programme (ULCVDP) that funded 8 projects between 2009 and 2013. The programme deployed 349 electric vehicles (including BEVs, hybrids, plug-in hybrids, and hydrogen fuel cell) from 19 manufacturers. The projects collected 52,000 charging events and 2.5 million kilometres travelled in 280,000 driving events. The aim of the programme was to assess the viability of EVs in real world environment and found that people enjoyed driving an EV albeit expressing the cars' driving range as a concern. Home charging was the main charging location and the participants expressed the importance of public charging infrastructure even if they could complete most of their trips without one [62]. SwitchEV, described in the following chapters, is one of the ULCVDP funded projects and data from SwitchEV was used to support the work in this thesis.

Some projects and studies focused on charging infrastructure requirements to support EV uptake. Data from the charging points that were funded as part of OLEV's PiP programme were sent to OLEV. Lessons learnt from rolling out infrastructure as part of the scheme were publicly shared to inform the roll-out of additional infrastructure in the UK. Some of the recommendations include ensuring ease of use and accessibility of chargers and considering interoperability with other schemes [106]. One study had access to charging data from the PiP midlands project and analysed approximately 22,000 charging events from 255 charging stations. As expected, the study confirmed that public charging took place away from peak-hours electricity demand [148]. Another study presented a framework for developing public charging infrastructure for an urban environment in the UK. The study indicated that planning for public charging should primarily target areas where private parking is not available. This is mainly in inner-city residential pockets with on-street parking and out of town public parking facilities such as at park and ride hubs, amenities and commercial centres [149]. A recent study commissioned by the Committee for Climate Change (CCC) assessed the requirements for public charging infrastructure to meet the anticipated growth of EVs in Britain. The study, published in 2018, analysed the requirements for long distance en-route charging on the Strategic Road Network across mainland Great Britain, and parking-based charging at the destination of trips. For the 2015 CCC Central EV uptake Scenario which accounts for 60% of new car and van sales by 2030, the study found that the number of fast chargers needs to increase from 460 in 2016 to 1,170 by 2030. In addition, the study found that the number of parking-based public chargers would need to rise from 2,700 in 2016 to over 27,000 by 2030 [150].

The Energy Technology Institute (ETI) is a public-private partnership between energy and engineering companies and the UK Government, with board members including representatives from Shell, British Petroleum, and EDF Energy. ETI funded several projects on electro-mobility including a 30-month project (2016-2018) to examine how the UK energy system needs to adapt to accommodate and encourage greater uptake of EVs. The project will include a trial of 300 EVs to test EV network integration solutions and test consumer response [151].

Ofgem (the UK energy regulator) established network innovation funds to encourage electricity network operators to develop and demonstrate cost-effective solutions to support decarbonisation of the power system while ensuring security of supply. Some of these projects included or focused on EVs. Selected innovation fund projects are described below.

The Low Carbon London (LCL) project was launched on January 2011 for 4 years by UK Power Networks (the DNO in the South East and East of England and London). The project collected data from 30 BEVs for one year and data from 120 private charging points and 391 public charging points located across London. The project estimated that without smart chargers, the uncontrolled charging of EVs will lead to a £6bn reinforcement cost across GB by 2050 depending on uptake levels [68], [152]. More recent real world demonstrator projects include My Electric Avenue (MEA) and Electric Nation. Scottish and Southern Energy (SSE) Power Distribution’s MEA ran between 2013 and 2016 and collected data from 206 BEVs for one year. The project estimated that using 3.5 kW EV chargers would double household peak demand; and demand side response technology could help avoid peak charging and reduce network upgrade costs by around £2.2bn up to 2050 [65]. Western Power Distribution's Electric Nation was launched in April 2016 and will run until October 2019 with plans to recruit and collect data from up to 700 electric vehicles [67]. Customer Led Network Revolution (CLNR) was a major smart grid demonstration project; it was hosted by Northern Powergrid and ran between 2010 and 2014. The project provided smart meter and electricity network data that supported the work in this thesis. SSE's Smart EV is an on-going project and it includes all six GB DNO groups as project partners. The aim of Smart EV is to inform a national engineering recommendation for the connection and control of EV charging to minimise costly and lengthy network upgrades. While the collaboration of all DNOs on this topic is important, this would require collaboration of National Grid, Ofgem, car manufacturers, consumer bodies, charger manufacturers, etc. Smart EV is running a consultation process and seeking the views of various e-mobility stakeholders [153]. Projects like Smart EV showcase that DNOs are working to identify solutions to efficiently integrate EVs. While Smart EV is encouraging the participation of different stakeholders, this participation can't be guaranteed. Consequently, a wide range of issues above DNOs requirements might not be considered when developing a national engineering recommendation.

In addition to research and innovation projects, there are several initiatives that are formed to discuss and consult on the potential challenges and solutions for the uptake of EVs and successful grid integration. These initiatives are bringing together different EV stakeholders such as car manufacturers, charging infrastructure providers and operators, distribution network operators, transmission system operator, energy suppliers, etc. The main two initiatives are described below.

The Energy Networks Association (ENA) represents the transmission and network operators of gas and electricity in the UK and Ireland. ENA is running the Open Networks project, which is a major energy industry initiative bringing together UK and Ireland's electricity grid operators, academics, NGOs, Government departments and the energy regulator Ofgem. The Open Networks project is investigating better coordination across the transmission and distribution boundary to ensure better operation of the electricity networks with the introduction of low carbon technologies such as EVs [154]. The Open Networks project is working to involve any party that has an interaction with the power system; however the

Project Advisory Panel Members don't include representatives from the automotive industry or charging infrastructure operators [155]. Other initiatives of ENA that support EV grid integration is setting out a process for connecting EV Chargers to distribution networks. The process is aimed at installers and it will help DNOs keep track of EVs that are being connected to their networks. As part of the process, an Adequacy of Supply Assessment is required to be carried out by the installer before any installation. If the connection won't cause network problems, the installer can connect then inform the DNO. If the connection would cause a network issue, the installer must notify the DNO and won't be able to connect before the DNO's remedial of the issue and approval of the connection [156].

Secondly, the Low Carbon Vehicle Partnership (LCVP) is a public-private partnership working to accelerate the transition to low carbon vehicles and fuels in the UK. The partnership has several working groups with approximately 200 organisations involved including automotive and fuel supply chain, academics and representatives from the Government. The members directory doesn't show any representatives from the electricity network operators [157]. One of the working groups is the EV Network Group with ENA and Ofgem on the project steering group. The aim of this working group is to make recommendations to government to support successful integration of EVs into the UK electricity distribution networks. The timetable of the working group is indicated to be for one year between April 2016 and April 2017 and it wasn't clear if the group will continue to operate beyond 2017 [157], [158].

2.4 Identification of a Research Gap and Overall Contribution of this work

The previous section looked at exemplary programs, emerging practices and findings from real world demonstrator projects and studies on EVs, charging infrastructure and electricity network impact and integration strategies in the UK and abroad. This section explains the original contribution of the work in this thesis beyond the state of the art described above.

Insights from international best practices constitute a valuable input for UK strategy and plans; however, some findings might not be applicable for the UK. For example, private parking in the Netherlands is relatively rare meaning there is additional need for public charging compared to the UK for example. Consequently the usage and requirements for public charging in the Netherlands would be much higher than in the UK where access to private parking and charging is more common [128], [159]. UK-based projects, that are the basis for this thesis, capture national and regional characteristics and would provide tailored insights to fit the UK context.

Furthermore, previous and some of the on-going projects in the UK focus on either BEVs without considering the electricity network, or focus on the impact of BEVs on the electricity network without considering the overall charging behaviour or requirements of users. For example, the government's Ultra-Low Carbon Vehicle Demonstrator Programme including the SwitchEV project focused on BEV user behaviour and did not collect data from the electricity network. Similarly, My Electric Avenue project investigated the residential BEV charging impact on distribution networks but did not consider work charging, the requirements for fast charging infrastructure, or different driving behaviours that would impact charging requirements. The original contribution of this work is that it is taking an integrated approach by considering the characteristics and actual usage patterns of BEVs, and similarly considering grid characteristics and existing energy usage patterns for the UK context. This was possible by working with more than one project and combining insights and findings from three early, real world demonstrators in the UK on BEVs and smart grids over a period of 5 years.

Finally, high resolution real-world datasets are required to develop empirical models providing robust evidence supporting the roll-out of charging infrastructure. Despite the trials described in the previous section, there was limited availability of a comprehensive dataset on BEV driving and charging patterns to allow an integrated assessment of a charging infrastructure. A document published by the EC has stated that the majority of data collected from the early EV demonstrators is not of good enough quality to allow complete analysis [160]. For example, several key measures were not collected such as location and SoC data. Consequently, the EC published a report to provide guidance on data monitoring and quality control for publicly funded European electro-mobility projects [160]. Similarly, the data loggers installed in the EVs in the LCL project exhibited various technical issues and the data coverage was not complete with significant number of driving events were not recorded [152]. Moreover, some trials collected data on charging events only. For example, the data collected on MEA included the start and end of the charging time and the initial and final SoC and did not include data on driving behaviour. Finally, the data collected was not publicly available in a format to allow further analysis, due to privacy and commercial sensitivity considerations.

In this work, datasets from 3 different projects were combined allowing a detailed assessment for planning charging infrastructure for private passenger BEVs. These 3 projects collected data from BEVs, charging infrastructure, and electricity distribution networks. The data included different types of charging infrastructure, at different locations, for a long period of time, and data from different types of distribution networks. By collecting data on driving behaviour and data from private and public charging locations, the findings gave an overall picture on the BEV usage and requirements. For example, the analysis is not limited to one charging location. This is important because the possibility and usage of charging infrastructure at one location (e.g. work charging or fast charging) would impact the usage and requirements of charging infrastructure at a different location (e.g. home). In addition, the information on driving behaviour captures several factors that could impact the charging requirement of users. The analysis in this work provides insights to support overall planning of charging infrastructure. This would support on-going efforts to inform policy and develop best practices to ensure successful BEV adoption.

Chapter 3. BEV Demonstrators and Data Collection[6]

3.1 Introduction

The analysis in this thesis was based on data collected from the three projects- SwitchEV, Rapid Charge Network (RCN), and Customer Led Network Revolution (CLNR). One of the objectives of this thesis is to design the BEV demonstrator and data collection method on the RCN trial, and this is described in this chapter.

SwitchEV was one of the eight projects of the Ultra-Low Carbon Vehicle Demonstrator Programme mentioned in the previous chapter. The dataset collected on SwitchEV was one of the first datasets to be collected in the UK on actual usage of BEVs. SwitchEV data was collected from 35 BEVs between 2011 and 2013. The BEVs were leased to a mixture of private individuals, organisations, companies and car clubs (i.e. car sharing groups) for 6 to 12 months as an alternative to their conventional petrol or diesel powered cars. Data was collected from a total of 125 participants on SwitchEV. The participants were able to charge at home, work and at the public network of charging points in the UK installed by the PiP programme [161], [162].

RCN was one of a number of European Commission's trans-European transport network (TEN-T) co-financed projects on EVs' infrastructure. RCN ran for two years between 2014 and 2015 and rolled-out 74 multi-standard fast charging stations along 1,100km of major UK and Irish roads. Currently, a fast charger can provide an 80% charge in approximately 30 minutes. Data was collected for one year from 40 BEVs owned by a mix of individuals and one company who chose to participate in the RCN data collection trial. Similarity to SwitchEV, users had access to home and public chargers, including the RCN network of fast chargers that was being installed. Some participants had access to work chargers [47], [123], [163].

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[6] The Rapid Charge Network (RCN) BEV demonstrator and data collection is described in the project's final report [47].
In addition, the author contributed to an European Commission (EC) Join Research Centre (JRC) report on "Data Collection and Reporting Guidelines for European electro-mobility projects" [160].

A summary of the SwitchEV and RCN trials is presented in Table 3. The selection of the participants is described in section 3.2, data collection in section 3.3 and the summary in section 3.4.

Trial	SwitchEV	RCN
Period data collection	2011-2013	2015-2016
Make of cars	Nissan LEAF (24kWh)*15 cars; Peugeot iOn (16kWh)*20 cars	Nissan LEAF (24 kWh)*29; Nissan e-NV200 (24 kWh)*5; Renault ZOE (18 kWh)*6
Number of users involved	125	40
Ownership type	6 and 12 month lease from the project.	People or companies owned the vehicles.
User type	49 Private; 76 fleet users (not considered in this work).	35 Private; 5 company e-NV van users (not considered in this work).

Table 3. BEV Trial details.

3.2 Participants Selection

On the SwitchEV trial, the participants loaned a BEV from the project to replace their conventional vehicle during the trial period. On the RCN project, the participants had already purchased a BEV before signing up to the trial and expressed that they are using the BEV as their primary vehicle. A £200 voucher was offered to attract BEV drivers to participate in the data collection trial on RCN and over 120 BEV drivers expressed interest in participating. The home locations of the interested BEV users and the location of the RCN chargers are shown in Figure 5. To select the drivers, the distances between the home addresses of every interested user and every charging point on the RCN network were calculated. A programme written in R and using Google Map Application Programming Interface (API) was developed by the author to calculate the distance between homes and all RCN network chargers. Forty drivers that were within a driving distance (BEV range) to at least one of the fast chargers on the RCN network were selected. Table 4 shows the distances between the home address of one selected participant and 10 RCN chargers. The location of the majority of chargers shown in Table 4 is anonymised (e.g. described as “Charging post 2” instead of actual location) to maintain the user’s privacy.

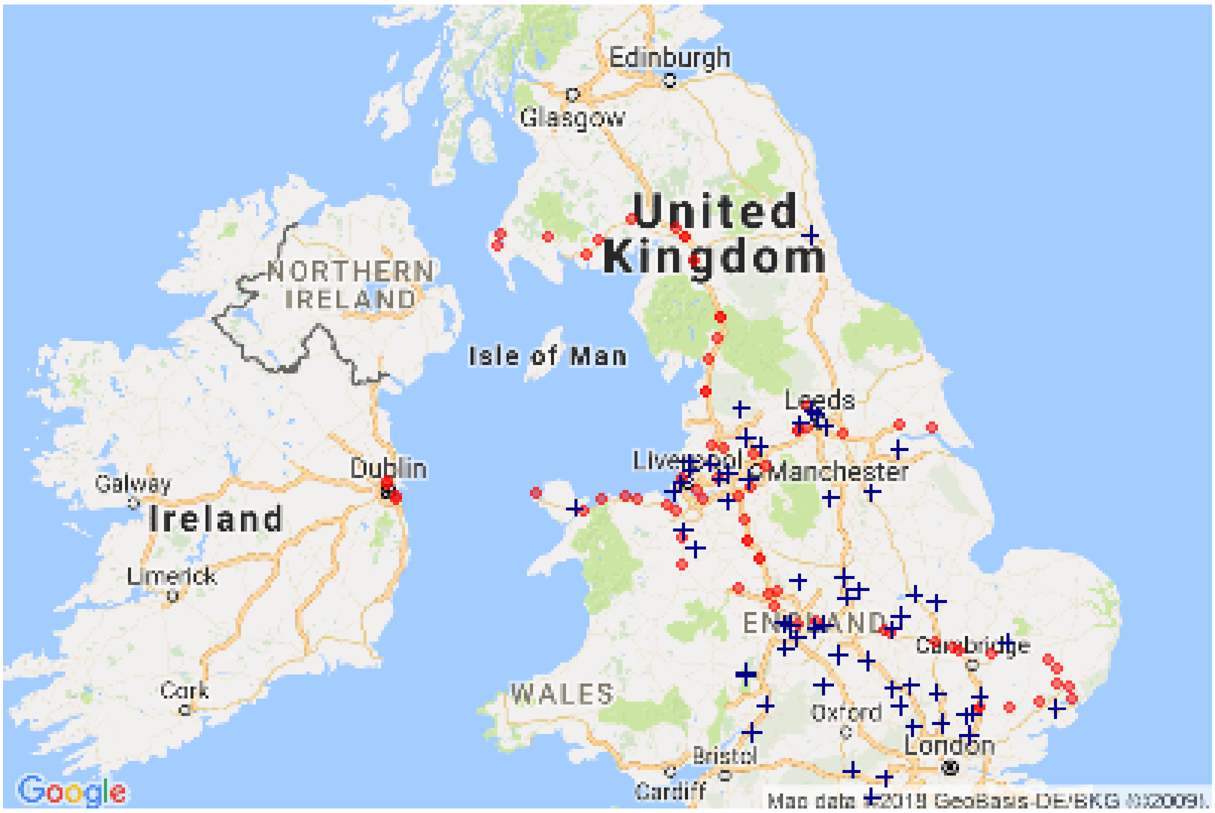

Figure 5: RCN network (red dots) and BEV drivers interested in the data collection trial (blue crosses).

Origin	Destination- RCN charging points	Distance (km)
User 1 Home	Birch services	34
User 1 Home	Charging post 2	40
User 1 Home	Charging post 3	42
User 1 Home	Charging post 4	47
User 1 Home	Charging post 5	54
User 1 Home	Charging post 6	84
User 1 Home	Charging post 7	180
User 1 Home	Charging post 8	289
User 1 Home	Port of Stranraer	349
User 1 Home	Charging post 10	391

Table 4: An example of the distances between the home address of one of the selected participants and 10 RCN chargers.

Age and income of the drivers participating in the BEV data collection trials were compared to the UK population demographics [17], [46]. The comparison is presented in the following paragraph. Previous studies have examined the characteristics of early adopters, reporting that these tend to be men, with high income level and aged between 25 and 59 years old

[164]–[166]. As demonstrated in the following paragraph, the participants of SwitchEV and RCN projects fit a similar profile [17], [46].

The SwitchEV cohort comparison can be found in [46]. For the RCN cohort, the age groups of the sample were compared to the age groups of the UK population holding a valid driving license [167], [168]. On RCN, there were no participants younger than 21 years old (2% nationally), 10% were between 21-29 years old (15% nationally), 37% were between 30-39 years old (17% nationally); 33% were between 40-49 years old (21% nationally); 10% were between 50-59 years old (17% nationally); 7% were between 60-69 years old (15% nationally) and 3% were 70 or above (13% nationally). Secondly, the income of the participants was compared to the average annual gross income of all households grouped by quintiles [169]. There were no participants belonging to the bottom quintile where the national average gross income is £14,765. 6.5% of the participants belonged to the second quintile (national average gross income is £23,509). 10% belonged to the third quintile (national average gross income is £33,820), 23% belonged to the 4th quintile (national average gross income is £48,008) and 61% of the participants belonged to the top income quintile group where the national average gross income is £87,625. Moreover, over 90% of the participants were Male.

3.3 Data Collection and Management

3.3.1 Data loggers

For in-depth monitoring of the usage of the BEVs, the cars on both the SwitchEV and RCN trials were fitted with data logging devices (logger, GPRS and GPS antenna) to monitor driving and charging behaviour of the drivers. Figure 6 shows an example of the data logging devices used. The data logger is an electronic device that connects to the vehicle's diagnostics port (Figure 7) and records some of the communicated messages on the vehicle's controller area network (CAN) bus, for example the state of charge (SoC) of the battery.

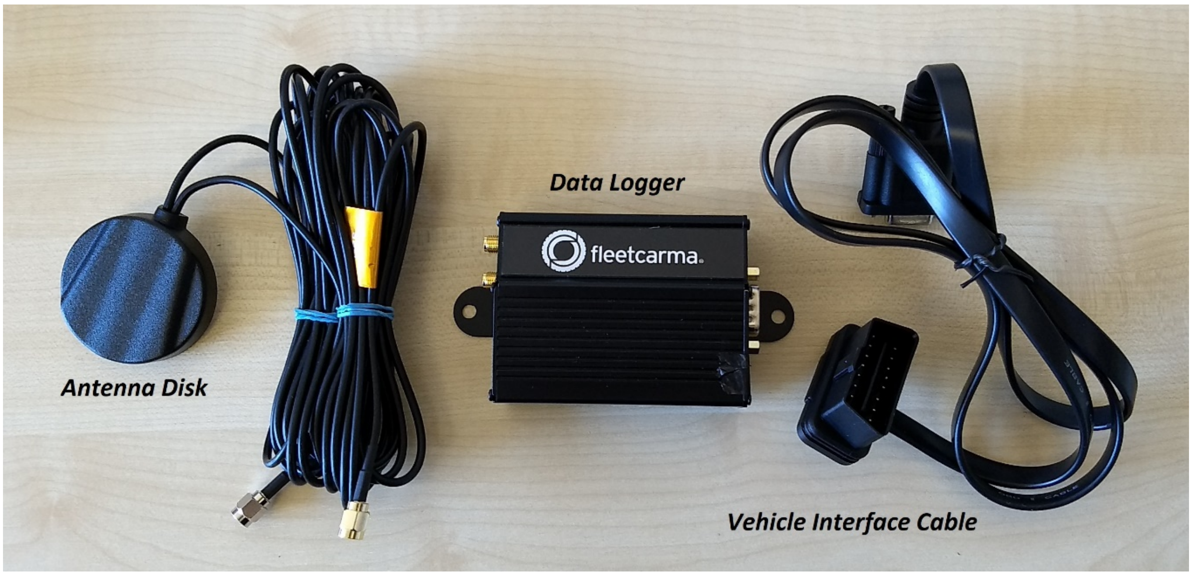

Figure 6: Antenna disk, data logger device and vehicle interface cable.

Figure 7: Vehicle's diagnostic port and logger interface cable.

The data loggers installed provided high resolution data, up to second by second, allowing accurate monitoring of how the vehicles were driven, where and when they were charged and how much energy was consumed. For example, the high resolution data incorporated the effects of second-by-second velocity profiles and topography on BEV energy consumption. Table 5 shows the key measures collected from the vehicles using the data loggers.

All data collected through the data loggers was anonymized and aggregated before publication and user agreements were developed and signed to cover data collection and users' privacy considerations.

Measure Name	Frequency-Charging	Frequency-Driving	Unit
Time stamp	minute	second	DD:MM:YYYY hh:mm:ss
GPS (Lat, Lon, Alt)	minute	second	
Ambient Temperature	minute	second	Degrees
Ignition signal (On/Off)	-	second	0/1
Charging Lead Indicator	minute	-	0/1
State of Charge	minute	second	%
Vehicle Speed	-	second	Kph
Battery Current	minute	second	A
Battery Voltage	minute	second	V

Table 5. Key measures collected by the data loggers on the SwitchEV and RCN BEV trials.

3.3.2 Data management

Once installed, the data loggers recorded all relevant activity of the vehicle during driving and charging events. Data files were automatically uploaded to the back-end server of the logger provider via GPRS cellular communication. These files were then made available to Newcastle University's data server via File Transfer Protocol (FTP). The high resolution dataset (i.e. min/min and sec/sec) required cleaning and pre-processing into event-based logs. A brief overview of the data pre-processing steps was provided in section 1.5. For SwitchEV, a colleague carried out data pre-processing, while for RCN the data logger provider carried out data pre-processing and provided event-based logs through FTP.

Using the event-based logs, the author carried out additional data processing on the dataset such as carrying out additional error checks, dealing with incorrect values, and calculating compound new measures from the original measures. For example, the GPS coordinates during a charge event were used to determine a new measure, which is the location of this charge event (i.e. home, work, public, public-fast, other). To determine the location of charge events, the events' GPS information from the data loggers was compared with the addresses of any private location that the users might charge at (e.g. home, work)[7]; and with the addresses of all the public chargers in the UK using the information available in the national charge point registry [170]. The programme to carry out the comparison was written in R. Once there was a match between the GPS information of a charge event and a charge post, the location of a charge event was updated according to the location of the matching charge post. An overview of data management including data collection, processing and analysis for the RCN BEV trial is shown in Figure 8.

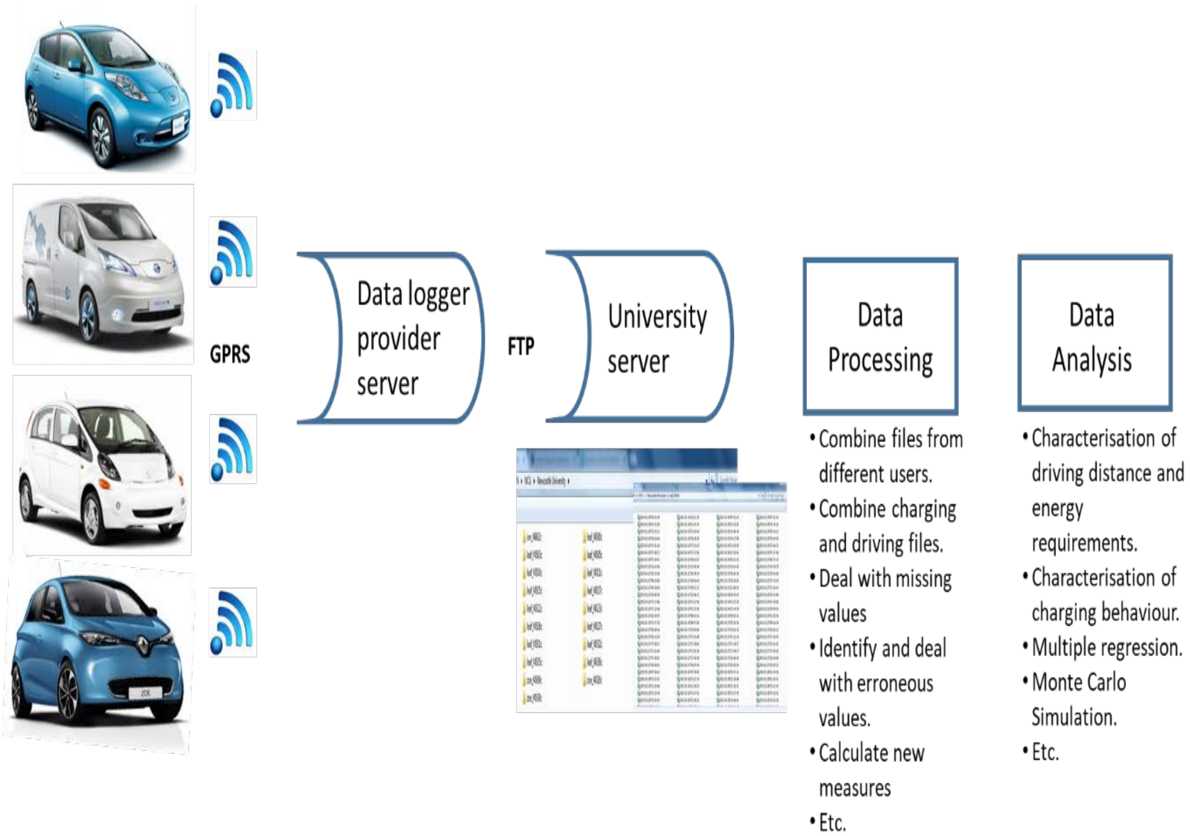

Figure 8: Data management diagram for the RCN BEV trial.

[7] Participants in the trial provided the postcodes of the private locations where they might charge (e.g. home, work, parents or friends' house). "Other" indicates when these users charged at a different private location than previously disclosed.

3.4 Summary

The dataset collected on the SwitchEV and RCN electro-mobility projects and used in this work is more extensive than publicly available information on BEV usage. In total, data have been collected and analysed from 84 private passenger BEVs participating in both projects, resulting in approximately 1.1 million kilometres driven in over 121,000 trips and 25,000 associated charging events. The data loggers captured high spatial and temporal resolution data, for extended periods of time (up to 18 month per user on the RCN trial), allowing a detailed examination of BEV driving and charging patterns. The dataset captured different driving behaviour (e.g. “eco driving” versus “aggressive driving”); and different road network (congested; free flow), topography and temperature conditions. In addition, data was collected comparing private (used for this work) versus fleet vehicle usage; urban versus rural user behaviour; and captured charging events at different times and different locations.

The comprehensive dataset is analysed in this work to identify charging and driving characteristics of users of private passenger BEVs. The examination of BEV usage patterns is covered in chapter 4. Using BEV usage patterns, real smart meter and network data, a probabilistic approach is developed in chapter 5 to investigate the impact of BEVs on LV distribution networks. The role and importance of fast charge infrastructure is examined in chapter 6.

Chapter 4. Analysing Driving and Charging Patterns of BEV Users using Data from Real World Demonstrators[8]

There is limited availability of a publicly available extensive dataset on BEV driving and charging patterns to allow a comprehensive assessment of an integrated charging infrastructure for private passenger BEVs.

The aim of this chapter is to analyse the extensive datasets collected on the BEV trials to determine driving and charging patterns of BEVs in real world conditions over an extended period of time. This will include analysing daily driving distances, factors that impact energy consumption of BEVs, and energy transferred at charging events at different times and locations. The analysis, using real world datasets, can inform theoretical assumptions on BEV usage and assist in more robust findings in subsequent studies. The open source R statistical computing language was used to carry out most of the analysis in this chapter [172]–[177]. The analysis revealed BEV usage insights that will form the foundation for the following chapters in this thesis. These insights will be used to investigate the impact of BEV charging on distribution networks and examine the importance of fast charge infrastructure.

4.1 Analysis of Daily Driving Distances

Daily driving distances of the participants on the BEV trials were measured to provide empirical evidence on BEV driving patterns, which will be used to inform the subsequent chapters in this work.

In addition, data from the National Travel Survey (NTS) was analysed to assess car driving patterns in the UK and compared with the daily driving distances of BEVs on the trials.

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[8] Parts of this chapter have been published in:

Neaimeh M, Hill GA, Hübner Y, Blythe PT. “Routing systems to extend the driving range of electric vehicles.” *IET Intelligent Transport Systems* 2013, 7(3), 327-336 [71].

Neaimeh M, Higgins C, Hill GA, Hübner Y, Blythe PT. “Investigating the Effects of Topology on the Driving Efficiency of Electric Vehicles to Better Inform Smart Navigation.” *In: Road Traffic Information and Control (RTIC)*. 2012, London: The Institution of Engineering and Technology (IET) [171].

National daily distances travelled by car and van drivers were extracted from the UK NTS Special License dataset. The NTS is designed to provide a representative sample of households and on average, drivers contribute around five driving days[9] each to the survey. The survey contained responses over a twelve year period between 2002 and 2014 with approximately 9,500 drivers providing responses to the survey per year. Therefore, the dataset analysed contained over 570,000 driving days [178]–[180]. The average daily driving distance calculated from the national dataset was 43.47 km and the distribution of the NTS driving days (up to 150km) is shown in Figure 9.

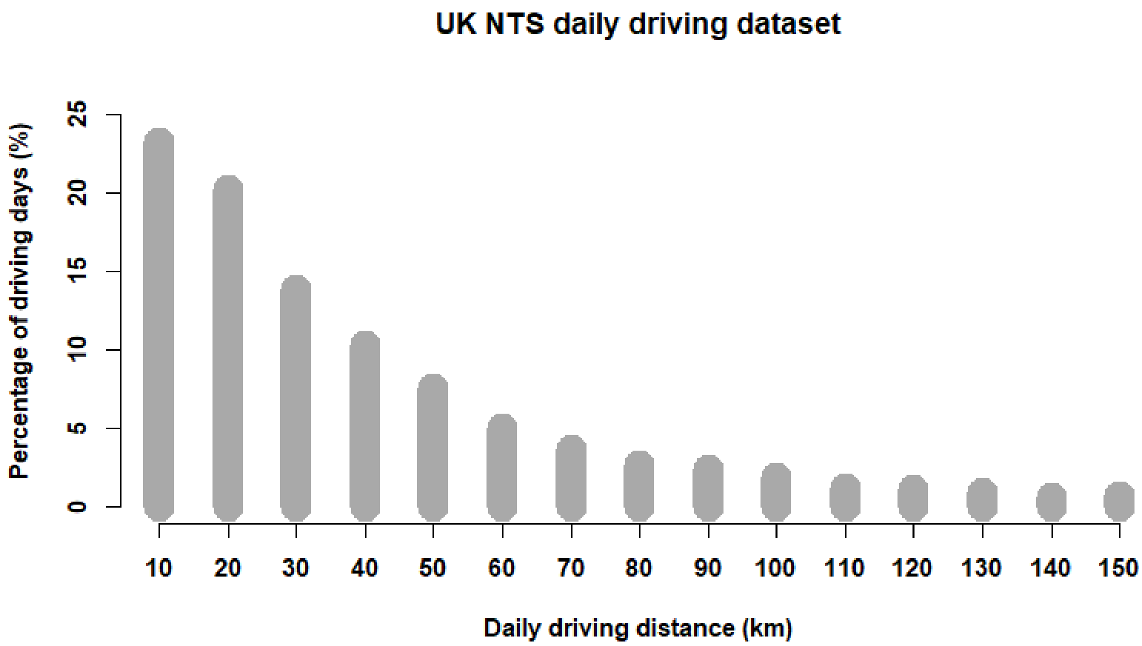

Figure 9: Percentage of driving days on the UK NTS dataset.

A total of 19,518 driving days were extracted from the BEV dataset. For every unique user ID (excluding pool BEV users), all trips carried out in a day were combined in one driving day. The distribution of driving days was positively skewed with a median daily driving distance of 45 km (Figure 10). The daily driving analysis combined data from the SwitchEV and RCN trials. The average daily distance driven on both BEV trials was 54 km which is above the national daily driving average (43.47km) and well within the driving range of BEVs.

[9] A driving day is a day when the vehicle was driven

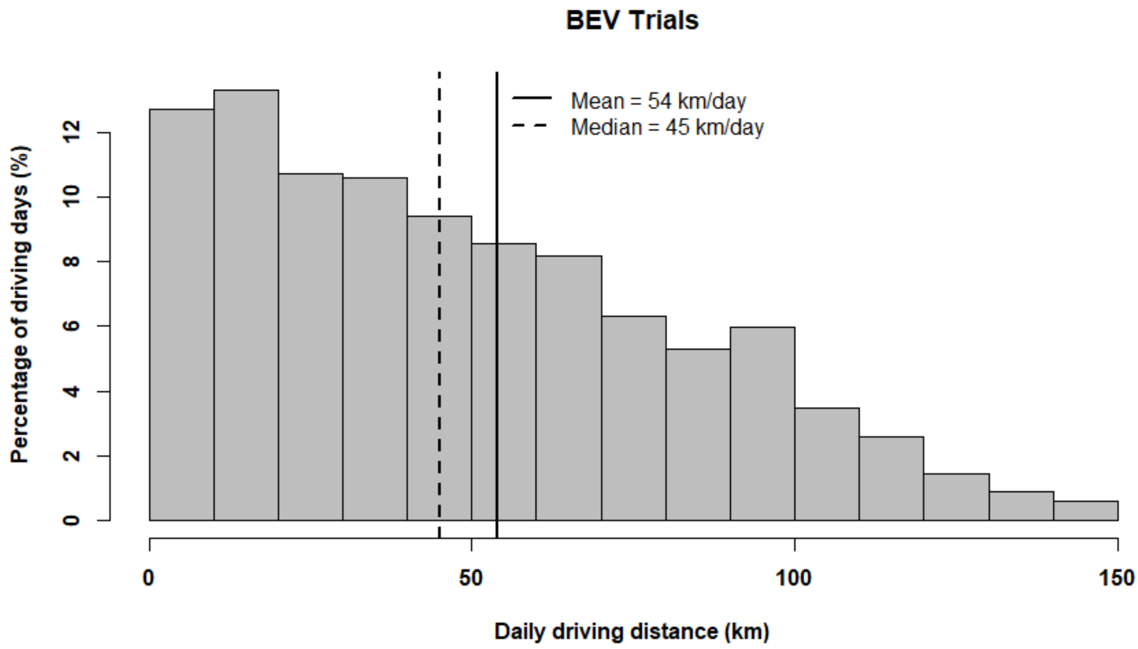

Figure 10: Distribution of daily distance travelled on the UK BEV trials (excluding pool vehicles).

Moreover, 88% of daily distances on the BEV trials are under 100 km which is similar to the NTS data with 90.7% of daily distances under 100km. These findings corroborate analyses on daily driving distances in other countries. For example, 93% of daily distances in Sweden are under 100 km on weekdays. Similarly, 91% of daily distances are under 100km in Norway, 88% in Finland, 89% in Denmark and 92% in France [181], [182]. Likewise 95% of daily driving in the US is less than 160km (100 miles) [15], [183].

This indicates that a typical BEV currently available on the market could satisfy the travelling requirements on most driving days before needing to recharge. This is also aligned with previous studies that confirmed the suitability of existing BEV models to meet almost all of the users' daily travelling needs on one charge [15], [51], [184]. For example, one study based on millions of trips across the US found that a 24 kWh Nissan LEAF can meet the driving requirements of 87% of driving days [185].

While most of the driving days can be carried out by a BEV, there are some days where a BEV is not suitable. Specifically, in 5% of driving days in the UK NTS the distance is above 150km. When a car purchase is made, the customer wants to be able to make all their journeys, not just the majority of their journeys [186]. Daily driving over 150Km is above the single-charge driving range of the vehicles being tested and would require recharging during that day. Figure 11 shows the daily distances recorded on the RCN trial for each of the 35 BEV users grouped in boxplots[10]. Notably, there is a variation in daily distances recorded on the trial and the median daily distances (horizontal bold line inside the boxes) range between 20km and 113km for these 35 drivers. While most of the events were under 150km (achievable range of the BEVs in this trial), over 3% of daily events were over 150 km and would have required recharging during that day. The data collected from this group of users is used to investigate the importance of fast chargers in chapter 6.

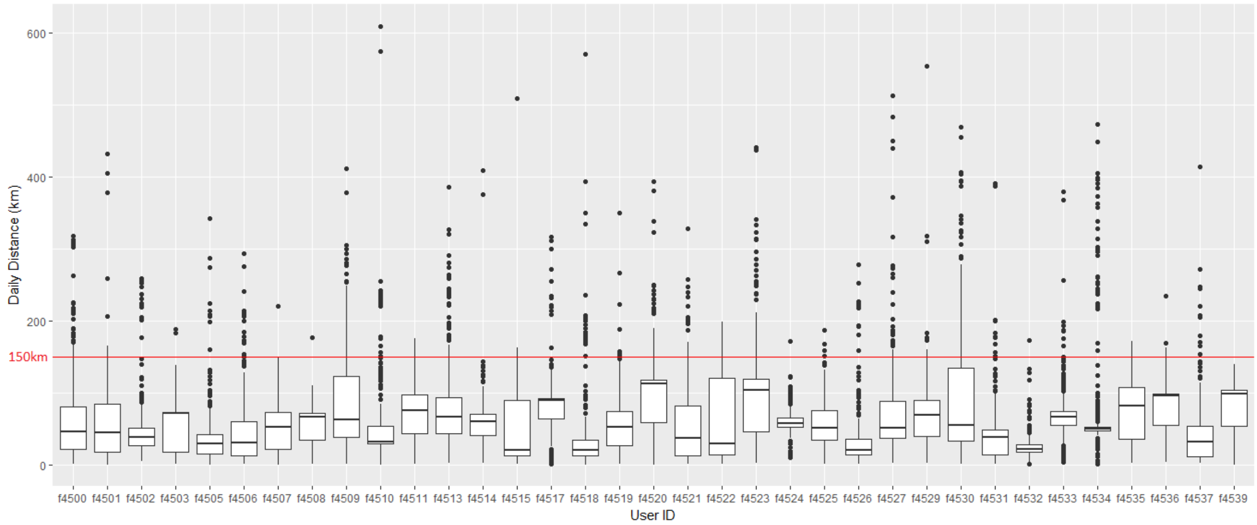

Figure 11: Distribution of daily distance for each of the 35 BEV participants on the RCN trial.

4.2 Factors Impacting BEV Energy Consumption

Several factors impact the energy consumption of BEVs. Consequently, this impacts the driving range achievable by the BEVs and their charging requirements. The main factors include weather conditions (e.g. ambient temperature), topography (ascending and descending road gradients), driving style (e.g. acceleration/velocity profiles), and loading of the vehicle (e.g. passengers). Previous studies investigated the impact of a combination of these factors on BEVs' energy consumption [51], [71], [148], [187]–[192]. Some of the results of these previous studies in described in the following text.

[10] The boxplots compactly display the distribution of daily distances. The bottom edge of the box is the 25th percentile of the data (value below which 25% of the observations are found). The top edge of the box is the 75th percentile of the data. The horizontal bold line inside the box is the median (50th percentile of the data).

A UK study measured the correlation between the values of several weather attributes and daily peak power charging demand from PiP chargers in the Midlands. The study analysed 22,000 charging events between 2012 and 2013 and weather data from the UK Met Office. The study found that the mean air temperature was the most influential factor on energy consumption [148]. The energy consumption of a BEV varies with ambient temperature due to battery efficiency and cabin climate control. Cold weather decreases the efficiency of the batteries performance and heating the interior of the vehicles drains the battery. Consequently, this drops the vehicle's driving range [188], [189], [191].

Another UK study investigated the impact of driver behaviour (i.e. style) on the energy consumption of BEVs. The study used one car with several drivers driving on a predefined route. The results showed that the difference in acceleration profiles of drivers (i.e. driving in a moderate manner versus driving in a more "aggressive manner") resulted in a 30% difference in energy consumption [190].

Similarly, a study analysed approximately 3 million kilometres of driving from over 200 plug-in hybrid electric vehicles in 23 states in the US, Canada, and Finland to investigate the impact of several factors on energy consumption. The results showed that driving at moderate speeds in an urban environment, in a non-aggressive manner, and at ambient temperature near 25°C without the use of cabin climate control resulted in low energy consumption [188].

It is important to identify the relationships between the energy consumption of BEVs and factors impacting the consumption. Firstly, this allows for a more accurate estimation of the driving range of BEV on one charge. Diverse real world driving conditions can deviate from laboratory conditions [192]. The advertised driving range of BEVs are obtained from laboratory testing and over-estimate real world driving ranges. It is estimated that the achievable range of a 24kWh LEAF, advertised at 200 km, would not exceed 150km [51], [71]. Secondly, identifying the relationships between the energy consumption of BEVs and the factors impacting the consumption improves the methods for predicting BEVs' driving and charging requirements. Improving energy prediction models is particularly important for grid impact studies and charge control strategies. Finally, analysing data incorporating various factors impacting energy consumption captures a comprehensive set of driving and charging patterns, which would enable an appropriate assessment of the required charging infrastructure.

The relationship between some of the factors impacting energy consumption are presented in this section. The results corroborate similar studies on the topic that were being carried out around the same time and in different geographic locations. The energy used per kilometre (kWh/km) is adopted as a metric to investigate the energy consumption of driving events.

The BEV trials data was used to examine the relationship between energy consumption and road topography and velocity profiles [71], [171]. The velocity profiles capture diverse driving behaviour of the trial participants. The analysis was carried out using blocks of 100 meter driving data to capture precisely the variation in altitude and driving speed. Dividing the data into 100 meter blocks allowed the measurement of energy regeneration (negative values) due to braking and deceleration. Figure 12 shows the impact of topography (road gradient) on the energy consumption (kWh/km) of BEVs. The range of 95% of the data values are shown on the graph with the average values shown in black.

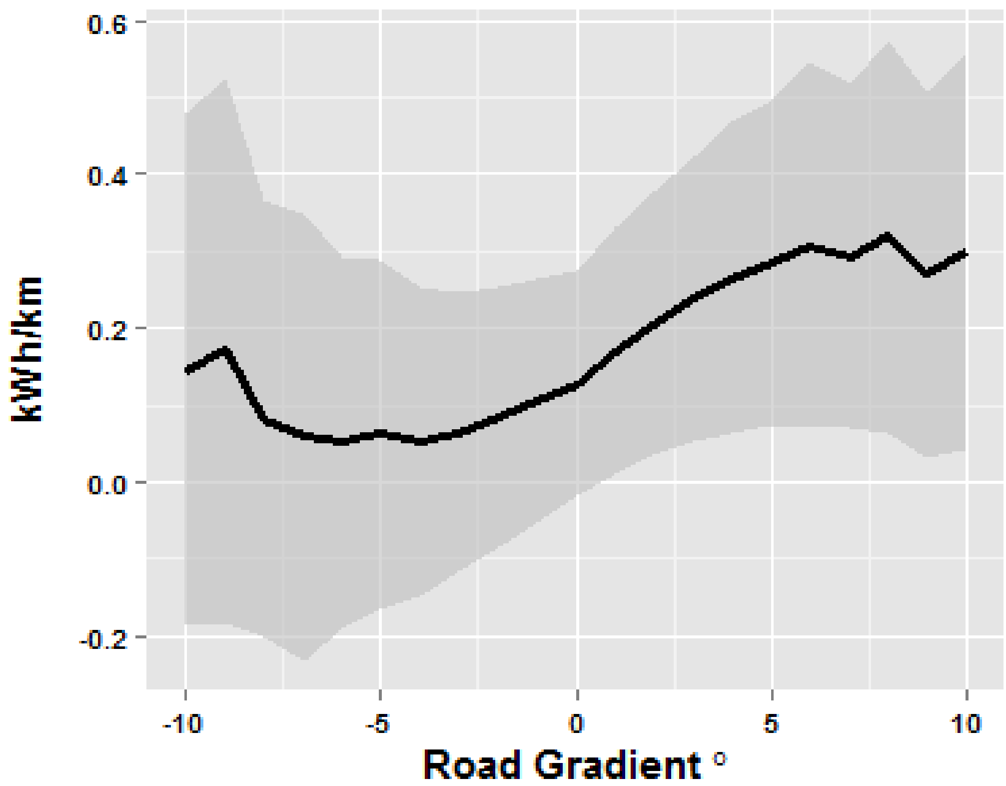

Figure 12: Different road gradients and the related BEV energy consumption [71].

Ordnance Survey (OS) transport network datasets (e.g. integrated transport network (ITN) geographic information system (GIS) dataset) were combined with the BEV dataset to illustrate the impact of velocity and topography on energy consumption. The OS transport datasets are a digitisation of the UK road network and include information on road types, altitudes, average speeds for the road network under different traffic capacities [193]–[196]. The traffic capacity conditions range from 15% (free flow speed) to 145% capacity (severe congestion). Capacities of 15, 60 and 90% are used for this work (cap15, cap60, cap90). More details on the modelling and spatial analysis can be found in [71], [171].

Using the combined BEV and road network datasets, ArcGis network analyst [197] was used to show how the BEV energy consumption, and consequently range, would vary with different values for topography and velocity (Figure 13). Figure 13 shows the areas that a BEV could cover on one charge. It can be noted that the driving range of a BEV is at its minimum (i.e. smallest area covered) under free flow conditions (cap15). This is when average speeds are highest with related high energy consumption. Energy consumption is optimal at Cap60 (condition between congestion and free flow), which allows driving at moderate speeds, leading to the highest driving range. Previous research has identified similar findings [188].

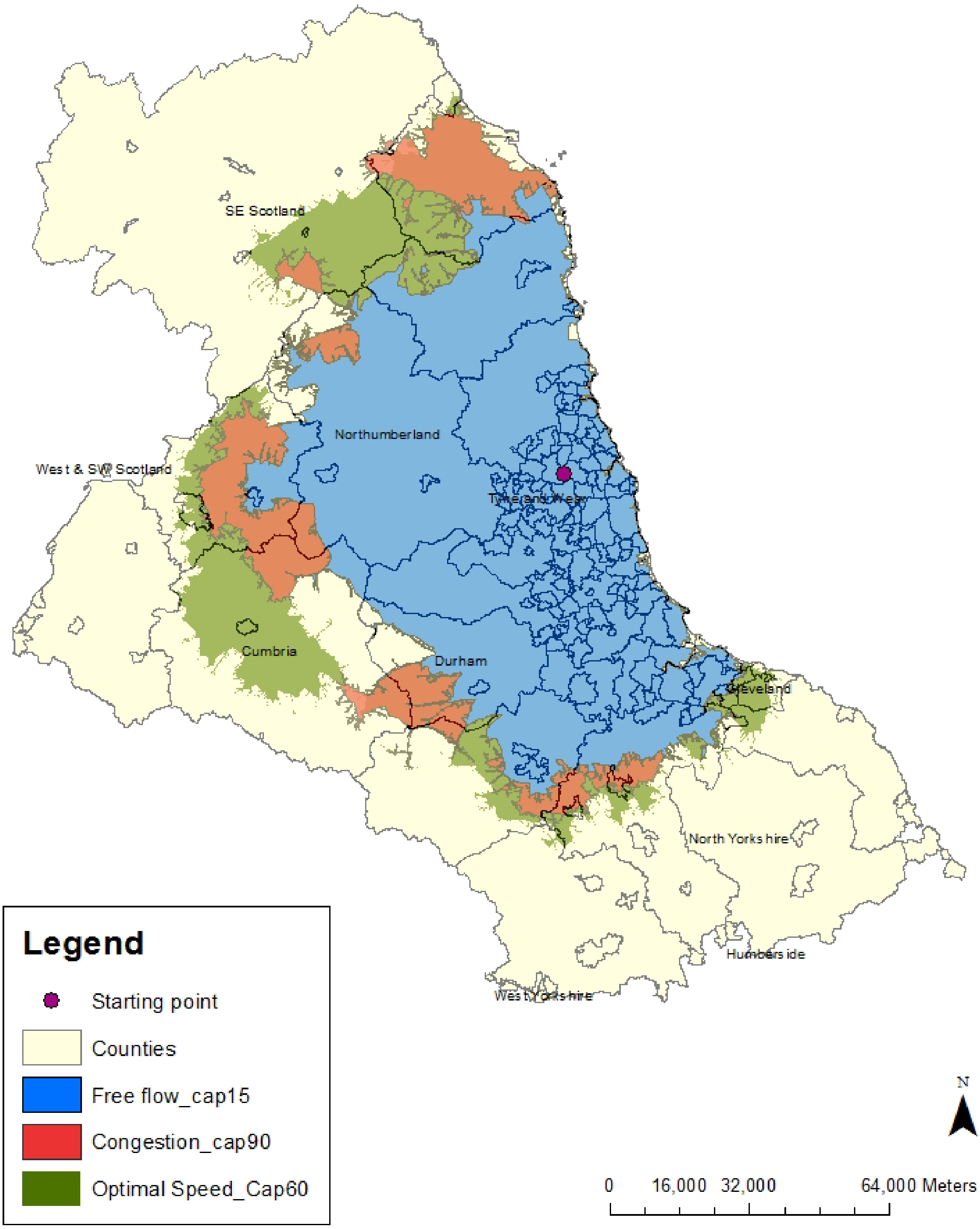

Figure 13: Driving range of a BEV for different levels of road network capacity.

In addition to examining the impact of road network conditions and drivers' velocity patterns, the relationship between ambient temperature and the energy consumption of the vehicle (kWh/km) was analysed (Figure 14). More energy is used at low and high temperatures, corresponding to the use of climate cabin control (i.e. heater at low temperatures and air conditioner at high temperatures). The findings corroborate similar studies indicating that the use of cabin climate control increase energy consumption of the vehicle.

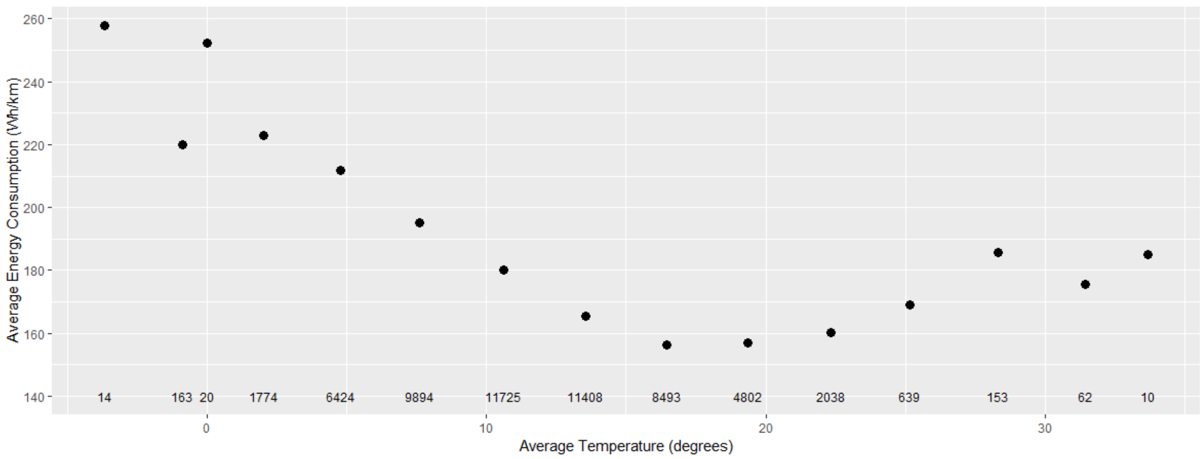

Figure 14: Variation of average energy consumption (Wh/km) with the variation of ambient temperature. The number of observations are shown at the bottom of the graph.

As demonstrated above, the energy consumption of a BEV over a given distance will depend on several factors such as road type, driving style, ambient temperature, etc. For every trip, the average energy consumption (Wh/km) was calculated by dividing the total energy used on that trip by the total distance travelled on that trip. This gives the average energy consumption in Wh/km for the whole trip. The distribution of the average driving energy consumption (Wh/km) for every BEV trip collected on the BEV trials is shown in Figure 15. The aim of the distribution is to illustrate the range of driving conditions captured that would impact the energy consumption. The distribution is based on 121, 000 trips and the overall average of energy consumption was 181 Wh/km. A high average energy consumption (e.g. > 300 Wh/km) could correspond to the utilisation of cabin climate control on that trip. The distribution in Figure 15 illustrates the range of values collected that captured several real world factors impacting energy consumption. This diversity shows the stochastic nature of BEV energy consumption, which will result in diverse charging requirements.

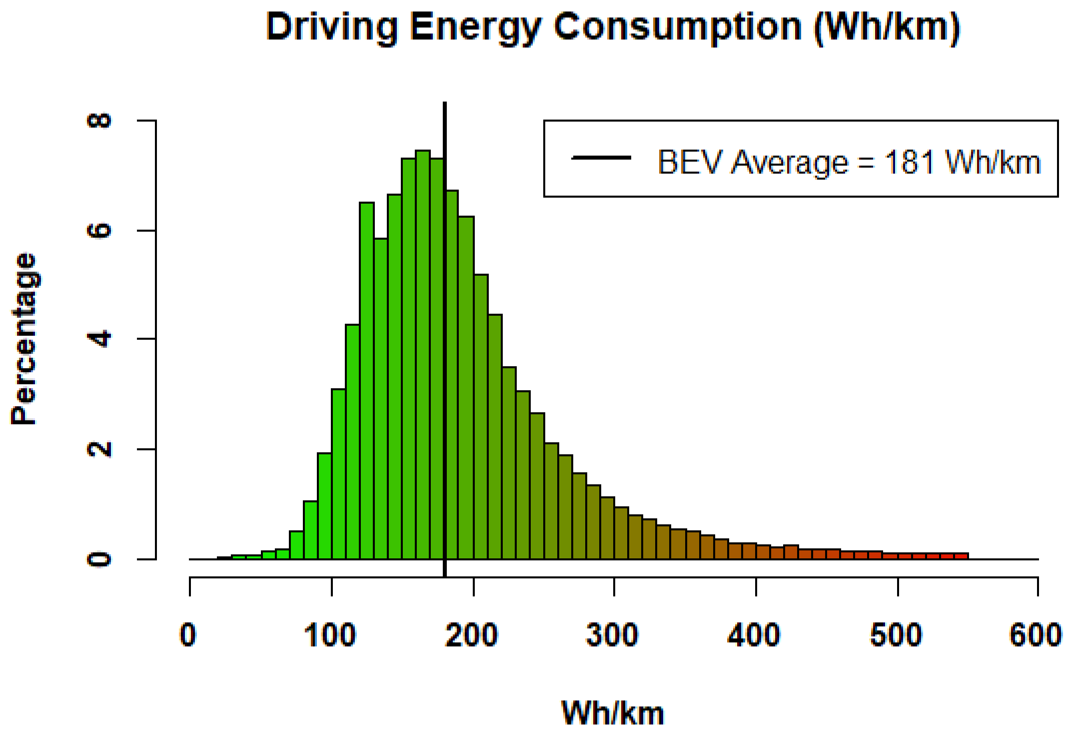

Figure 15: Distribution of average driving energy consumption (Wh/km) on the BEV trials.

To calculate the average energy consumption drawn from the electricity network, the efficiency of the vehicles' on-board charger should be taken into account. The AC charger is on-board the car and it converts power from the alternating current (AC) electricity grid to direct current (DC) in order to recharge the battery. The conversion will incur losses that needs to be accounted for and the efficiency of on-board charging systems will vary from vehicle to vehicle. Testing conducted by Idaho National Lab (INL) on several mass-market BEVs indicated that charger efficiency is generally 90% or greater [198], [199] which means that about 90% of the energy that comes from the grid actually goes to charging the batteries. A charger efficiency factor (1.1) should be included in the calculations of energy from the grid. Consequently, the overall average energy consumption for charging would be 199 Wh/km.

4.3 Analysis of Charging Patterns

Charging events on the SwitchEV and RCN trials are measured to provide empirical evidence on BEV charging patterns, which will be used to inform the subsequent chapters in this work.

It was demonstrated that driving behaviour of users, road network conditions and driving distance patterns are diverse. The –varied and diverse nature of driving patterns is reflected in the charging patterns, which will be used in this work. For example, at a lower battery SoC the battery would take more time and energy to recharge. The SoC levels recorded during the trial capture the behavioural diversity of the users. The boxplots in Figure 16 represent SoC levels for more than 25,000 charging events recorded on the trials. For half of the charging events, the SoC at the beginning of the events was above 54%, meaning that the battery was at least half-full when people plugged the car for charging (Figure 16, left). As expected, the batteries were close to fully charged at the end of charging events; however, there are some cases where a car was unplugged before it was fully charged (Figure 16, right).

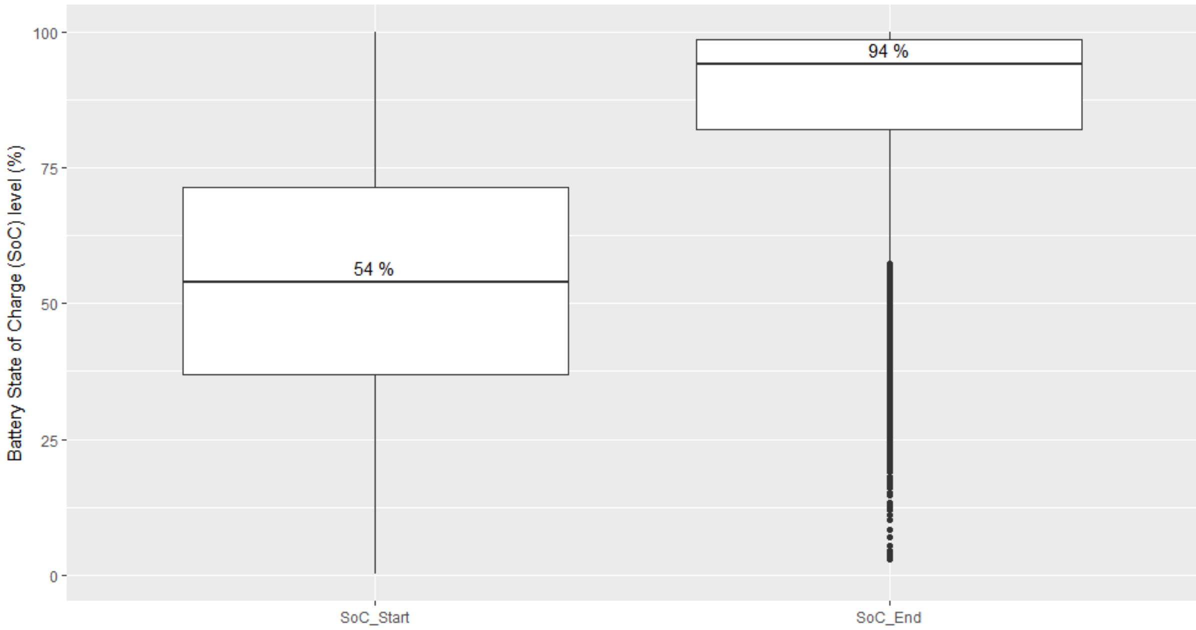

Figure 16: Boxplots of batteries' SoC at the beginning and end of charging events for private passenger cars on the BEV trials.

Figure 17 shows the range of values for the energy used between two consecutive charging events. The average energy used between charging events is 8.7 kWh for private passenger cars on the BEV trials. These findings are aligned with the distribution of SoC at the beginning of a charge event in Figure 16 (right), and showed that drivers were using less than half of the battery capacity between charging events.

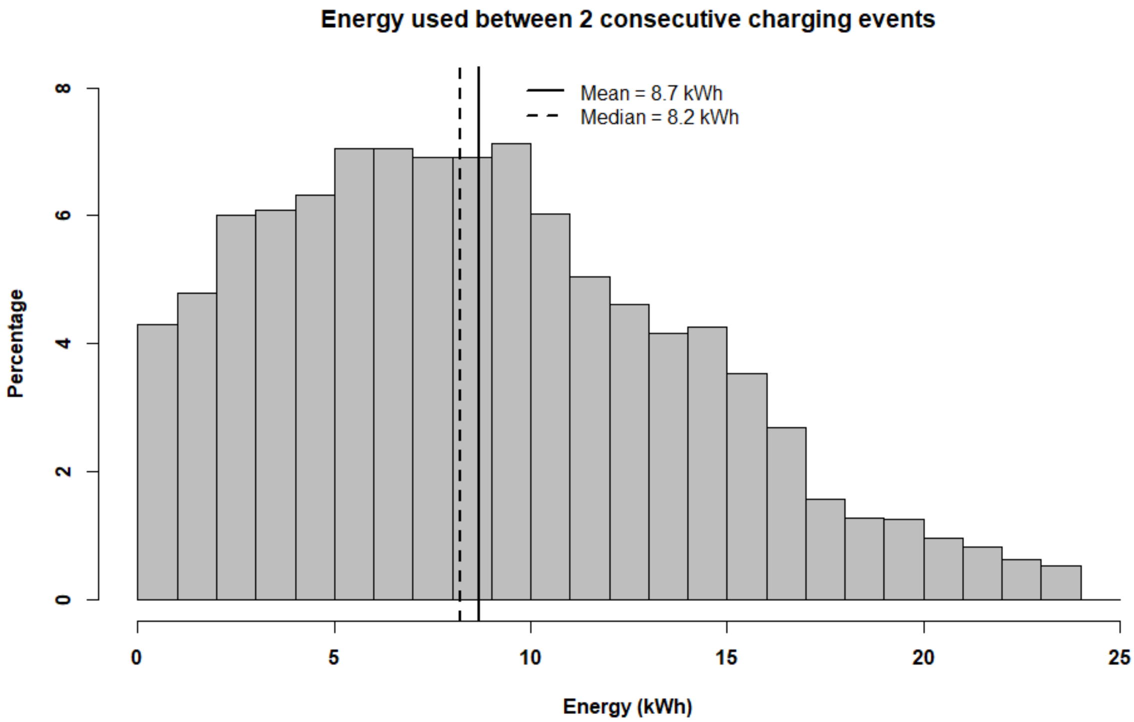

Figure 17: Energy used between two consecutive charging events.

Additional analysis was carried out to identify the percentage of the average energy transferred at different locations per hour of the day for urban and rural users on the SwitchEV trial (Figure 18 and Figure 19). To determine the residence setting (i.e. urban vs rural) of the users, the ONS postcode Directory (ONSPD) was used. Postcodes on the ONSPD are assigned to urban or rural categories [200]. The postcode of the participants were identified in the ONSPD and their residence setting was then determined. It was found that 70% of the users resided in urban areas while 30% resided in rural areas.

It can be observed that charging events were recorded at different locations (home, work, public, public-fast chargers). For urban users (Figure 18), most of the charging events happened during the day at work and at the public infrastructure, which included several chargers installed in city centre locations close to office buildings in Newcastle. For both participant types, home charging peaked in the afternoon as would be expected, and a noticeable additional charging peak occurred at midnight. The midnight peak could be explained by some home chargers equipped with a timer set to start charging at midnight. In addition, it could be that some users, especially in rural areas, are signed up for a differential energy tariff (i.e. Economy 7) where energy prices are cheaper for seven hours during the night. Finally, rural users (Figure 19) relied more on domestic charging compared to urban users.

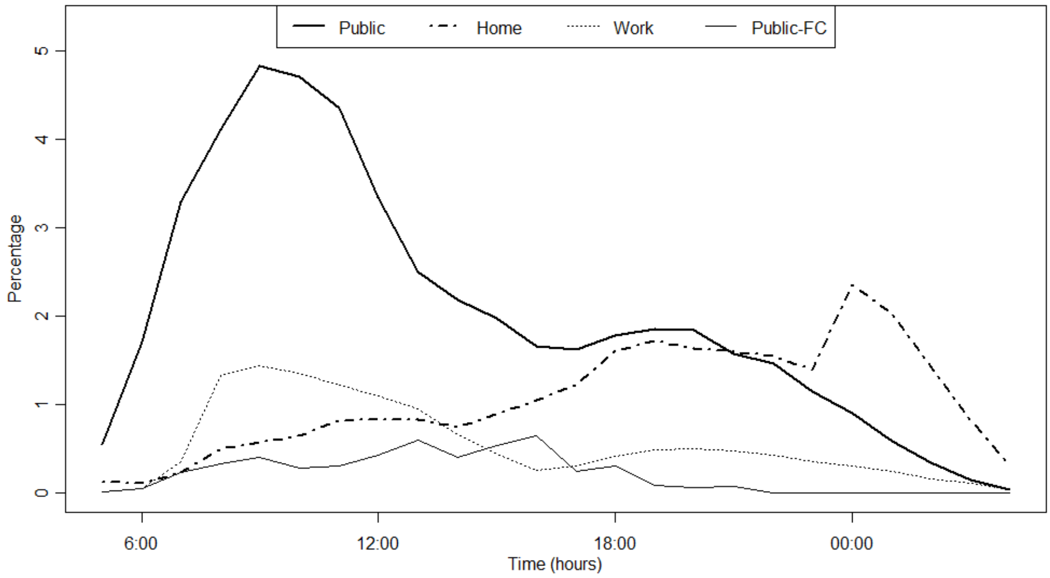

Figure 18: Percentage energy transferred at each hour of the day at different charging locations for urban users. Public refers to all public chargers except fast chargers (50 kW).

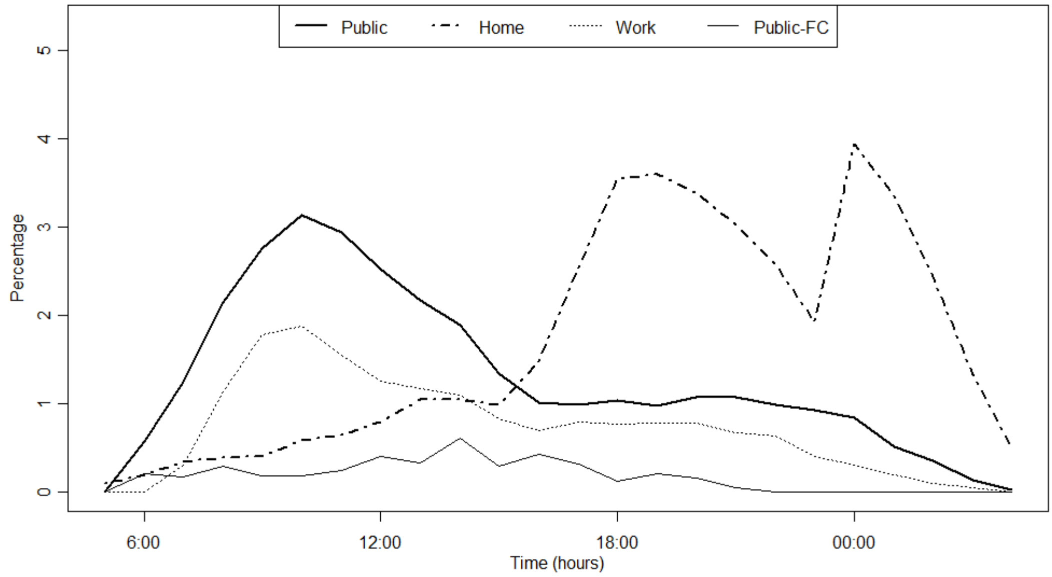

Figure 19: Percentage energy transferred at each hour of the day at different charging locations for rural users.

The extensive infrastructure allowed charging profiles to be spread across several locations and times. The charging events at home, for the urban and rural users were used in the electric distribution network impact study, which will be described in chapter 5.

4.4 Summary

The data collected on real world trials used for this work were described in chapter 3. In this chapter, the extensive dataset on driving and charging patterns collected was analysed using the R programming language. The analysis revealed usage patterns' insights that will inform the studies in the following chapters. The extensive dataset captured the stochastic nature of real world behaviour of BEV users and will enable detailed assessment of an integrated charging infrastructure appropriate for the uptake of BEVs.

Several factors impact the energy consumption on driving events, which will impact the achievable driving range of BEVs and the energy required at charging events. The trials' participants had access to an extensive charging infrastructure that spread their charging demand in space and time. In chapter 5, the home charging patterns will be used to investigate the impact on residential electricity distribution networks. While most daily driving distances can be met with existing BEV models on one charge, long driving events and associated charging events are analysed in chapter 6 to examine the importance of fast chargers for the adoption of BEVs.

Chapter 5. A Probabilistic Approach to Combining Smart Meter and Electric Vehicle Charging Data to Investigate Distribution Network Impacts[11]

In this chapter, a probabilistic method is used to combine two unique datasets of real world BEV charging profiles and residential smart meter load demand. The data was used to investigate the impact of the uptake of BEVs on electricity distribution networks. In addition, two real networks representing an urban and rural area, and a generic network representative of a heavily loaded UK distribution network were used for the impact assessment.

The findings show that distribution networks are not a homogeneous group with a variation of capabilities to accommodate BEVs and there is a greater capability than previous studies have suggested. Consideration of the spatial and temporal diversity of BEV charging demand has been demonstrated to reduce the estimated impacts on the distribution networks. It is suggested that distribution network operators could collaborate with new market players, such as charging infrastructure operators, to support the roll out of an extensive charging infrastructure in a way that makes the network more robust, increase its BEV hosting capacity, and create more opportunities for demand response.

Section 5.1 gives a brief overview of the power system, the challenges introduced by BEVs with an emphasis on electricity distribution networks, and a literature review of studies examining the impact of BEVs on distribution networks. The technical considerations of distribution networks are presented in section 5.2 and the contribution of this study in section 5.3. A brief overview of BEV charging control methods is described in section 5.4. The data, methods, results and interpretation of results are presented in sections 5.5 through 5.8.

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[11] The distribution network impact analysis has been published in the following papers:

Neaimeh M, Wardle R, Jenkins A, Hill GA, Lyons P, Yi J, Huebner Y, Blythe PT, Taylor P. A probabilistic approach to combining smart meter and electric vehicle charging data to investigate distribution network impacts. *Applied Energy* 2015, 157, 688-698 [16].

Neaimeh M, Hill GA, Blythe P, Wardle R, Yi J, Taylor PC. Integrating Smart Meter and Electric Vehicle Charging Data to Predict Distribution Network Impacts. *In: 4th European Innovative Smart Grid Technologies (ISGT) Conference*. 2013, Copenhagen, Denmark: IEEE [61].

5.1 Introduction and Related Work Within Area

Electric energy is the most versatile and useful form of energy available and the normal operation of our society depends on it. Electric energy is provided to customers by the electric power system, which consists of two subsystems. The physical subsystem involves the generation, transmission, and distribution of electricity to customers. Transmission refers to the transfer of large amounts of electricity at very high voltages from the main generation areas to major load centres, and distribution refers to the delivery of the electricity at lower voltages to customers. The second subsystem is the commodity subsystem in which the energy product is traded [201]–[203].

A traditional objective of system planning and operation of the power system is to provide secure, reliable and affordable electricity to customers. Conventionally, electricity is generated in controllable and centralised power stations based on fossil fuels, and transmission and distribution networks were designed for one-way power flows and uncontrollable loads [204]–[206]. However, the existing power system is experiencing fundamental change driven by a transition to a digitised, decentralised and decarbonised system including two-way power flows and the addition of new type of loads such as battery electric vehicles (BEVs) [207], [208].

If the number of BEVs increase to millions to meet the government's target of having all new cars zero emission by 2040 [28], the charging demand of these vehicles could have an impact on the whole power system (physical and commodity subsystems). The charging infrastructure of BEVs will be connected to low voltage (LV) distribution networks, therefore, it is likely that this part of the power system would face the first impacts of a large scale introduction of electric vehicles [7], [209], [210]. Consequently, LV distribution networks are the focus of this work as indicated in Objective 4 and Research Question 3 in chapter 1.

The average daily electricity use of a BEV is approximately 8kWh [17], [46], [47], which could almost double the average daily electricity consumption of a household-currently at around 10.8kWh [48]. Problems are more likely to arise if charging of cars coincide with each other or coincide with the existing peak electricity demand, which is at late afternoon until early evening in the UK [44], [49], [50].

Several studies have already examined the impacts of the uncontrolled charging of BEVs on distribution networks [7], [44], [45], [49], [50], [54]–[59], [211]–[214]. The predominant impacts on LV distribution networks are voltage drops and equipment overloading (e.g. transformers) which will be further investigated in this chapter. However, these previous studies based their work on estimated rather than actual BEV charging behaviour and real smart meter data. BEVs are not yet widely adopted[12] and most of the charging data used in these previous studies was derived from driving patterns collected in national transportation surveys. These surveys were analysed to estimate certain aspects of BEV usage such as journey distance and energy used, parking location and time, state-of-charge (SoC) at the beginning of a charging event and the plug-in time. Some of these studies assumed that the charging starts immediately upon the users' arrival at home while others assumed that a large proportion of charging starts from a low SoC. Furthermore, some of the studies considered that users would only charge at home and didn't consider the availability of a work and public charging infrastructure [44], [45], [49], [50], [54]–[59], [211]–[214].

Using these derived charging profiles for the studies, the impacts of uncontrolled charging scenarios in residential areas were demonstrated to be detrimental to the distribution network. Some work demonstrated thermal limit violations and voltage drops below acceptable limits for BEV penetration of 50% [54]–[56]. One study stated that with 50% BEV penetration, there would be significant impacts on the operating conditions of the distribution networks and uncontrolled charging could require major infrastructure upgrades [57]. Another study found that for a BEV penetration of 30%, voltage levels dropped to the statutory limit; actual load profiles were used but the BEV usage data was based on national transportation surveys and it was assumed that only home charging was available to the users [49]. One study showed that a 25% penetration of BEVs in residential areas would cause considerable voltage drops below the statutory limit [58] while [59] stated that the distribution network can handle only up to 10% EV penetration without changes in the usual electricity grid operation and planning procedures.

Some research was focused on British distribution networks. One of the earliest studies on the topic found that with a 30% BEV penetration level, the uncontrolled domestic charging

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[12] There were 230,000 BEVs worldwide and 10,000 BEVs in the UK at the time of the grid impact study in 2013 [215].

of BEVs starting at peak time caused voltage at the substation to drop below statutory limit [45]. Another study looked at the impact of uncontrolled charging of BEVs on the thermal ageing of transformers and found that BEV penetrations higher than 10% are detrimental to the transformer life [60]. Finally, a study found that 12.5% BEV uptake would cause severe impacts on the transformer and the LV underground cable supplying the households [44]. In that previous study, a probabilistic approach to address uncertainties associated with residential loads and BEV user behaviour such as plug-in time and SoC was used. The authors of that study suggested that real-world data of BEV usage comprising more accurate charge durations, connection times and a reflection on the use of the additional charging infrastructure (i.e. work, public) could be the focus of further work on the subject and may improve the probabilistic methods used [44].

5.2 Technical Considerations of Distribution Networks

BEVs could have significant impact on voltage and thermal overload levels at LV distribution networks as discussed in the previous section. Distribution network operators (DNOs) operate, maintain and invest in distribution networks. Consequently, DNOs need to properly understand the BEVs' impacts to maintain compliance with regulations and standards on electricity supply quality and security at the distribution level [216], [217]. This section describes in detail the technical considerations relating to voltage variation and thermal loadings in LV distribution networks.

5.2.1 Voltage

The power system consists of networks of various voltages[13] (Figure 20), with electricity transformers at substations used to change the voltage levels. High voltage levels are needed to maximise the transmittable power and reduce the power losses during transmission [201]. Voltage levels are then reduced in stages to reach safe and manageable voltage levels for consumer use [218]. In the UK, the final consumer feeders are at 400V three-phase, four-wire networks giving 230V single-phase supplies to houses and small commercial customers [204].

[13] Extra High Voltage (EHV) networks: voltage levels >300kV; High Voltage (HV) networks: voltage levels between 36 and 300kV; Medium Voltage (MV) networks: voltage levels between 1 and 36kV. Low Voltage (LV) networks: voltage levels < 1kV.

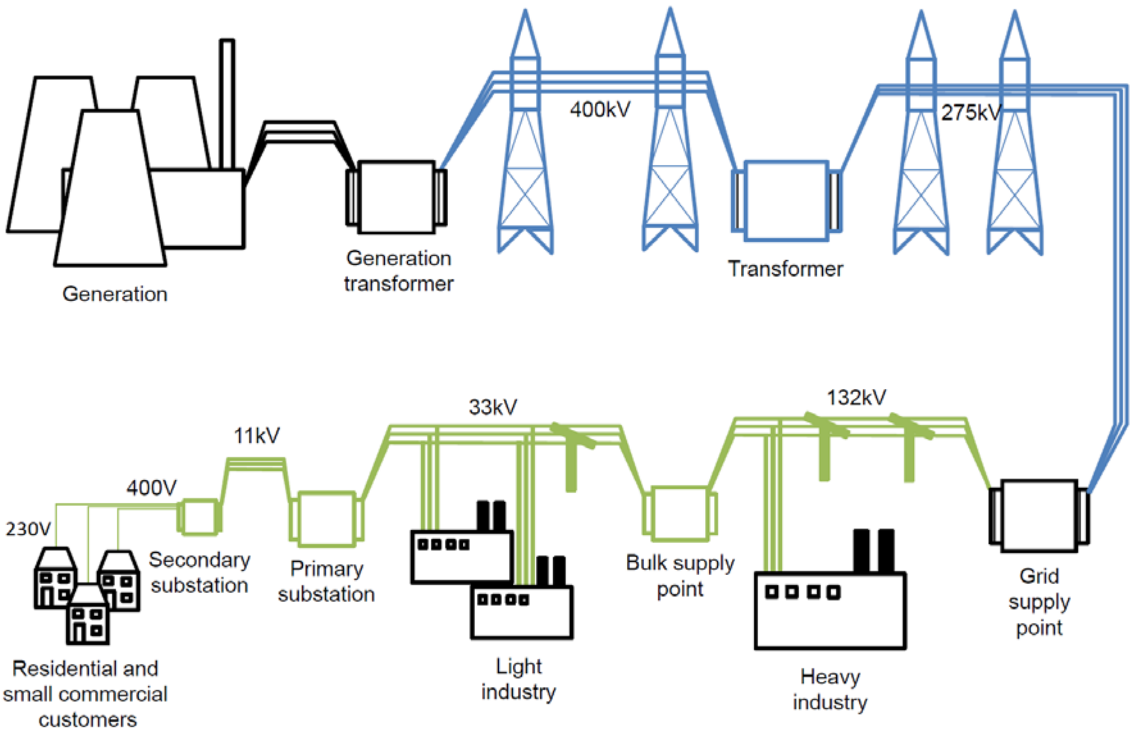


Figure 20: An overview of the power system (physical subsystem). The transmission network is shown in blue and the distribution network is shown in green [219].

The quality of electricity supply is considerably influenced by the quality of the voltage provided to customers. Equipment is designed to operate within a certain threshold and voltage characteristics outside prescribed tolerances can cause malfunction, shorten the life and even break the electrical equipment connected to the network and to the customers' appliances. The majority of customers take supplies at low voltage levels with no means of adjusting the voltage received, consequently an appropriate voltage quality is essential [220], [221].

5.2.1.1 Voltage quality standards

Voltage quality standards exist to ensure that the voltage supplied is within prescribed tolerances. The magnitude of the voltage supply to residential and small commercial customers should be 230 Volts. In the UK, the permitted deviations should not exceed 6% below or 10% above 230V (± 10% as per European standard EN 50160). This means that in the UK, the supplied voltage can vary between a minimum of 216.2V and a maximum of 253V and appliance manufacturers must take this allowed variation into account. In addition, 95% of the 10 minute mean voltages in a week should be within these limits with no overvoltage allowed [216], [217].

5.2.1.2 Voltage control

Networks experience voltage drops proportional to the loading, which is continually varying especially with the introduction of new and stochastic loads such as BEVs. There are several ways that DNOs employ to control the voltage. Transformers with on-load automatic tap changers are typically used on the HV/MV networks to regulate the voltages at the HV and MV busbars [220]. These transformers automatically change their turns ratios (and consequently voltage levels) in response to the changing load conditions. Transformers at the LV level have a pre-set and fixed tap position that can't be changed automatically. DNOs set this tap position to minimise the chance of under-voltage. In addition to tap-changing transformers, the DNOs can regulate the voltage by injecting or absorbing reactive power to maintain the magnitude of the voltage. This can be achieved by installing capacitor and reactor devices such as distribution static synchronous compensator (DSTATCOM) devices [204], [222]. Other methods include soft open points (SOPs) and energy storage systems (e.g. potentially BEV batteries) that could provide active and reactive power[14] management functions [222], [223].

The following section will demonstrate the relationship between voltage and real and reactive power flows. The aim of the following section is to demonstrate the impact of BEVs on voltage drops.

5.2.1.3 The relationship between voltage and real and reactive power flows and the impact of BEVs charging on voltage drops.

A simple system of a medium voltage MV/LV system supplying a load over a distribution line (Figure 21) is used to explain the relationship between voltage and power flow [201], [204], [220]. Figure 22 shows the equivalent circuit of the system in Figure 21 for the LV busbar and the load.

[14] Definition of electric circuit quantities including real, reactive, apparent and complex power can be found in circuit analysis books.

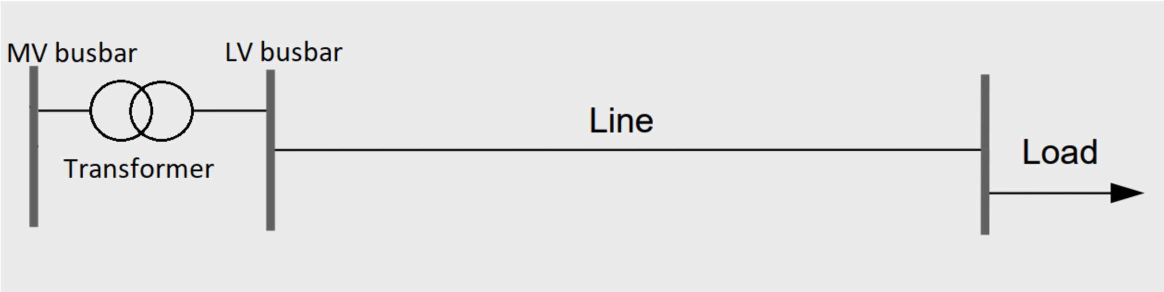


Figure 21: Illustration of a simple MV/LV feeder and load.

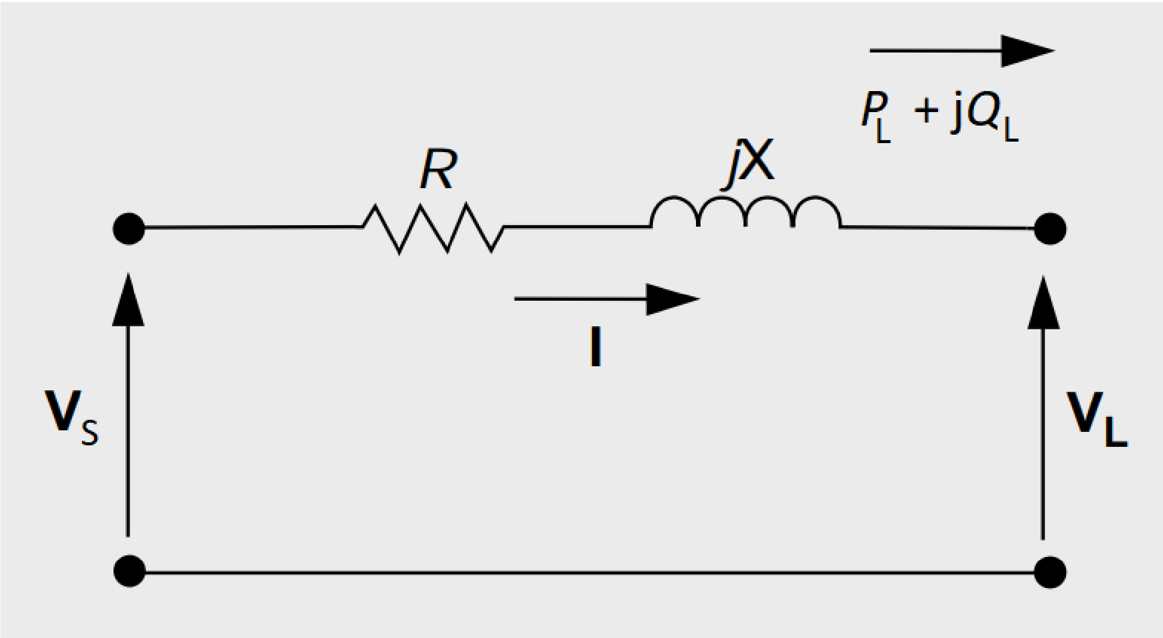


Figure 22: Power transfer between source and load.

The line resistance is R and the line reactance is X. The shunt susceptance of the line can be neglected for short lines [204] as is the case for a distribution network.

The complex power[15] of the load is expressed as:

$$\mathbf{S}_\mathrm{L} = \mathrm{P}_\mathrm{L} + \mathrm{jQ}_\mathrm{L} = \mathbf{V}_\mathrm{L}\, \mathbf{I}^*$$

And
$$\mathbf{I} = (\mathrm{P}_\mathrm{L} - \mathrm{jQ}_\mathrm{L})/\mathbf{V}_\mathrm{L}^*$$

The source voltage (voltage at the LV busbar) and load voltage are related by:

$$\mathbf{V}_\mathrm{S} = \mathbf{V}_\mathrm{L} + (\mathrm{R} + \mathrm{jX})\mathbf{I}$$

Substituting for $\mathbf{I}$ yields:

$$\mathbf{V}_\mathrm{S} = \mathbf{V}_\mathrm{L} + (\mathrm{R} + \mathrm{jX})[(\mathrm{P}_\mathrm{L} - \mathrm{jQ}_\mathrm{L})/\mathbf{V}_\mathrm{L}^*]$$

If the load voltage is chosen as the reference, then:

[15] Symbols in **bold** type represent complex quantities. A complex quantity can be written with real and imaginary parts (complex quantity= real + *j* imaginary); or complex quantity=Magnitude ∠ angle

$$\mathbf{V}_{\mathrm{L}}^{*} = \mathbf{V}_{\mathrm{L}} = \mathrm{V}_{\mathrm{L}}\angle 0^{\circ} = \mathrm{V}_{\mathrm{L}}$$

The voltage difference $\mathbf{V}_{\mathrm{D}}$ in the line is given by:

$$\mathbf{V}_{\mathrm{S}} - \mathbf{V}_{\mathrm{L}} = (\mathrm{R} + \mathrm{jX})[(\mathrm{P}_{\mathrm{L}} - \mathrm{jQ}_{\mathrm{L}})/\mathrm{V}_{\mathrm{L}}]$$

So

$$\mathbf{V}_{\mathrm{D}} = \frac{(\mathrm{RP}_{\mathrm{L}} + \mathrm{XQ}_{\mathrm{L}})}{\mathrm{V}_{\mathrm{L}}} + \mathrm{j}\,\frac{(\mathrm{XP}_{\mathrm{L}} - \mathrm{RQ}_{\mathrm{L}})}{\mathrm{V}_{\mathrm{L}}}$$

During normal power flow conditions, the angle between the receiving-end voltage (load voltage in this example) and sending-end voltage (LV busbar voltage in this example) is only a few degrees so the phase angle of $\mathbf{V}_{\mathrm{L}}$ can be considered equal to the phase angle of $\mathbf{V}_{\mathrm{S}}$ [220]. Consequently, the imaginary part of the equation above can be disregarded and the voltage difference is approximated as:

$$\mathrm{V}_{\mathrm{D}} \approx \frac{(\mathrm{RP}_{\mathrm{L}} + \mathrm{XQ}_{\mathrm{L}})}{\mathrm{V}_{\mathrm{L}}}$$

While the equations have been defined for flows along a line, they are appropriate for determining the voltage difference through any item of equipment in a network, knowing the equipment resistance and reactance and the load power or current and power factor[220].

It can be noted that the increase of real and reactive powers of the load by the addition of a BEV will impact the voltage difference V_{D} (i.e. voltage drop).

In LV distribution networks, the X/R ratios are typically low [221], consequently the impact of reactive power Q_{L} is lower than the impact of real power P_{L} on voltage. In addition, the BEV charger is assumed to have a lagging power factor close to unity (0.98) [224], therefore the impact on the voltage of the reactive power absorbed can be neglected in comparison to the real power absorbed.

As a result, it is clear that the addition of a BEV to the household ($\mathrm{P}_{\mathrm{Lnew}} = \mathrm{P}_{\mathrm{L\_household}} + \mathrm{P}_{\mathrm{L\_BEV}}$) will increase the active power demand and as a result the voltage drop is increased.

It is worth noting that most charging control strategies for solving voltage issues due to the introduction of BEVs would be modulating the charger active power demand.

On a side note, in the case of reverse power flow from distributed generation (real and reactive power is negative), the voltage difference might be negative and $\mathrm{V_L} > \mathrm{V_S}$ indicating a voltage rise instead of a voltage drop.

5.2.2 Thermal loading limit of equipment

The power handling ability of power systems' components such as overhead lines, cables and power transformers is limited by the thermal loading limit. The thermal loading limit (in volt-ampere) of a component is determined by the maximum current-carrying capacity $\mathbf{I}_{\mathrm{thermal}}$ of that component. If the thermal loading limit or the current-carrying capacity are exceeded, then there is a risk of irreversible damage to the equipment, which could lead to an interruption of electricity supply to customers [219], [225], [226].

An overload current, occurring during fault-free operating conditions, is a current greater than the maximum permissible current carrying capacity ($\mathbf{I}_{\mathrm{thermal}}$). The simultaneous use of several loads could lead to overloading of a cable or a line [227].

The thermal loading limit of a transformer is exceeded if the hourly maximum apparent power (kVA) is on average equal or above the transformer rating capacity (in kVA).

Communication with the DNO indicates that momentary and minor thermal limit violation (overload) are acceptable. An overload would need to be significant before it would be considered a problem, i.e. greater than 10% and present for 10 minutes or more.

It is worth noting that static ratings of power systems' components can be conservative. Actual component ratings is variable and influenced by environmental conditions such as air temperature or wind speed and direction. Replacing these static ratings with realistic ratings monitored and assessed in real-time could enable flexibility in distribution network management and increase the networks' hosting capacity to accommodate a higher share of distributed energy sources. Real-time rating technology includes distributed sensors and algorithms to estimate likely maximum component rating [228], [229].

5.3 Contribution of This Chapter

As discussed in the previous sections, the introduction of a large number of BEVs could have a significant impact on LV distribution networks. To accommodate a large number of BEVs while maintaining acceptable level of reliability and quality of supply at an economic cost, DNOs need to properly understand the changes on their networks for both long-term planning and real-time operation.

While previous studies based their work on estimated load and network data, the importance of real-world datasets to improve the findings has been emphasised [44], [222], [230]. The present work is significant because it is based on a unique combination of a comprehensive high resolution spatio-temporal real world dataset of BEV usage, residential smart meter dataset, and LV network dataset. The use of real-world data avoids the need to make assumptions about the stochastic nature of new disruptive loads.

The stochastic nature of vehicle use (e.g. variable plug-in time, plug-in duration and initial state of charge) introduces new patterns of loads that are not easily predictable. The uncertainties arising from BEV charging need to be properly examined to avoid underestimating or overestimating network impacts. Overestimating the impacts could lead to unnecessary and costly reinforcements. Underestimating the impacts could lead to breaching supply obligations, for example, an interruption of supply because of an outage caused by a transformer overload.

A deterministic method yielding a single answer won't be suitable to assess the impacts of stochastic BEV charging demand. In contrast, a probabilistic method, such as Monte Carlo simulation (MCS) used in this work gives a distribution of possible outcomes and how likely each outcome is to occur. As such, a probabilistic method captures the uncertainty and stochastic nature of BEV charging. The study provides the network operator with results in terms of a probability of encountering technical issues. This would allow the DNO to determine whether the probability of problem occurrence would be acceptable or whether remedial action would be required. The DNO may accept a low probability of a technical problem to avoid carrying out costly network reinforcements.

A robust investigation of LV networks, using real world data and a probabilistic analysis method, would help DNOs properly assess the capabilities of their networks to accommodate BEVs and examine the penetration levels that would trigger technical problems. The real world datasets and network models are described in section 5.5. The probabilistic methodology is presented in section 5.6, the results in section 5.7, and interpretation of results in section 5.8.

5.4 Brief Overview of BEV Charging Control Methods

This chapter proposes a preliminary approach to help DNOs optimise the infrastructure they currently have. This preliminary approach would help DNOs properly assess the capabilities of their networks and increase their hosting capacity to accommodate BEVs without significant changes to the planning and operation of their networks.

A subsequent approach, not examined in this work, is to investigate charging control methods that could further optimise the integration of BEVs in power systems. Control methods could shift BEV charging demand in time and/or reduce the charging power to avoid congestion of the electricity network. In addition, control strategies could match demand with supply from renewable energy, minimise the use of expensive fossil fuel peak power plants, and discharge BEV batteries to provide grid services such as frequency regulation or voltage support [231]. Various control methods exist to optimally integrate BEVs in power systems. These include simple charging control methods and complex charging optimisation methods. Simple control methods could be deployed locally in the car or the charger. The deployment of more complex methods, which simultaneously take into account the state of the network and a group of EVs would be distributed in several entities (i.e cars, chargers, an aggregator entity exercising some sort of control over a group of cars).

An example of a simple control method is setting a fixed off-peak charging profile to minimise the impact on local distribution network by shifting BEV charging from peak period. However, it is important to consider several objectives (in addition to minimising the impact on distribution networks) and constraints to optimally integrate BEVs in power systems. Some of the objectives include meeting user requirements, minimising cost of charging, minimising battery degradation, minimising impact on local distribution network, maximise integration of renewable energy, optimise whole-system integration (e.g. take into account trade-offs between local distribution networks and global transmission network) [232], etc. Some of the constraints include network limitations (e.g. voltage and thermal limits), user needs (e.g. high SoC by 7am), BEV characteristics (e.g. on-board charger power), etc. Consequently, optimisation methods are better suited than simple control methods for BEV charging. These optimisation methods take into account multiple objectives and constraints and use mathematical techniques to search for the optimal charging strategy [233], [234].

Example of optimisation methods used for BEV charging control include linear programming, mixed-integer programming, dynamic programming, game theory, and some meta-heuristic methods such as particle swarm optimisation (PSO) and genetic algorithms (GA) [233].

Several studies investigated the use of these advanced optimisation methods for the control of BEV charging [97], [233], [235], [236]. However, in real world demonstrations, most of the projects still focus on simple control methods. For example, My Electric Avenue is a real-world demonstrator of EVs and smart charging. In this project, a control algorithm managing EV charging points to mitigate thermal and voltage problems was implemented on 9 actual residential LV networks in the UK involving 86 EVs. The control algorithm consisted mainly of disconnection and reconnection of EV charging points depending on the state of the network. The infrastructure deployed on the charging control trial included controllable EV charging points, communication links, and substation sensors, making it a practical and acceptable solution to the DNOs [237]. Smart EV project is a follow-on project to My Electric Avenue and its aim is to investigate potential charging control strategies that could be practically implemented by the DNOs [153]. One of the most advanced real world demonstrators of managed BEV charging is the Parker project in Denmark. Parker project is a small scale project with 10 BEVs providing frequency response service to the TSO while respecting local LV networks constraints [135].

Complex optimisation methods require extensive information from the network, electricity markets and cars and communication and control infrastructure [237]. Real-time data and the communication and control infrastructure is still limited which could explain the simple control methods currently deployed in practice. In addition, advanced controllable EV charging hardware is still currently in very early stages of development. Also, there exist regulatory and market barriers that hinder the remuneration of services provided by an aggregated group of BEVs and controllable chargers. Consequently, there is an uncertainty regarding the business case of grid services provided by BEVs, lack of hardware, and uncertainty regarding customer acceptance. In summary, there are still many challenges facing the deployment of advanced control charging methods in practice.

The UK's Automated and EV Bill states the importance of charging solutions to mitigate the impact on power systems. The Bill gives power to government to mandate the provision of charge points that could adjust the rate of charging or discharging if these smart charge points are not delivered by the market. The Bill gives a clear signal to EV charging solutions industries to develop smart controllable charging points that could be implemented in practice on real networks. This could help the transition towards the development and deployment of more advanced controlled charging for an optimal BEV integration to the power system.

5.5 Data

5.5.1 Battery electric vehicles trial - SwitchEV project

High resolution spatial and temporal data on BEV driving and charging events were collected, processed and analysed during the SwitchEV project. The analysis of the SwitchEV dataset was carried out by the author. The dataset gave insight and illustrated the stochastic nature of real world behaviour of BEV users. The description of the SwitchEV trial and detailed analysis of the BEV data are presented in chapters 3 and 4. The dataset captured the diversity of the state of charge (SoC) of the BEVs' batteries at the beginning of a charging event (using 3.8 kW chargers) and the plug-in times, which resulted in a diverse range of realistic charging profiles. The SwitchEV trial collected data from users residing in urban and rural areas, subsequently highlighting their different charging requirements and behaviour. Finally, the participants had access to public, work and home charge locations and consequently were not limited to one charging location. This extensive charging infrastructure was reflected in the charging profiles and was key to the results obtained in this study that will be described in Section 5.7.

5.5.2 Smart meter data- Customer Led Network Revolution (CLNR) project

To understand present and emerging load and distributed generation patterns, the CLNR project conducted monitoring trials using data from over 9,000 smart meters placed in residential locations in the UK. The smart meter dataset is categorised by household income, presence of under 5s or over 65s, tenure, household thermal efficiency and area classification (urban/rural)[238]. UK ONS data was used to determine the characteristics of the study areas of this work, which are summarised in Table 6 along with the electricity network characteristics. Using the parameters in Table 6, a representative population of residential load profiles was extracted from the CLNR dataset representing the study areas.[16] Properties in the two regions were mostly mid-20th century semi-detached houses with adjoining off-street parking. Some communal parking facilities were also evident. Vehicle ownership was high and many households owned more than one car. Given these observations, these populations will be used in this work as model populations of potential future BEV owners on their respective networks.

	Urban	Rural
Substation	6.6kV / 400V 500kVA	20kV / 400V 315kVA
Feeders	4	2
Total LV customers	288	189
Number of Customers per LV feeder	A-59, B-66, C-84, D-79	A-123, B-66
Vehicle Ownership	86%	74.6%
No. of vehicles in vehicle-owning households	1.7	1.5
ONS Morphology Code	1 (Urban)	3 (Rural)
House thermal efficiency	Medium	Medium
Percentage households with under 5s or over 65s	44%	40%
Equivalent Annual Income (gross)	60%: >£30k 35%: £15-£30k 5%: <£15k	18%: >£30k 62%: £15-£30k 20%: <£15k
Tenure	Effective 100% home ownership	37% Renting 63% Owned
Household Occupancy	97%	97%

Table 6: Summary of LV network and population parameters [16].

[16] The ONS categorisation of the CLNR smart meter dataset and the data extraction from that dataset into several excel files was carried out by Robin Wardle.

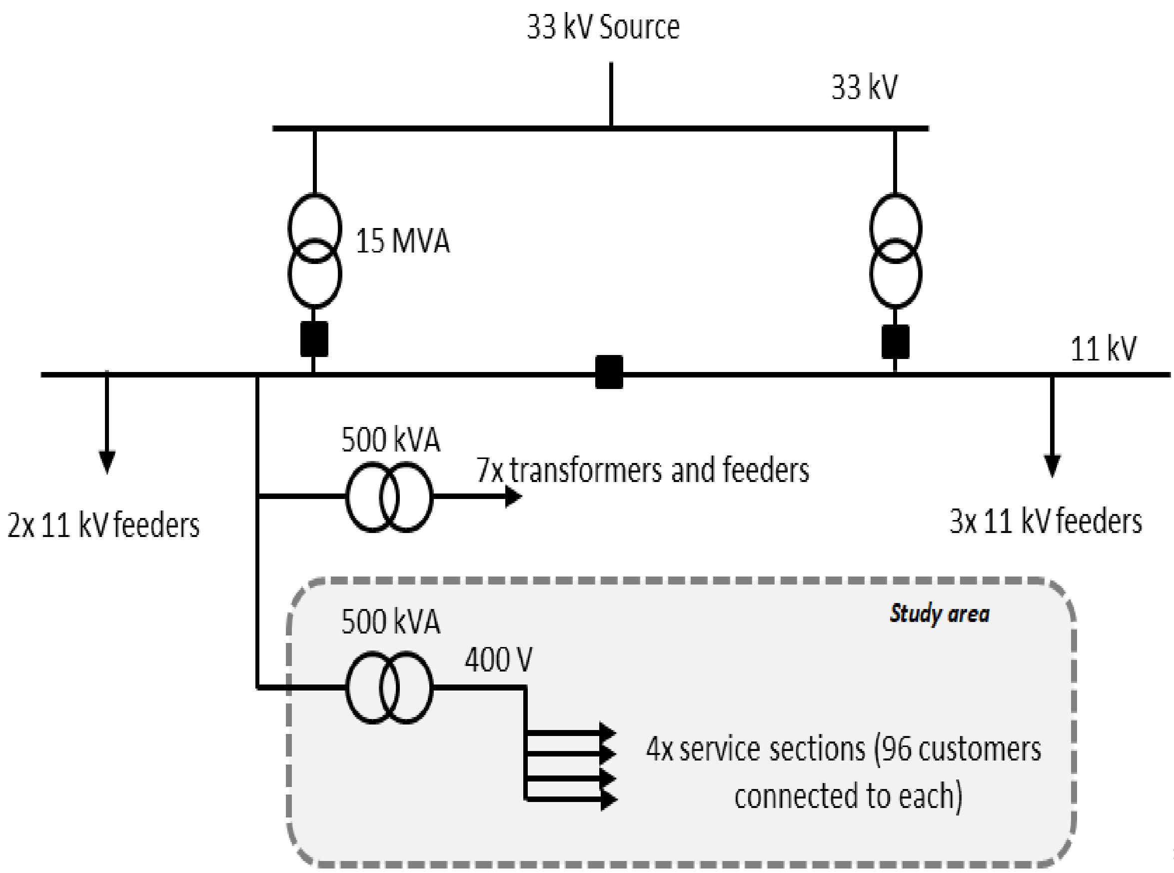
5.5.3 Network models

Three network models are studied in this work. One generic model representing a typical heavily-loaded UK distribution network and two case-study network models, one urban and one rural. The rural and urban networks give an indication to the problems that could be encountered in different types of networks. However, all networks are different and therefore the modelling of a specific system is required to establish if localised problems exist. The generic network has been used in this study to draw broad and generalizable conclusions across the UK LV distribution networks as a whole.

5.5.3.1 Generic network model

The generic network in this work is constructed following the specifications in [239] using OpenDSS version 8.1.4.1. OpenDSS is an open-source steady-state electric distribution systems' simulation tool developed by the Electric Power Research Institute (EPRI). It is designed for the unbalanced multi-phase distribution systems [240].

The generic network represents a distribution urban network from the 33kV substation down to the 230V low voltage distribution network. This network model is deemed to be representative of a heavily loaded UK distribution network by UK DNOs who were involved in specifying and creating it. For this work, the modelled area of the network is shown as *"Study area"* in Figure 23.



[17]

Figure 23: UK generic network used in steady-state OpenDSS and IPSA2 studies [16].

The modelled LV network starts at the 500kVA transformer, 400V substation. From the 400V substation, there are four 400V three-phase outgoing radial feeders, each 300 meters long. 384 domestic single-phase loads are distributed equally between the four feeders, resulting in 96 loads per feeder. The population parameters for the 386 customers under study on the generic network were assumed to be the same as the urban network described previously in Table 6.

Adapted from [239], Figure 24 illustrates one of the feeders that was modelled in detail and how the loads were allocated across the three phases of the feeder. The detailed feeder is divided into 4 segments. Each segment requires data for the feeder cable and service cable that are available from [239]; and customer load (including the BEV load depending on the BEV penetration level) available from the MC simulation results. The feeders' 96 residential loads are spread across 4 segments. Each segment has 24 customers- 8 customer per phase.

[17] Figure 23 illustrating the generic urban network and Figure 25 and Figure 26 illustrating the CLNR case-study urban and rural networks were carried out by Andrew Jenkins.

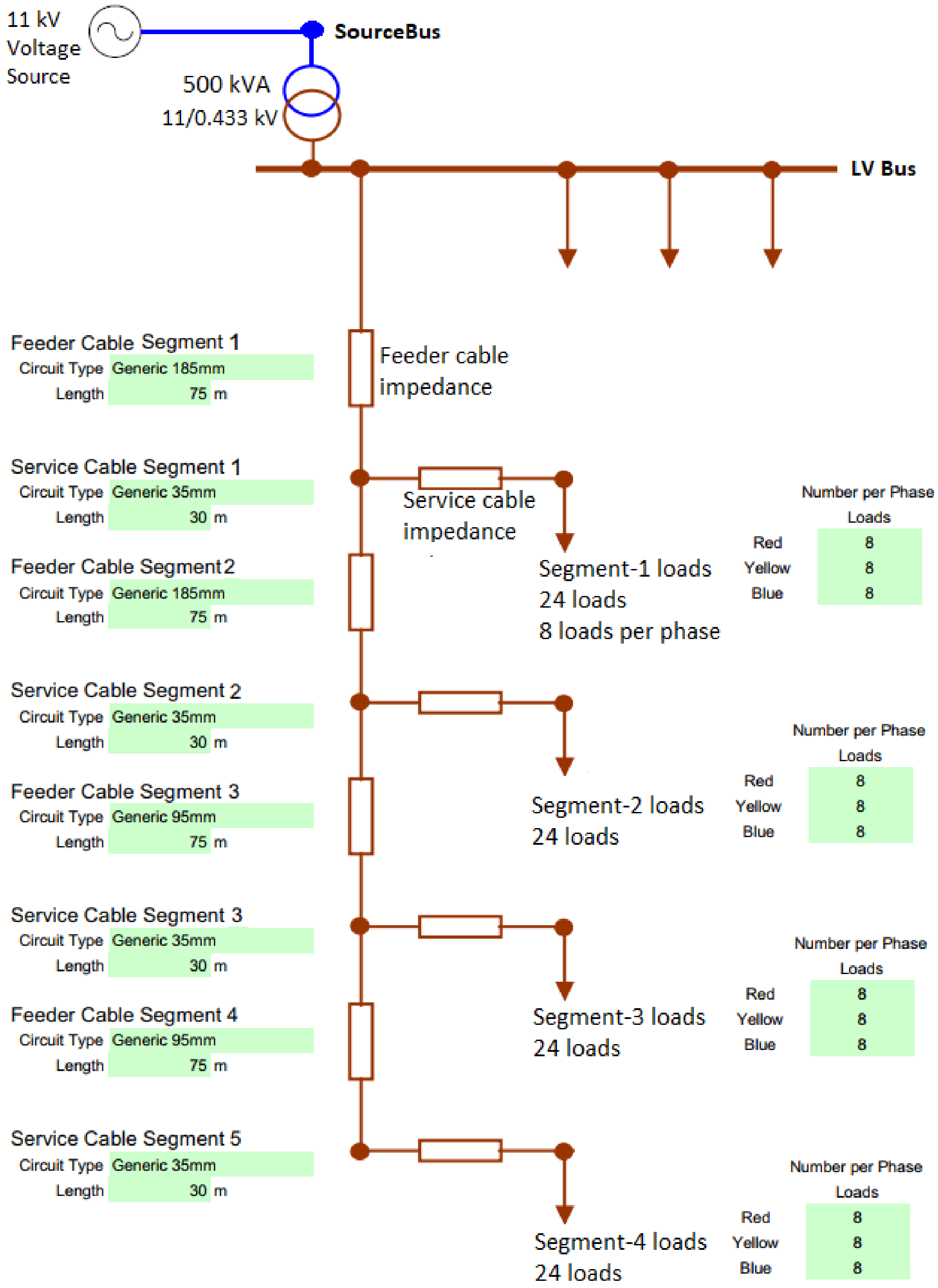


Figure 24: Detailed modelling of a LV feeder. Adapted from [239].

5.5.3.2 Case study real-world urban and rural networks

Previous work suggests that densely-populated urban and sparsely-populated rural LV networks are both likely to be vulnerable to the mass uptake of EVs [212]. As these two network types are estimated to represent approximately 80% of UK networks [214], it is of critical importance to further examine these scenarios. The CLNR project used two real networks within Northern Powergrid’s licence area – one rural and one urban – to enable evaluation of load growth and active network management. Models of the trial networks have been developed in IPSA2, a steady-state power system simulation application. These have been extensively validated with two years of detailed network data and against existing DNO network models (using data provided by Northern Powergrid).

The urban network under study (Figure 25) is a 6.6kV network supplying approximately 6,000 customers, with a mixed load curve and an early-evening peak. One particular HV/LV substation supplying 288 customers via a 500kVA transformer and 4 LV feeders has been studied in detail as a test case for BEV penetration.

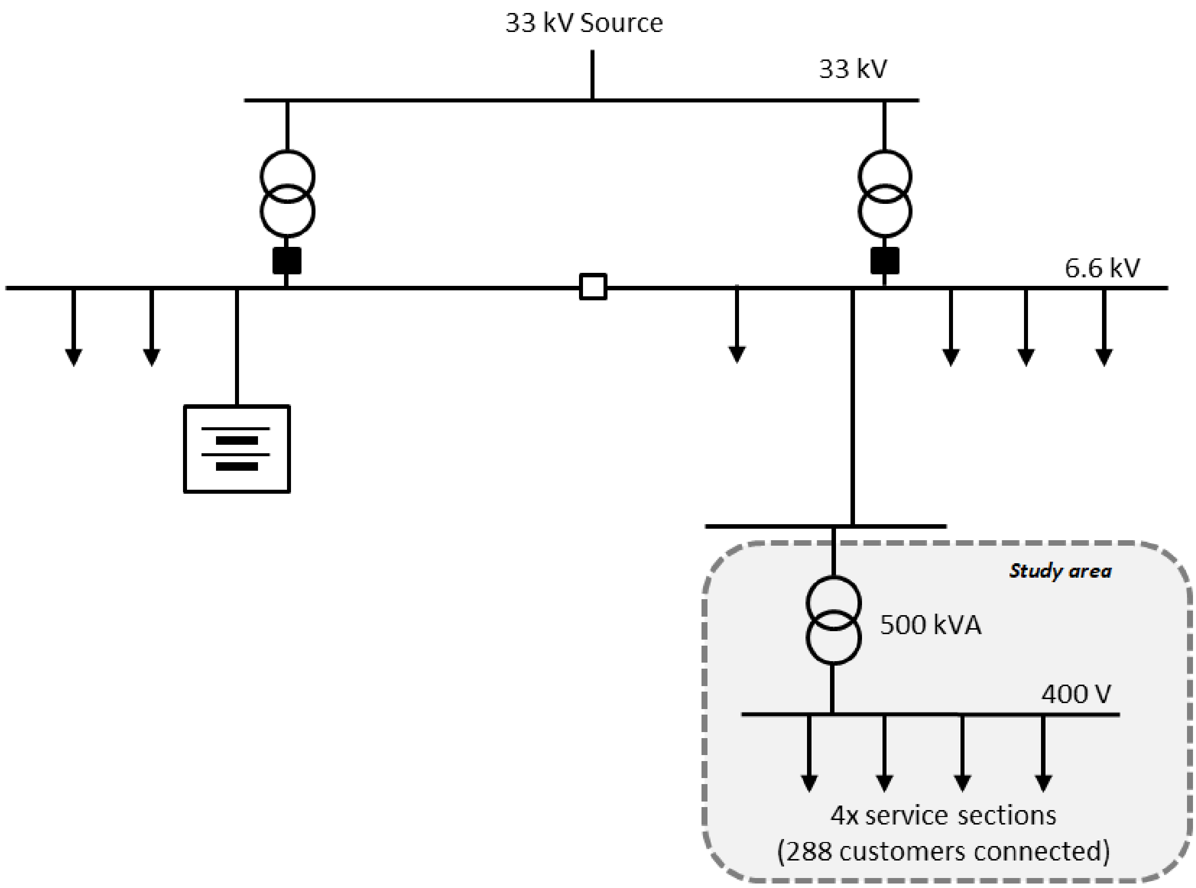


Figure 25: Diagram of the 6.6kV case-study urban network used in steady-state IPSA2 study [16].

Figure 26 shows the rural network under investigation. This consists of a 20kV feeder, approximately 40 km long, supplying a number of towns in Northumberland in northern England. Three HV/LV substations supply one of these towns; and this paper focuses on one of these substations which supplies 189 residential properties through two multiply-branched LV feeders.

The LV network sections under study are exclusively residential with no industrial or commercial facilities or public BEV charging infrastructure supplied by the HV / LV transformer

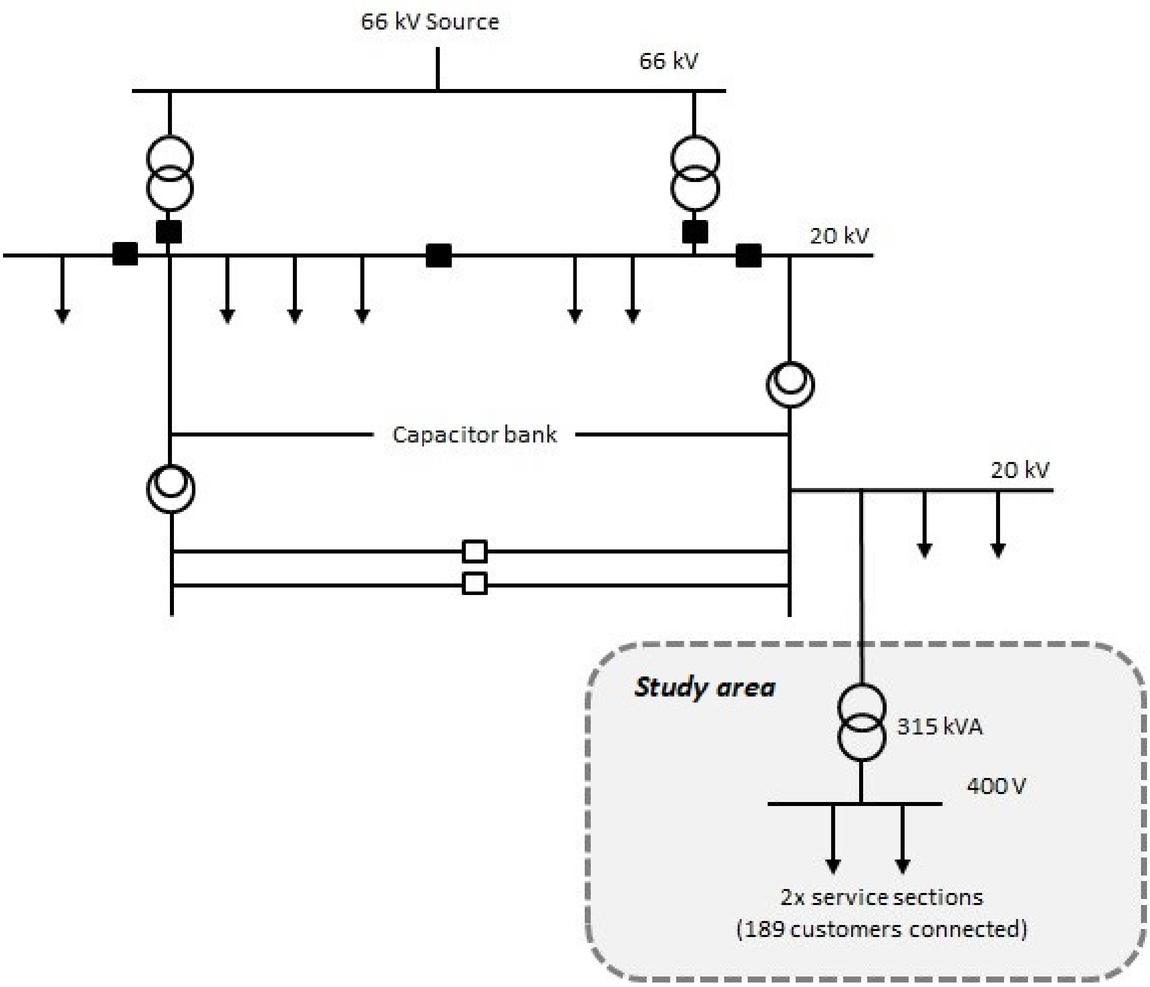


Figure 26: Diagram of the 20kV case-study rural network used in steady-state IPSA2 study [16].

5.6 Analysis Methods

5.6.1 Monte Carlo simulations

Peak consumption of electricity is in winter in the UK. To assess the additional impact of BEVs during an existing peak loading event, a single peak load test day corresponding to the DNO's system peak load day in January is studied.

Monte Carlo Simulation (MCS) was used to build up a distribution of possible demands on the trial networks. Data for the simulation was produced by sampling the domestic load profile and BEV charging profile populations. Households on the LV networks were randomly assigned load profiles in proportion to the local demographic makeup. A defined percentage of these users, corresponding to a level of BEV penetration, were further assigned a BEV load profile which was added to their base domestic profile. BEV penetration is defined as the ratio of BEVs to the number of vehicle-owning households. For the case of the urban network with 288 customers and a vehicle ownership of 86%; 60% penetration (149 EVs) represents an approximate nominal upper bound on the test networks whereupon all households owning more than one vehicle have a BEV as the second vehicle.

1,000 simulated peak days (i.e. 1,000 MC simulation runs) were generated to ensure adequate variation of customer behaviour, BEV charging profiles and customer location on the network. The generation of multiple random configurations naturally captures any spatial concentration of households with BEVs (e.g. at the remote end of the longest feeder) which could cause additional voltage drops. Figure 27 shows some illustrative examples from the urban profiles population assigned to customers. Specifically, peak day load profiles for two random customers are shown for two different Monte Carlo simulation runs out of the 1,000 simulation runs. It can be noted that for three out of the four illustrated profiles, BEV charging took place around the existing electricity peak demand, which is at late afternoon until early evening in the UK. There was no BEV charging for one out of the four illustrated profiles (first customer at the 1,000 MCS run).

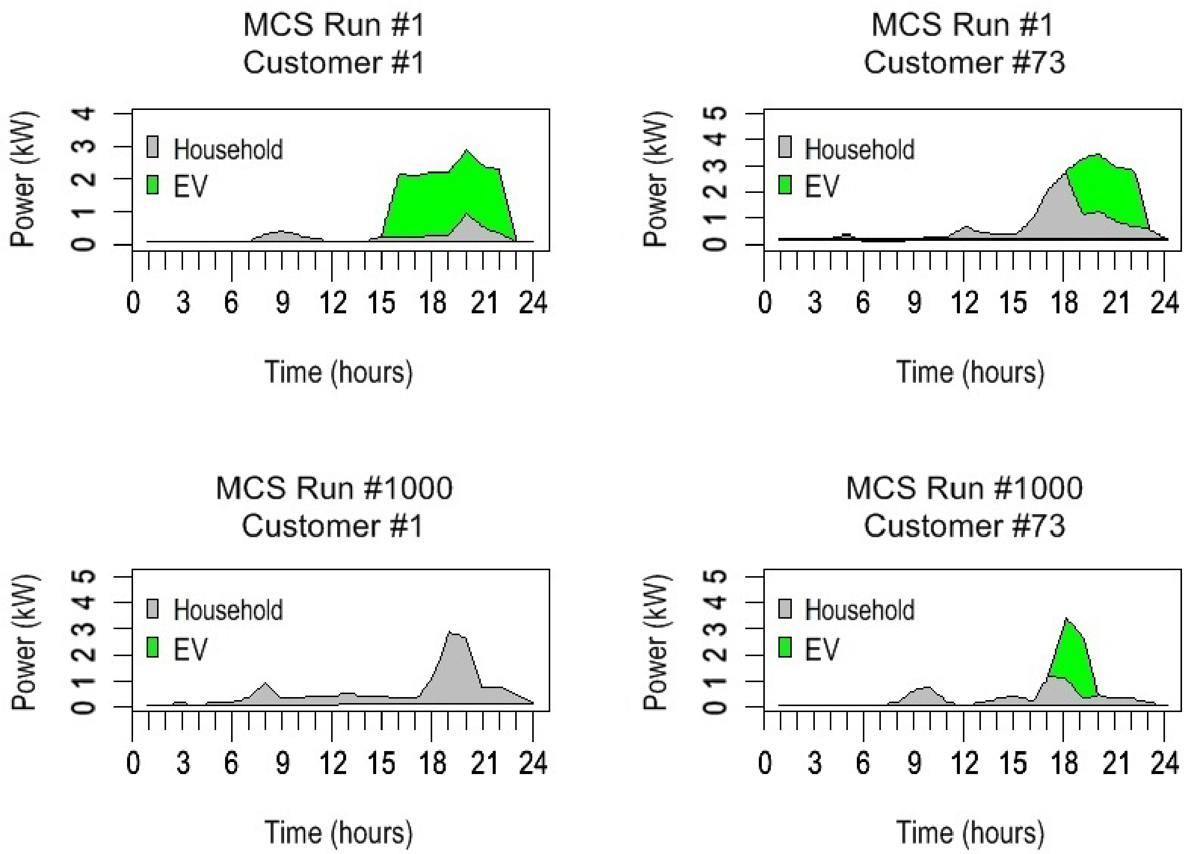


Figure 27: Example of peak day load profiles for 2 customers (#1 and #73) on the network for 2 different MCS runs (run #1 and 1000). Each MCS run generates a population of customers as defined by the network topology.

The average hourly load profiles (expected values) of the households on the networks with a defined BEV penetration were calculated from the 1000 runs. In addition the 2.5% and 97.5% lower and upper bounds of the data were calculated. Figure 28 illustrates these calculations for the remote end of the longest feeder on the urban network (10 households connected) at 60% EV penetration; the expected values are represented by the black dots and 95% of the data falls within the grey area. The MCS code was developed in the R programming language and can be found in Appendix A- R code for Monte Carlo Simulation. The resulting distributions of possible demand are then used to run power flow simulations as illustrated in Figure 29 and described in the following section.

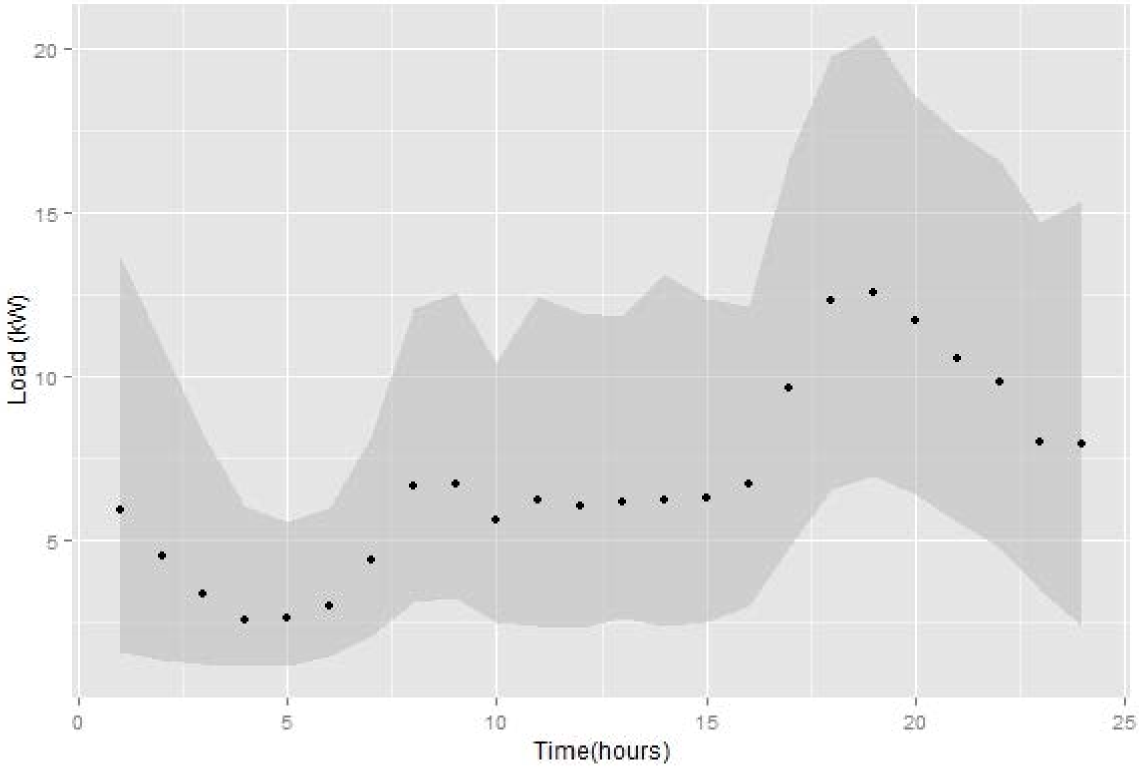


Figure 28: Remote end of longest feeder-Urban 60% EV penetration. Average load values (dots) and 95% data bound (Grey area).

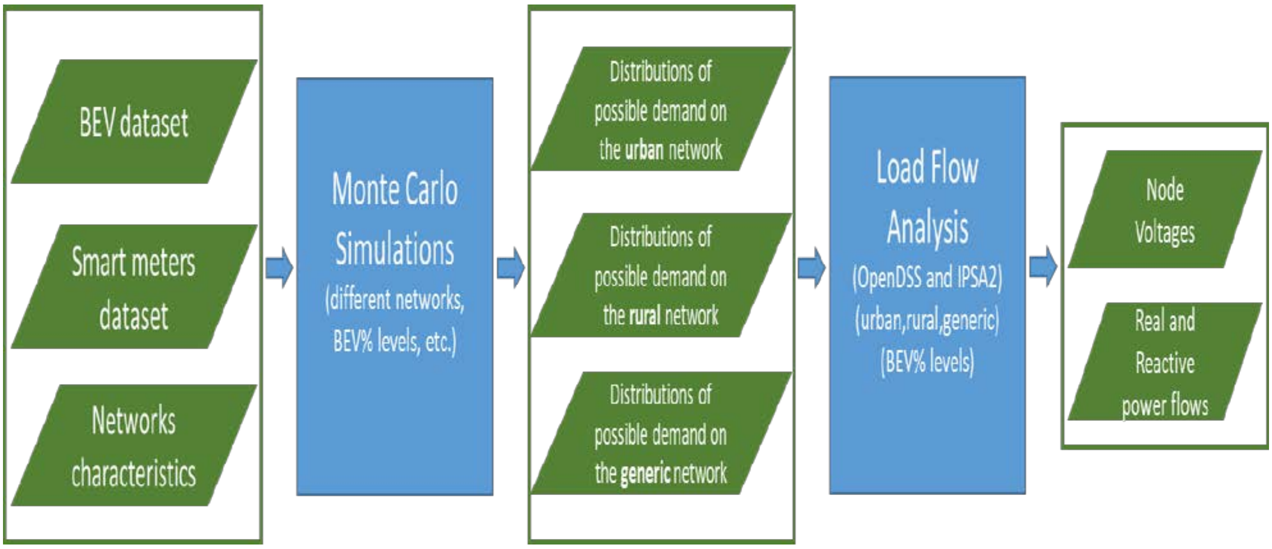


Figure 29: Methodology process diagram.

5.6.2 Power flow analysis[18]

To determine the voltage levels at different nodes of the network and the loading of equipment, a power flow analysis, also known as load flow analysis is undertaken. Power flow studies are the backbone of the power system and they are necessary for the planning and operation of power systems [204], [225]. A power flow study provides information on the voltages of the busbars and the flow of real and reactive powers in each line of the electric network, under existing and anticipated conditions of normal operation[202].

The objective of a power flow analysis is to solve a group of non-linear equations representing the state of the power network in steady-state conditions. The node-voltage method, based on Kirchhoff's current law (KCL), is commonly used to formulate the network equations for power system analyses. The set of non-linear equations are solved using iterative techniques [201], [218], [225].

There are several mathematical methods to solve a system of non-linear equations. Common methods used to solve power flow problems in networks include Gauss-Seidel and Newton-Raphson and these methods are the basis for many power flow computer programmes [241]. The description of the power flow solution in OpenDSS is described in Appendix B. OpenDSS was chosen as the main power flow simulation tool because it is open-source and allows three-phase four-wire representation of networks, therefore avoiding the need to assume balanced conditions across the three-phases.

5.6.2.1 Power flow study in OpenDSS for a UK generic network

To assess the BEV hosting capacities of LV networks, time series power flow simulations for the generic network were carried out in OpenDSS. OpenDSS adopts a realistic representation of the unbalanced nature of LV networks. The 97.5% upper bound load data was used for BEV penetration levels of 15, 30 and 60% to investigate voltage drops. Two additional BEV levels, 40% and 50%, were studied to consider the thermal loading of the transformer in

[18] All the impact analysis work was carried out by the author except the IPSA2 modelling and simulation which was carried out by Jialiang Yi. The urban and rural IPSA2 models had been already developed for the CLNR project prior to the BEV impact study carried out for this thesis. The data preparation and the Monte Carlo Simulation to provide input the IPSA2 and the analysis of the results from IPSA2 were carried out by the author.

greater detail. The 97.5% level gives a probability that 97.5% of load will be equal or less than a certain value. Therefore, the results of the network simulation produced voltage and thermal overloads levels for 97.5% probability of the load level. The OpenDSS simulation files examining voltage drops for 60% BEV penetration are presented in Appendix C.

5.6.2.2 Power flow study in IPSA2 for the urban and rural networks

The urban and rural networks were simulated as a balanced three-phase networks in IPSA2. Time series network simulation was performed using the mean and 97.5% upper bound load data for BEV penetration levels of 15, 30 and 60%, producing corresponding power flow and voltage drop results for the various configurations of the two networks.

In addition, IPSA2 was used to simulate voltage drops in the generic network modelled as balanced three-phase. This allows the comparison of voltage drops on the generic network simulated using OpenDSS.

5.7 Results

The results from the simulations were collected and examined to assess the impact of BEVs on transformer loading and voltage drops.

5.7.1 Transformer loading

Figure 30 shows power demand profiles for the generic LV network on the test day for the different BEV penetration values. Using the 97.5% upper demand limit, the loading exceeded the transformer rating capacity (500kVA) at 30% BEV penetration.

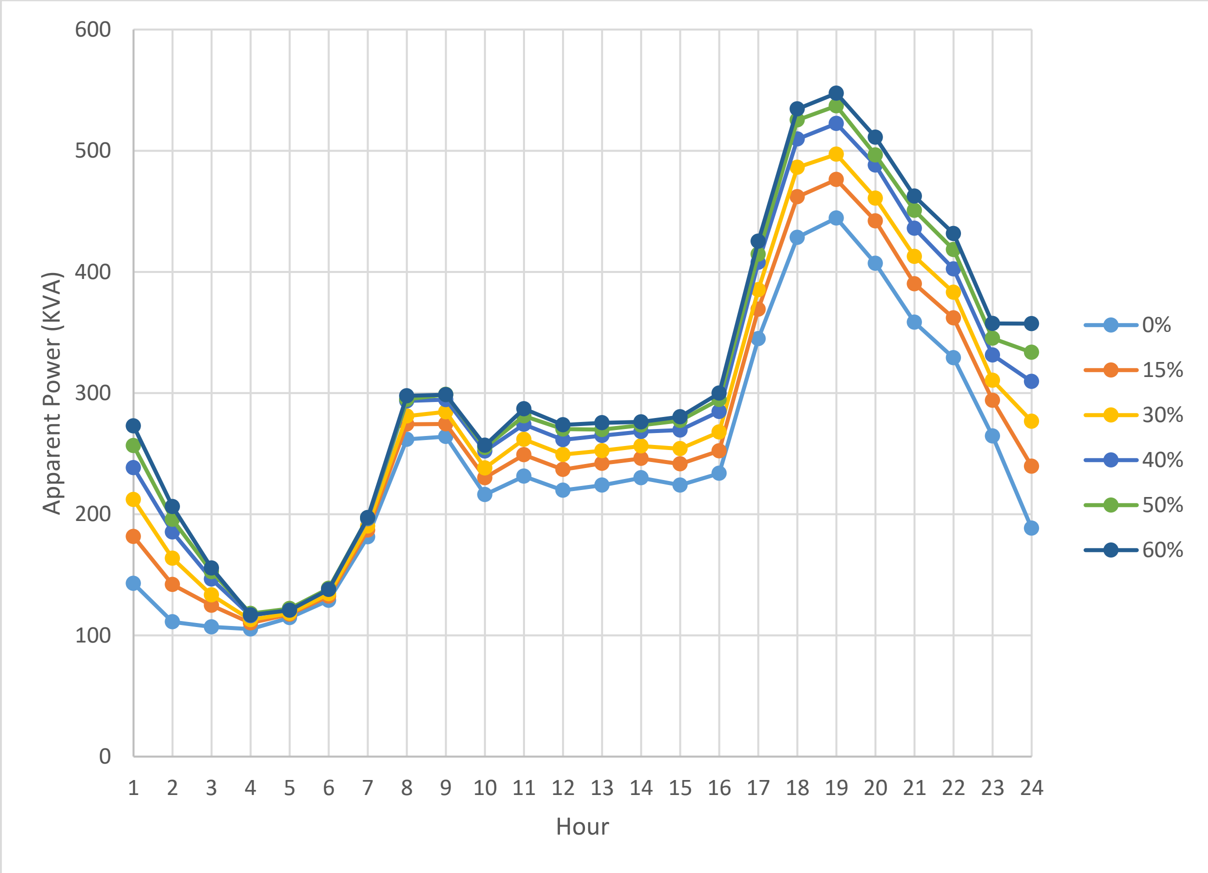


Figure 30: LV transformer loading for the generic network at different BEV% levels.

The power demand profiles for the urban and rural networks on the test day are shown in Figure 31. The transformer thermal limit was not exceeded using the mean load data. Using the 97.5th upper bound load data, the urban network was not compromised even at 60% BEV penetration, although at this point the load was approaching the transformer rating (500kVA). The rural network was compromised at 15% penetration.

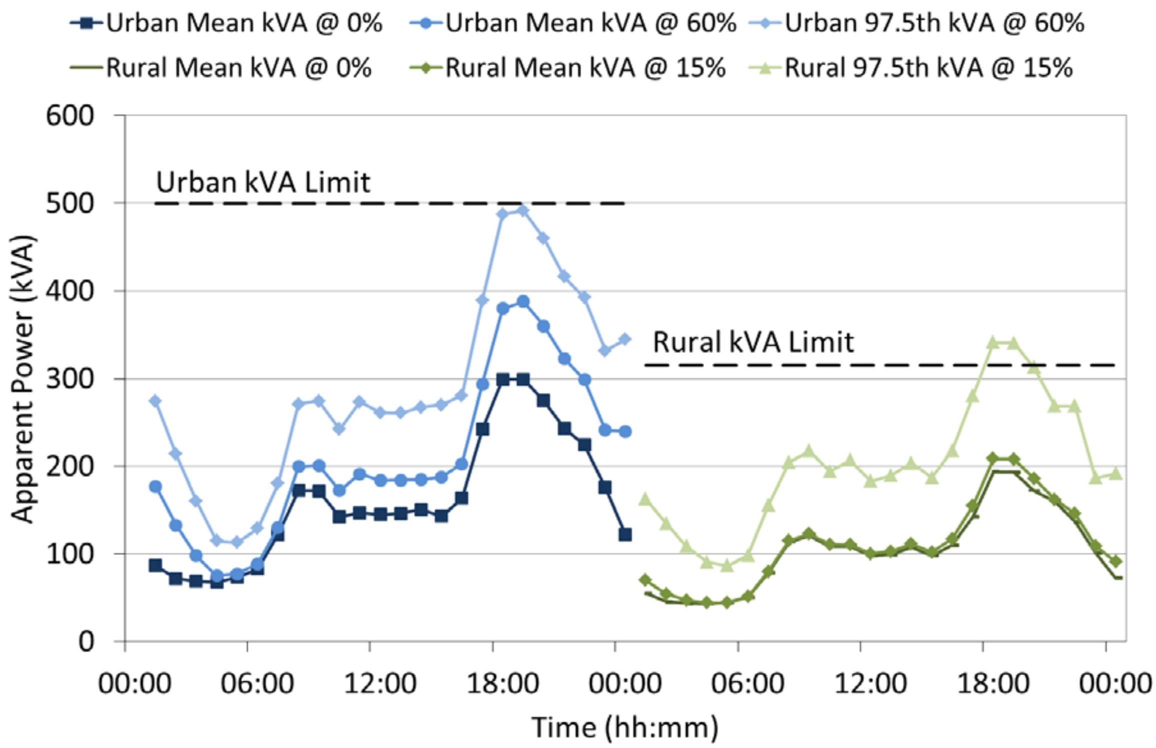


Figure 31: LV transformers loading for the urban (left) and rural (right) networks[16].

A comparison between the number of customers and transformer capacity rating between the generic network and case study urban network could explain the occurrence of transformer overload at a lower BEV penetration for the generic network. While the transformer capacity rating is 500 kVA for both networks, the generic network accommodates 386 customers compared to 288 for the case-study urban network. The network characteristics (number of customers and transformer rating) of the generic network were also compared to a number of real world LV residential networks in the North West of England that were modelled and characterised [242], [243]. Some of the main features of these characterised networks include an average number of 58 customers per feeder, an average capacity of 735kVA for the distribution transformers, and an average number of 5 LV feeders per substation [243], [244]. Comparing the characteristics of the generic network used in this study to several real world residential networks could indicate that the transformer loading results obtained using the generic network might be conservative.

5.7.2 Voltage drops

The voltage magnitude in LV networks is required to be within the statutory limits -6/+10% [216], [217]. As previously explained, the additional load from BEVs would cause the network voltage to drop and the minimum allowed statutory voltage limit is 216.2 V.

The lowest voltage magnitude levels for the generic network were captured at 19:00 and the voltage drop along one of the phases of the modelled feeder is shown in Figure 32. The voltage magnitude at the substation is 249V, which reflects a voltage boost employed by the DNOs to offset typical LV distribution networks voltage drops [204]. It can be noted that, for all the BEV uptake levels simulated, the minimum voltage magnitude occurring at the customer connection point (237.6 V) is well above the minimum statutory limit (216.2 V).

There will be a difference in voltages at customer connection points depending on the customer's distance from the substation, with customers at the lowest end of the feeder having lower voltages [204]. The variation in voltage levels between customers is illustrated in Figure 33 for 60% BEV penetration between a customer at the beginning of the feeder (closer to the substation) and a customer at the remote end of the feeder.

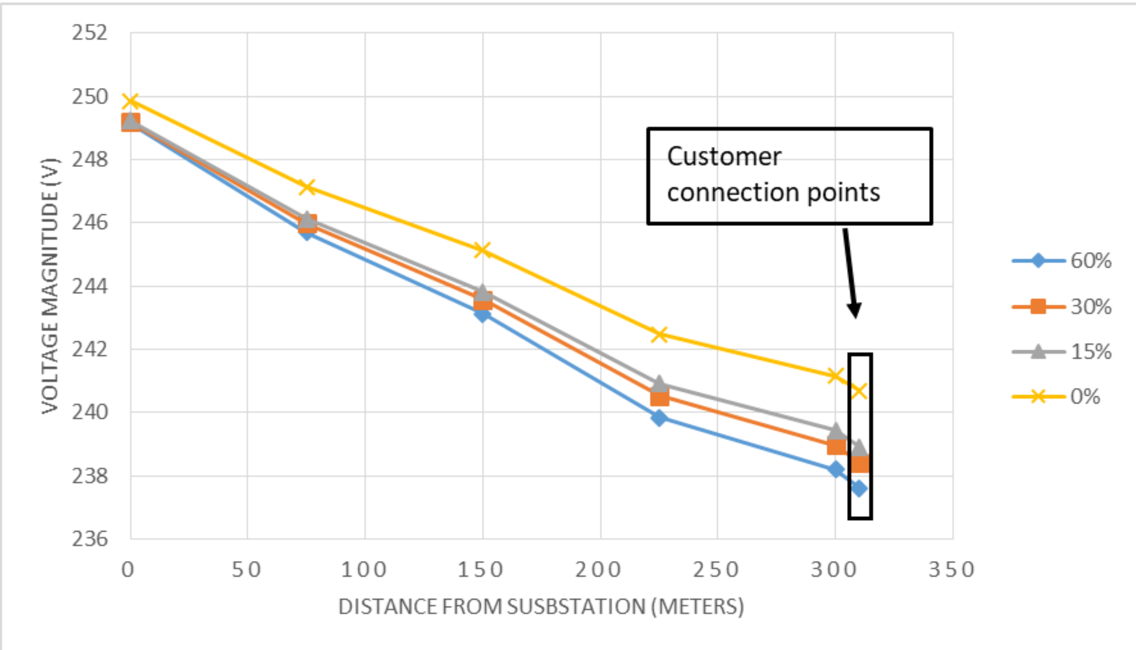


Figure 32: Voltage levels at 19:00 for different BEV % - voltage drop along one of the phases of the feeder and at customer connection point (example for a customer at the end the end of the feeder).

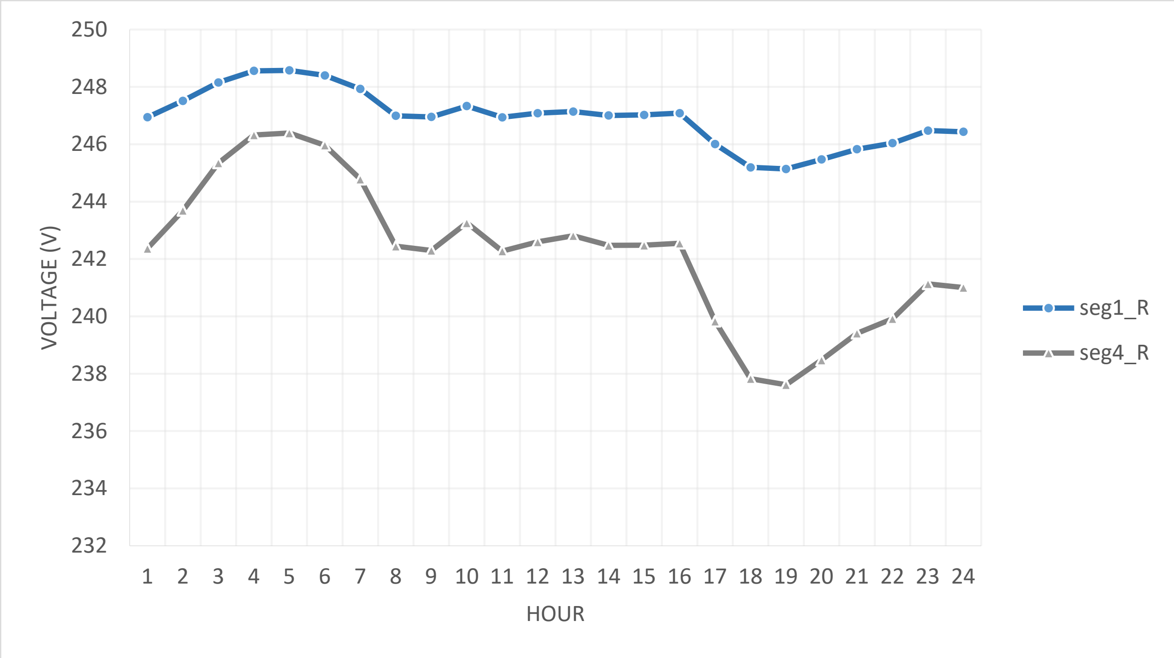


Figure 33: Voltage variation at the beginning (seg1) and at the remote end (seg4) of the feeder for 60% BEV penetration.

The maximum voltage drops on all the studied networks, for different penetration levels, are shown in Tables Table 7, Table 8 and Table 9. The voltage drop is expressed as a percentage drop from the voltage measured at the substation (e.g. 249.1 V for the generic network). As an example, 4.63% drop corresponds to (237.6 – 249.1)/249.1=-4.6%. The negative sign of the voltage change indicates a voltage drop. Voltage drops on all networks for all BEV penetration levels were above the minimum statutory limit.

Lowest voltage drop (Generic network)	15% BEV (97.5% load)	30% BEV (97.5% load)	60% BEV (97.5% load)
OpenDSS-unbalanced	-4.14%	-4.32%	-4.63%
IPSA2- balanced	-2.67%	-2.79%	-3.02%

Table 7: Maximum voltage drop on the generic network calculated using OpenDSS and IPSA2.

Lowest voltage drop	0% BEV (Average load)	60% BEV (Average load)	60% BEV (97.5% load)
IPSA2- balanced	-1.4%	-1.72%	-2.90%

Table 8: Maximum voltage drop on the urban network [16].

Lowest voltage drop	0% BEV (Average load)	15% BEV (Average load)	15% BEV (97.5% load)
IPSA2- balanced	-2.33%	-2.52%	-5.39%

Table 9: Maximum voltage drop on the rural network [16].

It can be noted that there is a difference in the value of voltage drops obtained using OpenDSS and IPSA2 for the same generic network (Table 7).

Voltage unbalance exacerbates voltage drops. In IPSA2, the network is simulated as a balanced three-phase network and phase imbalance caused by possible phase concentration of BEVs could not be captured. OpenDSS uses a 3-phase 4-wire representation of the network and this would capture phase unbalance. If the system is not balanced, a current in the neutral might flow, which will increase the losses and voltage drops.

Consequently, the estimated maximum voltage drop along a feeder phase is underestimated using IPSA2 compared to OpenDSS, which uses a 3-phase 4-wire representation of the network, which will capture phase unbalance.

5.8 Interpretation of Results- BEV Impact on LV Distribution Networks

This work used a probabilistic method to combine unique datasets of real world BEV charging profiles and residential smart meter load demand. The datasets were used to study the impact of the uptake of BEVs on LV distribution networks. The study used real, validated networks of an urban and rural area and a generic network, representative of heavily-loaded UK distribution networks.

5.8.1 Urban vs rural study

The urban network under study was able to accommodate a much higher BEV penetration compared to the rural network. These results stem from the differences in BEV charging profiles, network topologies and impedances between the urban and rural areas. The BEV trial data showed that rural users relied on domestic charging more than the urban users participating in the trial. The median SoC at the beginning of charge events for urban users was 56.3% compared to 47.9% for rural users, indicating higher energy requirements for journeys of rural users, and suggesting longer-distance trips back home.

5.8.2 Urban vs generic study

The generic network gives broad and generalizable findings in comparison to findings specific to one network (i.e. real urban network). However, the generic network is a heavily loaded network and simulating it using peak day load data at the 97.5th upper demand bound could be considered conservative. Lower BEV penetration rates (30%) caused thermal overloads on the generic network in comparison to the urban network. Working with the heavily-loaded generic network gives insights to future problems on the networks due to a transition to a low carbon economy (i.e. distributed generation and the likely growth in BEV battery capacities and charger power).

5.8.3 Spatial and temporal diversity of BEV charging demand.

Spatial, temporal and behavioural diversity of BEV charging demand has been demonstrated to alleviate the impacts on distribution networks. Based on real world trials of BEV usage, the results of this study show that distribution networks could accommodate higher BEV penetrations than previous studies have suggested. The diversity of charging demand in time and space was a consequence of an extensive charging infrastructure available to the BEV users. This gave them multiple options (work, public, fast and home charging) and flexibility of when and where to charge. People charged at more than one location and did not rely only on residential charging. Therefore, additional energy was supplied to BEVs from non-domestic sources and people arrived home with a higher SoC on their BEV batteries than what would have been assumed. Figure 34 shows an example of the spatial diversity of the BEV charging events used in this work, and the diversity in charging times, duration and frequency. This diversity illustrates the stochastic nature of the expected new electricity demand.

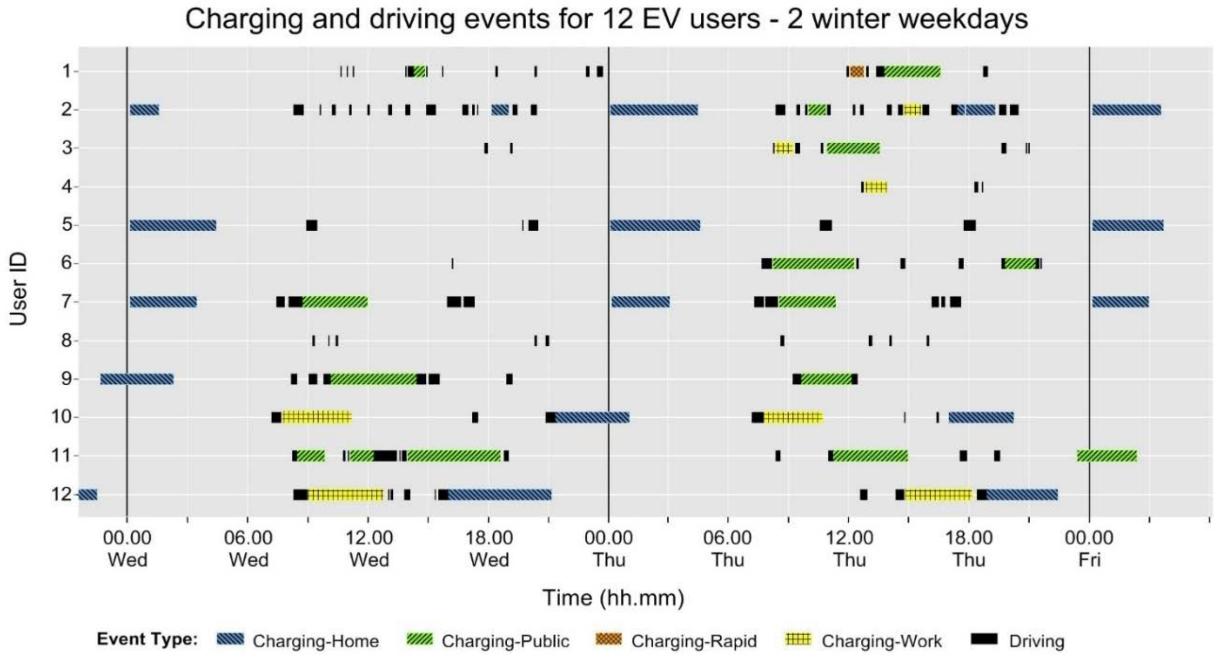


Figure 34: Spatial and temporal diversity of BEV charging demand.

The distribution network impact study carried out in this work focused on low rate (3.8 kW) chargers in residential locations and did not consider the impact of fast chargers (50 kW). While it is necessary to understand the impacts of both charging rates on the network; in the short term, it is imperative to understand the impact of 3.8 kW chargers first. If the number of BEVs increase to meet the 2040 government adoption target, then millions of charging points would be installed at residential LV networks in the next decade. These chargers can be connected to the network before informing the DNO [156]. Consequently, DNOs need to understand the impact of these, potentially ubiquitous, chargers before a possible BEV uptake. In contrast, if the installation of a 50 kW would exceed the network supply capacity, then the charger will not be installed before the network is upgraded to ensure that the new connection is made without affecting other customers' quality of service [245].

In the following chapter, long driving events and their associated charging events are analysed to examine the importance of fast chargers for the adoption of BEVs.

Chapter 6. Investigating the Importance of Fast Chargers for the Adoption of Battery Electric Vehicles[19].

An appropriate charging infrastructure is one of the key aspects needed to support mass adoption of battery electric vehicles (BEVs), and it is suggested that publicly available fast chargers could play a key role in this infrastructure. As fast charging is a relatively new technology, very little research is conducted on the topic using real world datasets, and it is of utmost importance to measure actual usage of this technology and provide evidence on its importance to properly inform infrastructure planning. 12,700 driving days collected from 35 BEVs which used fast chargers were analysed. Using multiple regression analysis, the relationship between daily driving distance and slow and fast charging was analysed to investigate the role and importance of fast chargers for the adoption of BEVs. Fast chargers become more important than slow chargers for daily journeys above 240 km. Fast chargers enabled using BEVs on journeys above their single-charge range that would have been impractical using standard chargers. Fast chargers could help overcome perceived and actual range barriers, making BEVs more attractive to future users.

Sections 6.1 and 6.2 introduce the relevance and contribution of this study. The data, methods, results and interpretation of results are presented in sections 6.3 through 6.6.

6.1 Introduction and Related Work Within Area

An appropriate charging infrastructure is one of the key aspects needed to support the mass adoption of battery electric vehicles (BEVs) [41]–[43], [246], [247]. A public network of fast[20] chargers is argued to be a key component of an overall BEV charging infrastructure [248]–[250]. A study investigated the near term interventions needed to enable a BEV

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[19] This work has been published in:

Neaimeh M, Salisbury SD, Hill GA, Blythe PT, Scoffield DR, Francfort JE. "Analysing the usage and evidencing the importance of fast chargers for the adoption of battery electric vehicles." *Energy Policy* 2017**,** 108**,** 474-486 [17].

Neaimeh M, Hill GA, Guo W, Wardle J, Bramich A, Blythe PT. "Understanding the role of a rapid charging infrastructure on urban and interurban mobility patterns." *In: Electric Vehicle Symposium (EVS29)*. 2016, Montréal, Québec, Canada [72].

[20] Terminology varies by location; it is called "fast" charging in the US, "rapid" charging in the UK and Europe, and "quick" charging in Japan.

breakthrough over the next 15 years in the EU and recognised that the availability of public fast charging is an important signal for consumers and it will support BEV growth [251].

Unlike conventional slow charging stations that take hours to recharge a vehicle, current 50kW fast charging stations can recharge a BEV from an empty battery to about 80% of full state of charge (SoC) in approximately 30 minutes [70]. Fast charging is a relatively new technology that barely existed for public use before 2013 [215] and it is of utmost importance to measure the usage of this technology, understand individuals' behaviour, and provide evidence on the role and significance of this infrastructure. This can appropriately inform the expansion and planning of the BEV charging infrastructure and inform subsequent studies on the topic.

Using assumptions instead of real world behaviour datasets, some studies assessed the business models for fast charging infrastructure to guide prospective investment. Profiling charging demand is critical in evaluating the profitability of BEV fast charging infrastructure business [250] and yet because of the lack of real-world data, assumptions had to be used when assessing the business case for this technology [129], [250], [252], [253].

Similarly, some studies used assumptions instead of real BEV charging behaviour data to investigate the impact of fast charging on the electricity grid. In particular, these studies assumed that all BEV charging takes place on fast chargers and did not consider that BEVs can be easily charged at home for most car owners [254]. One study adapted the arrival time distribution of conventional vehicles at petrol filling stations to determine a typical arrival time distribution of BEVs at the fast chargers; this study found that fast chargers would affect the quality of power supply (e.g. voltage dip, flicker) and actions such as deploying energy storage solutions need to be taken in order to avoid these quality issues[255]. Another study found that fast charging has the potential to quickly overload local distribution equipment at peak times [256] and even cause failure in lines and transformers unless the size and location of fast chargers are modified to avoid these impacts [257].

Using real world datasets, one study investigated the impact of the availability of fast charging on people's assessment of electro-mobility and found that the participants' attitudes towards BEVs improved when they used a fast charger. While the results indicated the importance of such an infrastructure in encouraging the uptake of BEVs, they were based on an experiment that exposed 62 participants who don't own a BEV to a fast charge event [258]. Another study analysed 252 responses to an online questionnaire to identify users' requirements of fast chargers, including preferred locations. The online questionnaires targeted current and potential EV owners and a third of the participants owned or had access to a BEV. The results showed that people see motorway service stations, shopping facilities and traditional fuel stations as potential locations for fast chargers. In addition, the analysis showed that users are not willing to accept waiting times to charge nor detours to find the charging station [259].

One study analysed approximately 5000 charging events from 127 fast chargers (50kW) between 2012 and 2013 in Japan to estimate the future waiting time for charging. Average energy transferred per charging event was 8.8 kWh and the average duration was 27.5 min. The study recommended installing an additional fast charging unit when the usage frequency of the charger exceeds 7 vehicles per day. The study found that if a location had 2 fast charge units then the usage frequency before the need to install an additional charger increase to over 30 vehicles per day [260].

One study analysed charging infrastructure data for the whole of Ireland including 11,000 fast charge events from 83 fast chargers (50 kW) [130]. An interesting finding from the Irish study is that the mean energy consumption for fast chargers at car parks was 7.27 kWh per charge event which is similar to the mean recorded for standard public car park chargers at 6.93 kWh. While the authors in [130] provided a preview of how BEV drivers are using fast chargers, their work did not investigate if fast chargers have an impact on driving behaviour.

6.1.1 Fast charging and battery degradation

Current BEV models almost exclusively use lithium-ion traction batteries [73]. Lithium-ion batteries undergo degradation (ageing) during both storage (ageing with time whether the battery is used or not) and cycling (ageing with use). Several chemical and mechanical processes lead to battery degradation which is typically quantified by capacity fade and power fade. Capacity fade, through the loss of cyclable lithium and other active materials, shortens the achievable range of a BEV. Power fade, through the formation of interface films and loss of electrolyte, leads to the increase in the internal resistance of the battery's cells and consequently decreases the battery's available power output (e.g. decrease the capability of the car to accelerate) [261]–[263]. The end-of-life of a lithium-ion battery is reached when available capacity or maximum power under reference conditions has decreased by 20% of its original value. The loss of capacity is usually the determining factor (i.e. battery reaching 80% remaining capacity) [262].

The rate of battery degradation is often governed by ageing stress factors [261]. The stress factors impacting battery degradation include temperature, state of charge, depth of discharge, battery calendar age, capacity throughput, and current rate [264].

During fast charging the current rate is increased. The increased charging current rate could adversely affect the safety, performance, and life of the battery [73], [96]. One of the widely discussed battery degradation impact of fast charging is a chemical process called lithium plating on the negative electrode of the battery (anode) [262].

One study investigated the impact of different charge current rates on battery degradation and found that the end of life of the battery is reached faster with increasing charge current rate [265]. These results are illustrated in Figure 35 where cycle life is the number of complete charge/discharge cycles that the battery is able to support before its capacity falls under 80% of its original capacity [265].

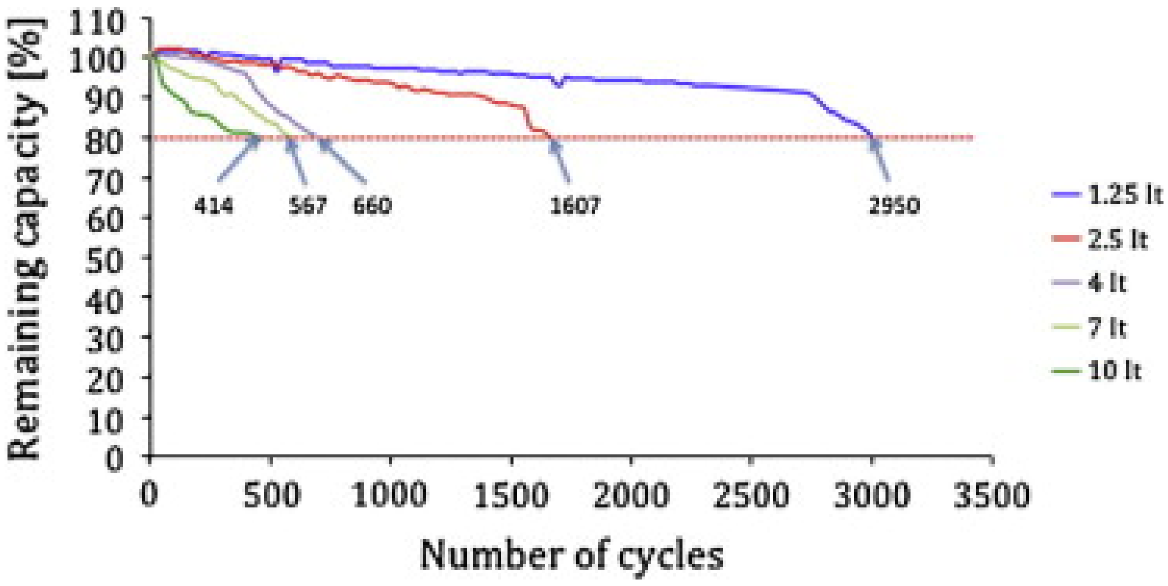

Figure 35: capacity decrease versus number of cycles and charge rate [265].

To bring Figure 35 in context, the study considered a 300V, 80Ah, 24 kWh BEV battery. The current rate (I_t) = 1 corresponds to a battery current= 80A, charging power= 24 kW, and a charging time of 1 hour. I_t = 2 corresponds to a battery current= 160A, charging power= 48 kW, and a charging time of 0.5 hour. Similarly, $I_t = 4$ corresponds to a battery current= 320A, charging power= 96 kW, and a charging time of 15 minutes.

A typical fast charger, circa 2018, is rated at 50kW (400V* 125A) and the 150kW chargers being introduced maintain the same voltage (400V) but increase the amperage to 375A [73], [92]. Based on the results of the study above, a 50kW charger at 125A ($I_t < 2$ at 400V) does not have a significant impact on the remaining capacity of the battery. However, the capacity degradation impact could become much more pronounced when the charge current is increased to 375A.

Another study indicated that daily fast charging at 50kW reduced battery life by 1.1 to 1.3 years. In contrast, the same study reported that aggressive driving could reduce the EV battery life by 2.6-2.9 years compared to a gentler driving style [266].

In contrast to current fast charging technology, the future power standard for ultra-fast charging is 400kW (1,000V *400A) for the CCS standard. There are several barriers that need to be addressed before ultra-fast charging becomes possible. These include the development of additional safety measures, new thermal management strategies for cell and pack cooling; improving on-board electronics to be able to handle high charging power, justifying the economic costs associated with ultra-fast charging to the batteries, vehicles, charging infrastructure and electricity grid, etc.

Some solutions are being investigated to overcome some of the barriers to ultra-fast charging. For example, some of the issues associated with high charging currents during ultra-fast charging could be reduced by increasing the pack voltage. Compared to the existing 400V packs, an increase of charging voltage to 800V would reduce the charging current by 50% [73]. Several car manufacturers (e.g. Porsche, Volkswagen) have started developing battery packs beyond 400V. For example, Porsche has already demonstrated a 220kW charger (< 300A), which can charge an 800V battery pack in 19 minutes [73].

Modifying the charging current profile could minimise lithium plating on the negative electrode and consequently minimise battery degradation. A typical fast-charge profile consists of a constant high applied charge current rate (Constant Current phase) which is cut-off when the cell voltage reaches its defined safety limit. A constant voltage (CV) is applied after the safety limit voltage is reached and until the current drops below a predefined value. It is suggested that alternative charging protocols to the commonly used

CCCV could be better suited for ultra-fast charging [73]. For example step-wise charging where the charge rate decreases with time or state of charge, decreases the rate at which lithium is deposited on the anode. This is in contrast to constant-current charging where lithium is delivered at a constant rate to the anode [73]. Thought step-wise charging is more complex and expensive to implement compared to CCCV [73]

The development of new batteries consisting of different materials could allow much higher charging rates. For example solid- state batteries replacing the liquid electrolyte solutions with solid components could enable higher charging rates [31]. As part of the UK government Faraday funding, a new project is investigating the next generation solid state batteries [267].

Battery degradation prediction and modelling is a difficult task with several processes interacting with each other [268]. Experimental duty cycles carried out in labs that informed most of the current studies might not correspond to real-world cycles and consequently degradation results might not be representative of a real word situation. In addition, experimental studies might not take into account all the combined effects and interactions of ageing stress factors and their entire ranges, as lab based studies could not replicate all real world conditions. [261], [263], [268]. The aim of another recently funded Faraday project is to develop a comprehensive understanding of the relationship between external stress factors (e.g. temperature) and the physical and chemical processes accruing inside the battery that lead to degradation [269]. Consequently, some questions remain on the impact of fast charging on battery degradation, especially with the on-going development of battery and charging technologies.

6.2 Contribution of This Chapter

Higher power rate chargers (150kW+) are in an early stage of development (briefly described in chapter2). Studies and data are not yet available to allow the examination of these ultra-fast chargers nor the comparison of usage patterns between fast and ultra-fast chargers.

Using a comprehensive dataset of driving and charging patterns, the objective of this chapter is to explore the impact of fast chargers (50 kW) on driving behaviour, specifically on driving distance, to investigate the importance of fast chargers for the adoption of BEVs.

The work in this chapter will be carried out by analysing 12,700 driving days including 67,000 driving events and 18,000 charge events from all types of charging infrastructure. The data was collected from data loggers installed in 35 BEVs that accessed and used fast chargers as part of the RCN project. Multiple linear regression and relative importance of predictors are used to explore the influence of fast charging on daily driving distance.

6.3 Data

The recruitment and data collection from 35 BEVs on the RCN project was presented in chapter 3. As previously described, the 35 selected BEVs were privately owned and their users were able to access the RCN fast chargers and expressed that they will be using the electric car as their primary vehicle. Data was collected over a period of 18 month between February 2015 and July 2016. On average, the users drove on 83% of the days during the trial (i.e. almost 6 days per week) and the standard deviation was 11%. The users contributed a similar number of driving days each, with an average of 3% driving days per participant and a standard deviation of 0.67%. In total, 12,700 driving days were collected on RCN with 12% of these days included one or more fast charge event. The analysis of the daily distances for each of the 35 BEV users was shown in chapter 4 (Figure 11). It was noted that most of the daily events were under 150 km (achievable range of the BEVs on RCN). In addition, 5% of the recorded daily distances were over 150km and spread among the users, with the highest recorded daily distance was 610 km.

In total, 11.9% of the charging requirements of the 35 users were met by fast chargers. The proportion of energy transferred on fast chargers for each of the 35 users is shown in Figure 36. The x-axis shows the median daily driving distance for each user (same information shown by the boxplots' bold lines in Figure 11). It can be noticed that most of these 35 participants used the fast chargers that they had access to, with one participant (f4527) relied on fast chargers for 78% of their BEV's total charge energy demand. Five participants used fast charging for less than 1.5% of their total charge energy requirements including one user (f4535) who did not use fast charging at all.

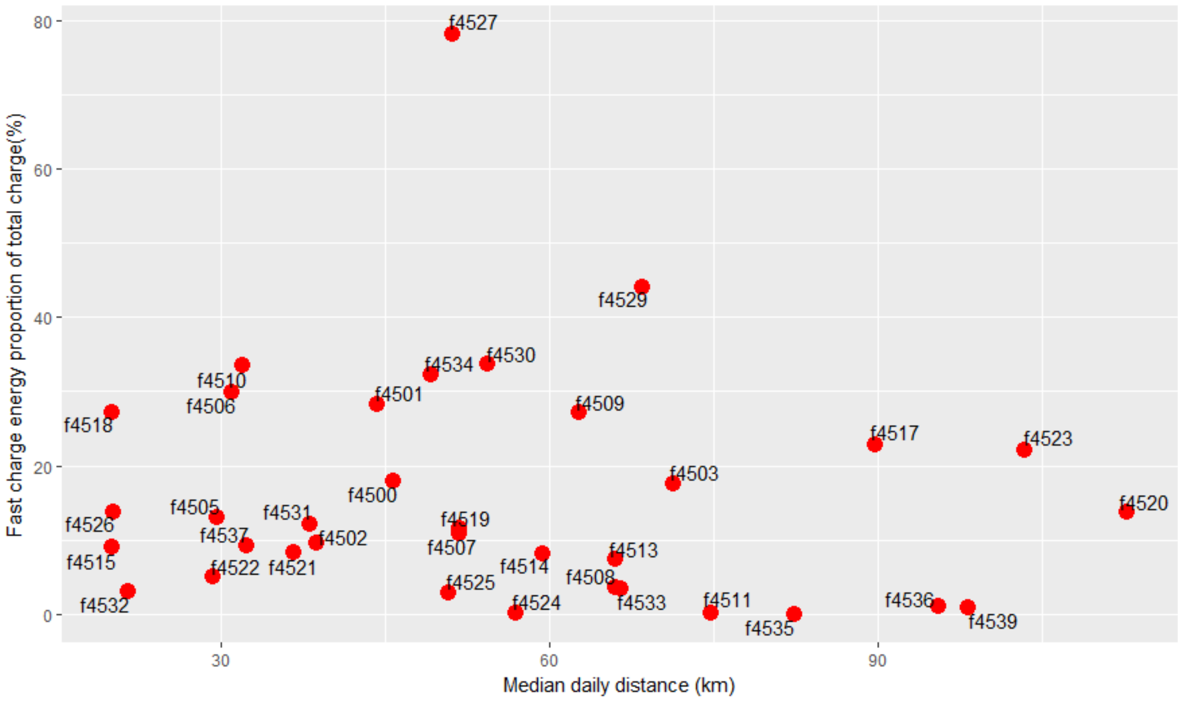

Figure 36: Median daily distance and proportion of fast charge energy for the 35 BEV users.

6.4 Analysis Methods

Some initial descriptive data analysis on BEV usage was presented in chapter 4. In this chapter, additional descriptive analysis was used to explore the relationship between fast charging and driving distance. In addition, multiple linear regression was conducted for a more detailed study on the driving behaviour of the BEV drivers. For the regression, the outcome variable was daily distance and the predictors were daily standard charge and fast charge energy.

Daily distance was thought to be an appropriate unit to use. Some of the units used in transport modelling include trip mileage, vehicle annual mileage and daily activity-travel schedules [270]. For instance, using trip unit, it is hard to understand the importance of fast chargers i.e. do we use the trips before the fast charge event or the trips after the fast charge event? To capture the before and after trips, daily distance is used. Daily distance captures all the trips that happened on that day and takes into account the limited amount of time available to recharge (i. e. if a user is planning to go on a long journey above the single-charge range of their vehicle).

Additional predictors have been added to the model in addition to daily standard charge and fast charge energy to investigate if the inclusion of additional variables to the regression analysis would improve the model's fit. The additional predictors included day of the week: weekday or weekend; and temperature. The model's explanatory power slightly changed with R^2 increasing from 0.64 to 0.65. Akaike information criterion (AIC) was used to compare both models. While the model with additional variable represents a better fit of the data, the increase is small and for the purpose of this work, only standard charge and fast charge will be kept.

Multiple regression is used in two distinct applications: prediction and explanation [271], [272]. For this work, the more interesting use of multiple regression is for the explanation of the contribution of each predictor (standard charge energy, fast charge energy) to daily distance. This allows the identification of which predictor is relatively more important than the other- which what is typically meant by the relative importance of predictors in multiple regression [273].

Many metrics exist to assess the individual predictor's importance in a model. A most typical approach of assessing importance is to examine the magnitude of the standardized regression coefficients associated with each predictor, where predictors with larger coefficients are viewed as more important than those with smaller weights. However, other methods for establishing predictor importance are more accurate [274], [275] and for this work, Lindeman, Merenda and Gold (lmg) method in the Relaimpo package in R is used to assess predictor's importance [276]. For this method, the relative importance of a predictor is defined as the proportionate contribution each predictor in a linear multiple regression model makes to the model coefficient of multiple determination, R^2, considering both the unique contribution of each predictor by itself and its incremental contribution when combined with the other predictors [273], [276]. All the relative R^2 sum to the model R^2.

Since the collection of new (or fresh) data from the BEV users beyond the trial period was not possible, resampling was used instead to investigate the model's performance. Resampling methods can produce reasonable predictions of how well the model will perform on future data[277], [278]. Resampling consists of using a subset of the data to fit a model and using the remaining data to estimate the efficacy of the model. This process is repeated many times and the results are aggregated and summarised [277]. The resampling method used in this work is called "repeated 10-fold cross-validation" where the dataset is randomly partitioned into 10 sets of roughly equal size. A model is fit using all the dataset except for the first set (called the first fold). The data points in this first set (i.e. daily distance) are predicted by this model and used to estimate performance measures (e.g. R^2). The first set is returned to the dataset and the process repeats with the second set held out and so on until the tenth set. The 10 resampled estimates of performance are summarised usually with the mean and standard error [277].

There were 23 data points (driving days) out of 12,700 between 400 and 600km; in order to ensure that this small number relative to the remainder of the data did not have a disproportionately high influence on the regression analysis, robust regression was explored. Ordinary least squares (OLS) regression can be sensitive to unusual data (e.g. outliers and high leverage points). Robust regression is an alternative to OLS regression when the data contain potentially influential observations. The robust regression is done by iterated re-weighted least squares (IRLS) and the idea is to down-weight or ignore unusual data [279].These data points were deemed valid and weren't data entry errors, nor were they from a different population than most of the collected data. Therefore, there was no compelling reason to exclude them from the analysis. In this work, the robust regression implements M-estimation with Huber weighting where observations with small residuals get a weight of 1 and the larger the residual, the smaller the weight [272], [279].

6.5 Results

The graphical representation of the data to identify general trends is presented first. Then the results of the statistical models fitted to the data for a more robust analysis are presented.

6.5.1 Graphical exploration of driving distance and fast charging

The relationship between daily distance and the number of daily fast charge events is shown in Figure 37. The graph displays the mean daily distance at different numbers of fast charge events performed in a day, and the confidence intervals of those means based on bootstrapping. It can be seen that there were days when drivers used fast charging infrastructure multiple times and it can be appreciated that the relationship between fast charging and increased daily distance is obvious.

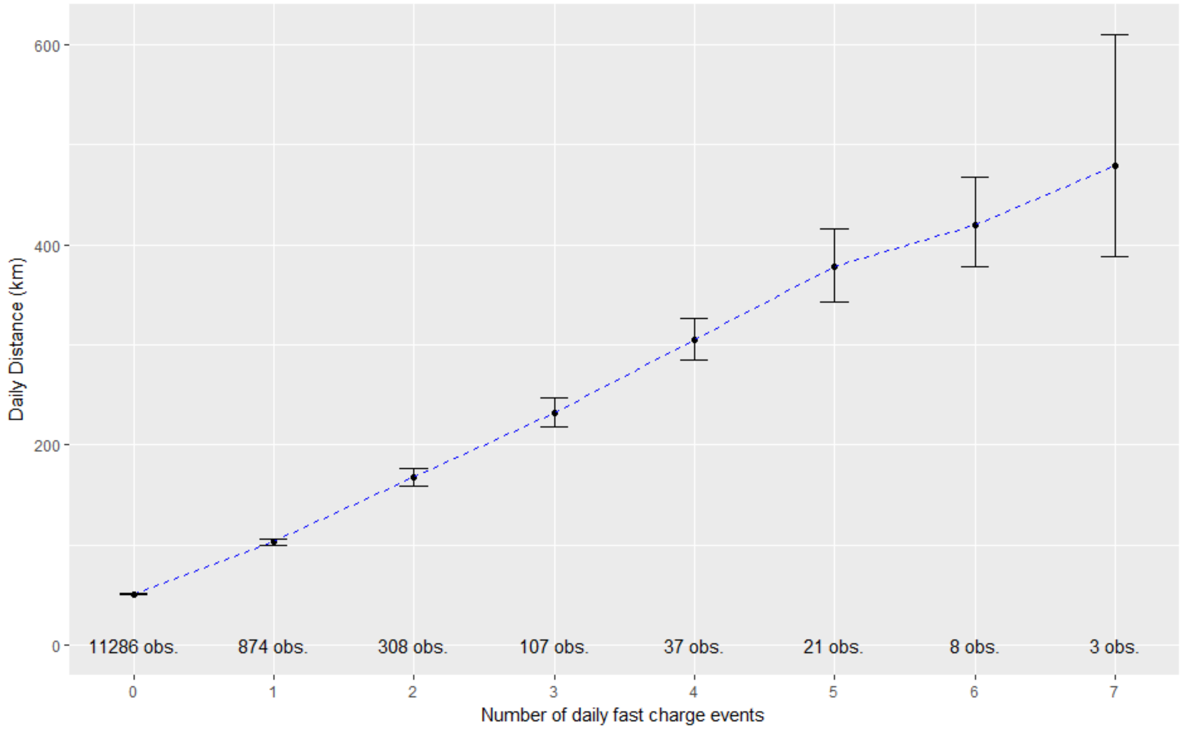

Figure 37: Relationship between daily distance travelled and fast charge events.

Similarly, the positive relationship between driving distance and number of fast charge events can be strongly identified when aggregating the data by weekly events. The data were separated in three groups, each represented by a boxplot (Figure 38) with the median weekly driving distance increasing with an increase in the number of fast charge events. The number of observations for each group is indicated on the graph.

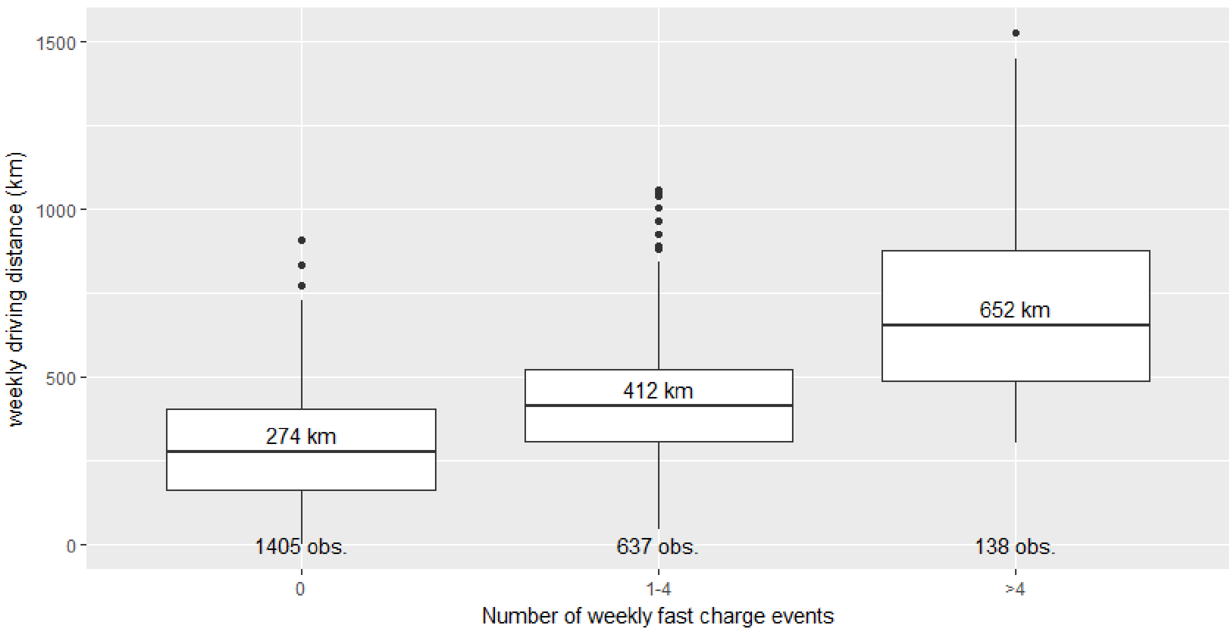

Figure 38: Weekly driving distance and weekly number of fast charge events.

6.5.2 Evidencing the role of fast chargers in enabling driving distances above the single-charge range of BEVs.

The graphical exploration of the data in Section 6.5.1 indicated a relationship between fast charging and increased driving distance. A robust analysis of this relationship was carried out using multiple regression where daily distance is predicted from standard charge energy and fast charge energy. The regression results, described in the following sections, showed that both predictors have a statistically significant and positive effect on daily distance at over 95% confidence level (Table 11) and fast charging was determined to be more influential than slow charging.

6.5.2.1 OLS and robust linear regression results

A few observations with either high leverage or large residuals were identified as possibly problematic to the model. The mean daily distance for these observations was 430km. Robust regression was carried out to deal with these potentially influential observations that could be problematic when using a simple ordinary least squares regression. Figure 39 shows that the predicted values from the linear model and the predicted values from the robust linear model fall on a straight line indicating the similarities between the models, also evident in Table 10. The R^2 statistic is not given in the context of a robust regression[272]. The results of the robust regression were similar to the OLS regression (Figure 39, Table 10) and as such, the analysis in this work will be based on the OLS linear model.

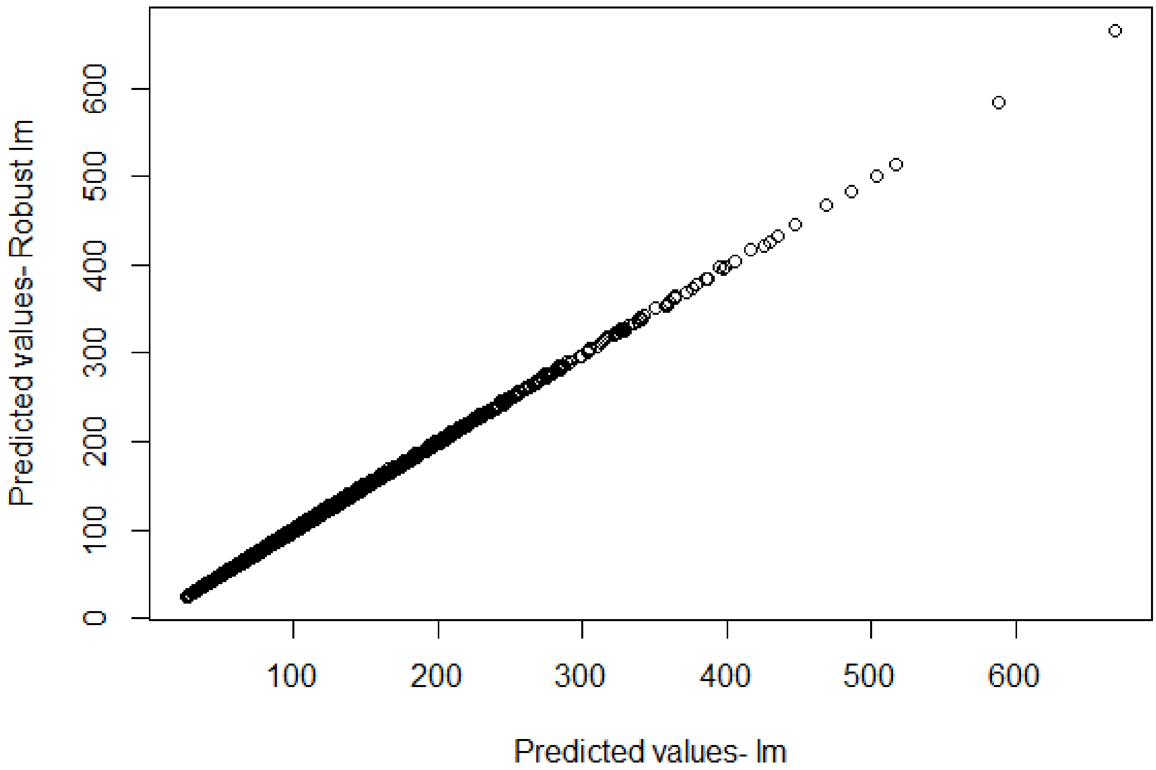

Figure 39: Predicted values of the OLS regression and predicted values of the robust regression.

Beta values	OLS Linear Model	Robust Linear Model using Huber Weights
Intercept/constant (b0)	26.28	24.64
b1	2.67	2.78
b2	5.58	5.54

Table 10: Comparison between linear and robust linear models.

6.5.2.2 Overall fit of the model, cross validation and model parameters

To assess how well the multiple regression model fits the data, we look at the values of the coefficient of multiple determination-R^2 and the F-ratio of the model outcome [280]. R^2 is a measure of how much of the variability in the outcome is accounted for by the predictors. For this model, the adjusted $R^2 = 0.64$ and as such 64% of variation in daily distance can be explained by daily standard and fast charge energy. This also means that 36% of the variation in daily distance cannot be explained by daily charging energy alone. Second, we look at the value of the F-ratio that indicate how much variability the model can explain relative to how much it can't explain. A good model should have a large F-ratio value and the statistical significance of this value should be assessed. For this dataset F is 11,180, which is significant at p-value<.001. Therefore, it can be concluded that the regression model results in significantly better prediction of daily distance than if we used the mean value of daily distance. In other words, the 64% of variance that can be explained is a significant amount. In short, this regression model overall predicts daily distance significantly well.

In the absence of a fresh dataset from the BEV drivers, resampling was used to examine the model's performance. The mean of the 10 resampled estimates of performance (R^2) is 0.635 which is almost the same as the R^2 of the model used in this work. The standard error is 0.014.

After looking at the overall fit of the model and realising that it significantly improves the ability to predict daily distance, the next part is to look at the b-values in the model outcome. Table 11 shows the estimates, standard error, *t*-value and *p*-value of these b-values. If a predictor is having a significant impact on the ability to predict the outcome, then its associated regression coefficient value (b-value) should be different than zero and large relative to its standard error (SE b). A t-test is used to determine whether the b-value is different from zero, where *t*-value=*b*-value/SE b. If the t-test is significant (if the value under the *P* column is less than 0.05) then the predictor is making a significant contribution to the model. The regression coefficients of this model are significantly different from 0 and we can conclude that standard charge energy and fast charge energy make a significant contribution (P <0.001) to predicting daily distance.

	Adjusted R^2	b	SE b	t-value	P
	0.64				
Intercept (b0)		26.28	0.43	61.24	<0.001
Standard Charge Energy (b1)		2.67	0.034	78.42	<0.001
Fast Charge Energy (b2)		5.57	0.044	127.86	<0.001

Table 11: Multiple Regression Report.

In the context of linear regression, the variance inflation factor (VIF) can be used to diagnose multicollinearity. The VIF indicates if there is a strong correlation between the predictors. If there is multicollinearity then the coefficient values are untrustworthy and makes it difficult to assess the individual importance of a predictor[280]. The square root VIF values of the predictors is 1.000027 (<2) indicating that there is no multicollinearity between standard and fast charge energy. Finally, we used graphical analyses (histogram and scatter plot) to ensure that the data met expectations of linearity, homoscedasticity and normality.

Additional predictors have been added to the model (i.e. day of the week: weekday or weekend; and temperature). The model's explanatory power slightly changed with R^2 increasing from 0.64 to 0.65. Akaike information criterion (AIC) was used to compare both models. While the model with additional variable represents a better fit of the data, the increase is small and for the purpose of this work, only standard charge and fast charge were used.

6.5.2.3 Relative importance of fast and standard charge energy

It is interesting to look at the individual contribution of the predictors (standard charge, fast charge) in the model and identify which predictor makes a greater contribution to daily distance. The results of the analysis indicated that fast charge energy most influence daily distance, explaining about 46% of the observed variation, while standard charge energy explains 18% of the variation. The sum of the proportionate contribution of each predictor is equal to the total R^2 of the model (64%). Thus, fast charge energy is about 2.5 times as important as standard charge energy in predicting daily distance for BEV users who have access and use fast chargers.

Furthermore, the model R^2 and the proportionate contribution of each predictor to R^2 was investigated in an incremental approach. The contribution of each predictor was measured at incremental daily distance values of 50km, starting with daily distance up to 50km per day and going to up to 600km per day. The results are shown in Figure 40. The values of proportionate R^2 at daily distance (up to) 600km correspond to the values for the whole dataset.

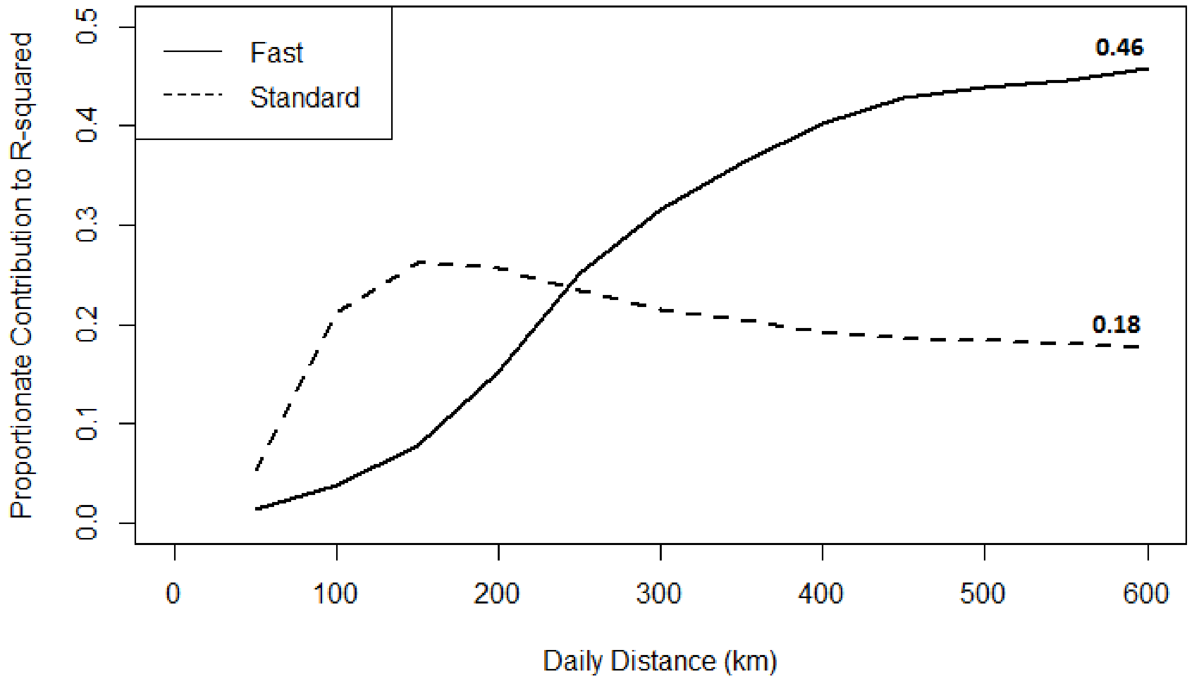

Figure 40: Proportionate contribution to R^2 for fast and standard charge energy predictors.

It can be noticed that standard charge energy is more important than fast charge energy up to daily distance =240km. After 240km, fast charge energy becomes more important.

6.6 Interpretation of Results- a Network of Fast Chargers

Actual driving and charging event data of BEV owners over a period of 18 months were used to carry out an explorative multiple regression. The analysis examined the relationship between daily distance and standard and fast charging and showed that both predictors have a statistically significant and positive effect on daily distance. The R^2 of the regression model was 0.64, which meant that almost two thirds of the variation in daily distance was explained by daily standard and fast charging. In addition, the relative importance of the predictors in the regression model was calculated. Fast charging was determined to be more influential than standard charging (higher contribution to R^2) and it starts to become more important for journeys that are above 240km per day. This demonstrates the importance of fast chargers in enabling driving distances beyond the single-charge range of a BEV. Fast chargers become more important the farther we drive; their availability extended the BEV driving range and enabled driving distances that would have been otherwise impractical using standard (slow) chargers with associated long recharging times.

Yet, the analysis of the NTS and BEV trial data in chapter 4 indicated that journeys above 240km per day are rare. 5% of the journeys were above 150km – which is the driving range of a BEV on a single-charge, and 2% of daily driving recorded in the UK NTS dataset [178] and 1.5% of journeys recorded on the RCN trial were above 240km. It is clear then that the majority of daily driving can be met with current BEV models and slow chargers at private locations (i.e. home or work). This is aligned with previous studies that confirmed the suitability of existing BEV models to meet almost all of the users' daily travelling needs, even if relying only on slow night-time charging [15], [51], [184].

While this raises the question on whether a fast charge infrastructure is required, especially that it is expensive to install [47], [52], it is important that policy makers don't interpret actual daily distance requirements as evidence against supporting the roll-out of a fast charge infrastructure.

Without fast chargers, the transition from liquid-fuel vehicles to BEVs will be affected. First, it may be possible to overcome perceived range barriers with fast chargers. Fast chargers could provide assurance and comfort to reduce range anxiety and the perceived unsuitability of BEVs beyond short city driving. Second, fast chargers can add range quickly into a BEV to make the occasional long journeys possible. Consequently, a network of fast chargers might help overcome both these perceived and actual range barriers, making BEVs more attractive to potential buyers and helping to increase their adoption rates. Both these points are expanded in the following paragraphs.

Driver range anxiety is the fear of depleting the battery and therefore lack sufficient range to complete a trip. Range anxiety can lead to underutilizing the available range and limit the number of kilometres travelled in a BEV, even when the BEV is capable of adequately completing the required journey [41], [281], [282]. This reduces the utility of BEVs that are then considered only suitable for short city driving and unsuitable for long-distance journeys [184]. However, this work provided evidence that drivers are using their BEVs to go on long-distance journeys that are above the single-charge range of the vehicle and fast chargers were used to enable these long journeys. This indicates the importance of fast charge infrastructure because their availability, and usage, allowed drivers to use a limited-range car on long-distance journeys thought only possible using conventional liquid-fuel vehicles.

Second, when a car purchase is made, the customer wants to be able to make all their journeys, not just the majority of their journeys [186]. Even with BEVs with increased battery capacities (e.g. 2018 40kWh Nissan LEAF), a remaining small number of driving days won't be met without recharging [51]. In addition, not every household has access to an additional vehicle that will allow the occasional long journeys; in England, only one third of the households have access to two or more cars [167]. A network of fast chargers could enable the occasional long-distance journeys with limited time spent charging (for example, during a typical rest stop).

While fast charging degrade current lithium-ion battery technology, questions remain on the extent of the degradation and whether it would impact people's charging behaviour (i.e. avoid using fast chargers).

Some studies showed that 50kW fast chargers won't have significant impact on battery degradation [265], [266]. One of the studies found that using a 50kW charger daily could reduce battery life by 1.3 years, which is less than half of the reported degradation caused by aggressive driving (2.9 years). Consequently, these reported fast charging impact on battery degradation might not deter people from using this charging technology, especially that car companies do not exclude fast charging from battery warranties.

While there are several barriers facing the deployment of ultra-fast charging, many governments and car companies perceive the technology as necessary to the adoption of BEVs and consequently are supporting its development. For example, the U.S. Department of Energy has set an average fast charge goal of 20 miles per minute or more. To compare to current numbers, Tesla with its 120kW (the highest charging rate amongst currently available BEVs), can achieve up to 5.6 miles per minute [73]. In the newly published Road to Zero Strategy, the UK government indicated the importance of ultra-fast charging (up to 350 kW) to allow convenient charging when travelling long distances. As mentioned already in the review of on-going projects, major car companies are setting up organisations to roll-out ultra-fast charging networks (e.g. Ionity, Electrify America).

Government and industry backing implies that ultra-fast charging would be a key aspect in BEV charging infrastructure. Some solutions are being investigated to overcome some of the challenges facing ultra-fast chargers. For example, increasing pack voltage to reduce charging current to minimise degradation has already been showcased by some car companies. Furthermore, new battery technologies (e.g. solid state batteries) and modelling tools are being developed as part of the £246 million Faraday Battery Challenge, which is a collaboration between government, industries and academia.

Chapter 7. Discussion

The analysis in this work revealed insights on driving and charging patterns of BEV users in a real world setting, with access to home, work, and public chargers including fast chargers (50 kW).

Daily driving distances were analysed from the BEV dataset and the UK NTS. The findings corroborate similar studies on daily driving patterns in several countries and showed that the majority of driving days can be completed with existing BEV models on one charge. The analysis incorporated weather and real driving conditions that impact the achievable driving range by BEVs, which is less than the advertised range determined in laboratory conditions. Moreover, drivers were not using all the available capacity in their BEV battery prior to recharging; on half of the charging events collected, the batteries were at least half-full when people plugged the car for charging. BEV participants used different types of charging infrastructure that were available to them at different locations. This resulted in charging events that were distributed in space and time. A Monte Carlo simulation was used to combine BEV usage with real smart meter and network data to examine distribution network impacts of residential slow-rate charging (3.8 kW). A statistical model using multiple regression and relative importance of predictors was developed to analyse BEV usage patterns to investigate the role and importance of fast chargers for the adoption of BEVs.

The methods and findings in the previous chapters examined individual aspects of BEV usage. The following paragraphs combine these findings to help inform and support various public and private stakeholders including network operators in the planning of the UK's BEV charging infrastructure.

7.1 Refuelling Paradigm Shift- Charging at Home and at Work

The pattern of recharging BEVs is different than the pattern of refuelling a conventional vehicle. It is much easier to deliver a large amount of energy in a short time to a conventional vehicle than to a BEV. On the other hand, electric power is available in almost all locations and BEVs can be recharged at locations that conventional vehicles cannot—such as at home.

The cost of BEV charging infrastructure increases with charge rate, so it is desirable to charge BEVs at lower charge rates when possible to reduce the costs of rolling out charging infrastructure [52]. Charge rates and charge time are inversely proportional. Higher charge rates require less time than lower charge rates to transfer a given amount of energy. A 50kW fast charger can charge a 24 kWh BEV from empty to 80% full in approximately 30 minutes. Currently available low power-rate (slow) charging stations can charge a BEV from empty to full in between 3 to 7 hours. The charging duration mainly depends on exact charging rate (e.g. 3.8 kW or 7.7kW) and size of the battery [3], [199]. Home and the workplace are ideal locations to charge BEVs at low charge rates where the cars are routinely parked for long periods of time and can be fully recharged while not affecting the availability of BEVs for travelling [52], [185], [283]. Installing low power-rate charging infrastructure at these locations is less expensive and less complicated [52] than rolling out a network of fast chargers to replicate the existing conventional fuelling infrastructure.

The majority of drivers in the UK (73%) could install a charger on their private property (i.e. home) to meet their daily charging demand. However, approximately one quarter of drivers do not have access to private charging such as a garage or private property parking space [159], [284]. By installing public charging infrastructure on-street parking spaces and car parks, primarily in densely populated areas with a predominance of apartments and high-rises, residents without private parking could plug-in their BEV close to their home. Recognising the importance of residential charging the UK, government is continuing the On-street Residential Charge point Scheme, with £6m funding available between 2017 and 2020 to support the installation of public on-street residential chargers [285]. As an example of increasing the availability of on-street residential charging infrastructure, a German start-up company is retrofitting streetlamps with power outlets and rolling-out charging cables to use these streetlamps as charging points for EVs. The charging cables contain a mobile electric meter used to invoice the user for the energy drawn to charge the EV [286]. Similarly, in the UK, BMW has showcased a street lighting system that doubles as a charging station for BEVs [287] and there are plans to install car-charging street lighting in London as part of the GUL scheme [99].

Workplace charging could support the charging requirements of BEV users with no access to residential private charging locations. In addition, workplace charging is a valuable range extender for drivers who live far from work, as well as drivers who sometimes need additional driving range beyond their typical commute. As part of the US EV project, data from 622 LEAF drivers with access to workplace charging in the US and found that on 22% of the days analysed (53,351 driving days over 30 month period), daily driving could not have been completed without workplace charging. The US study included high-mileage drivers with average daily driving distances of 76.25 km compared to 60.8 km for the US national average [185], [288].

Furthermore, extending the charging infrastructure to the workplace would enable BEVs to be connected most of the time to the electricity network. BEV drivers could charge at more than one location and at different times. The probabilistic distribution network impact study carried out in chapter 5 demonstrated the distribution network benefits of maintaining load diversity by spreading BEV charging demand both in space and time. Actual BEV charging patterns reflected the use of additional charging infrastructure, such as home and workplace charging. This diversity of charging patterns hasn't been considered in previous studies, which overestimated network impacts. For example one study focusing on UK LV distribution networks found severe impacts at 12.5% BEV penetration [44].

Additionally, the range of networks used in this study demonstrated that LV networks are not a homogenous group and have different characteristics, sets of parameters and customer behaviour, which illustrates the importance of bespoke studies. The comparison between the generic and urban networks shows that while currently few networks are likely limited to accommodate BEVs, distribution networks in general are more robust than previous work has suggested. In addition, the urban network under study was able to accommodate a much higher BEV penetration compared to the rural network. Differences in BEV charging profiles between these 2 groups of users, and differences in network topologies and impedances between urban and rural areas contributed to these findings.

DNOs are legally responsible for ensuring the long-term ability of the distribution system to meet the demand for electricity [217]. An uptake of BEVs could create significant new electric demand that the DNOs would need to accommodate, while maintaining acceptable level of reliability and quality of supply at an economic cost [220]. Consequently, DNOs should properly understand the changes on their networks introduced by a large number of BEVs. A robust investigation of LV networks, using real world data and a probabilistic analysis method is needed to avoid underestimating or overestimating network impacts. Overestimating the network impacts of BEVs could lead to unnecessary costly grid reinforcements, which would drive up consumer bills. And underestimating the impacts could lead to breaching reliability and quality of supply obligations. Therefore, the findings of the probabilistic study carried out in this work could help DNOs properly assess the capabilities of their networks to accommodate BEVs. DNOs could use the findings to examine the penetration levels that would trigger technical problems, evaluate the probability of the occurrence of a technical problem requiring intervention, and devise strategies to increase their network capability to accommodate more BEVs.

It is suggested that a preliminary demand management strategy for DNOs could be to support the roll out of the BEV charging infrastructure to places where cars are routinely parked for a long period of time. In addition to alleviating the impacts and increasing the hosting capabilities of distribution networks, charging demand that is spread through space and time could present more opportunities for demand response schemes to support the operation of the power system. Therefore, the findings from this work suggest that DNO could be working closely with new market players (e.g. charging infrastructure operators) as a way to efficiently manage existing distribution network infrastructure. The on-going California-based projects where distribution network operators are rolling-out charging infrastructure could provide learning and best practices [147]. An active participation of DNOs in rolling out the BEV charging infrastructure could enable a wider and faster roll-out of the infrastructure, which could encourage the adoption of BEVs.

7.2 A Network of Fast Chargers

To complement home and workplace charging, a public network of fast chargers is argued to be a key component of an overall BEV charging infrastructure. This work provided empirical evidence on the significance of this type of charging infrastructure.

Fast chargers could help overcome actual and perceived range barriers and make BEVs more attractive to future users. The driving range of BEVs (150km circa 2017) is lower than the driving range of conventional vehicles (approximately 600 km), and BEV limited range is one of the main barriers to adoption [40], [187], [289]. A network of fast chargers could provide comfort and reassure drivers about the possible driving range of a BEV. This could help reduce range anxiety and make BEVs more attractive to potential buyers. In addition, fast chargers can add range quickly into a BEV to make the occasional long-distance journeys possible. This was evidenced by the long-distance journeys collected on the RCN trial, made possible by the availability and usage of fast chargers. These long journeys would have been impractical using slow chargers with associated lengthy recharging times.

The results are not intended to demonstrate that fast chargers promote or encourage long-distance journeys. Instead, these results show that fast chargers allowed drivers to use a limited-range car on long-distance journeys thought only possible using conventional liquid-fuel vehicles. It is argued that informative interventions to increase awareness on BEVs could support its adoption [247], [290]. The findings of this study can be communicated to potential buyers as a way to enhance the perception towards BEVs and their suitability to meet drivers' needs; for example, through the UK Go Ultra Low (GUL) campaign.

While previous research, for example the North Sea Region E-Mobility project, suggested that fast charging may not be essential for the introduction of BEVs [126], the work in this thesis argues that developing the BEV market to reduce emissions from road transport could be predicated on the availability of a fast charge network. Road transport accounts for 21% of the country's CO2 emissions and most of these emissions come from cars and light vans [291]. The total distance travelled by cars and light vans in 2015 was 475 billion kilometres. It is worth noting that the Strategic Road Network, where the RCN chargers are installed, carried 144 billion kilometres in 2015, almost one-third of all motorised traffic in England [292]. Road traffic is expected to rise in the coming years, predominately because of the projected growth in the population levels, and this growth is expected to be particularly strong on the Strategic Road Network, between 29% to 60% from 2010 to 2040 [293]. During the period of study, the RCN chargers delivered around 300 MWh of energy that approximately equates to 1.66 million electric kilometres driven[21]. The RCN network operator is a renewable energy electricity company that generates and supplies near-zero carbon emission electricity [294]. As such, the RCN network has saved 230 tonnes of CO_2 when compared against the emissions which could have been produced by new registered cars (140 gCO_2/km) [295]. Expanding the fast charge infrastructure on road networks that carry a significant share of motorised traffic can support the electrification of kilometres driven on these roads and contribute to meeting decarbonisation goals.

Governments and car manufacturers have financed the majority of the current pilot deployments of fast chargers [252]. Nonetheless, finding a profitable business case for future investment in fast charging is becoming imperative as government or automakers financial support is unlikely to continue forever. Yet, at current BEV market share, fast charge networks might not be profitable in the near-term [129], [250] to encourage private investment. This is a particular political challenge as withdrawing the financial support for the fast charge infrastructure too early, before the market and rates of BEV adoption have matured to a point where this support is no longer needed, could inhibit the growth in BEV numbers. As an example of this challenge, the UK government financed early deployments of fast chargers; however, current policy support for this type of infrastructure is not currently clear. The UK National Infrastructure Commission identifies the need to electrify transport; however, the importance of fast chargers hasn't been highlighted yet as a key component necessary in the overall BEV infrastructure. In addition, the 2017 UK Autumn Statement supports charging infrastructure but doesn't specifically mention fast chargers [110]. Highways England's £15 million plan to install fast chargers every 20 miles on the SRN will accelerate the development of the fast charge network. However, detailed plans were not found and it is not clear how many fast charging points will be installed at each location. In addition, it is not clear if Highways England is collaborating with all DNOs in the country to make sure the identified installation sites are being prepared for more than one charge point of higher power rate. Finally, clause 10 in the Automated and Electric Vehicles Bill provides

[21] Using an average BEV energy consumption of 181 Wh/km (Figure 15). $300*10^6$Wh/181Wh/km=1.66 million km.

powers to require large fuel retailers and motorway service areas operators to install public charging infrastructure:

"(2) Regulations under subsection (1) may, for example—

(a) require large fuel retailers or service area operators to provide public charging points;

(b) require public charging points to be available for use at prescribed times;

(c) require services or facilities prescribed by the regulations to be provided in connection with public charging points."

The EV Bill mentions charge points but does not specify fast charge points, and fuel retailers and motorway service operators could install cheaper slow chargers, instead of more expensive fast chargers. Slow chargers are not fit for purpose for long-distance travel and this could negatively impact people's perception on the suitability of charging infrastructure, and consequently impede BEV adoption. In contrast, the German government announced €300 million in early 2017 to support national public charging infrastructure. Two-thirds of the funding will be used to deploy up to 5,000 fast chargers [128].

The fast charge infrastructure provision is expensive and its utilisation levels are going to be low in the coming few years [249] which is not appealing to private investors. Policy makers will have to make a judgement on the costs of supporting the early development of this infrastructure and the associated adoption rates and emissions' benefits. Evidence from this work can be used to justify decisions to dedicate some funding to specifically support fast chargers and the roll-out of an extensive national charging infrastructure.

7.3 Slow Chargers at Home and at Work Complemented with a Network of Fast Chargers

An appropriate charging infrastructure is essential for the adoption of BEVs. It is essential to take an integrated approach to planning charging infrastructure to ensure a successful and cost effective BEV transition. At the heart of the integrated approach is the need to understand the characteristics and actual usage patterns of BEVs, and similarly grid characteristics and existing energy usage patterns. The comprehensive datasets of real BEV usage patterns, smart meter and network data; combined probabilistic methods allowed a robust analysis to support planning an integrated charging infrastructure.

The findings indicate the importance of installing low power-rate charging infrastructure at home and at work to increase the spatial and temporal distribution of charging events. This will alleviate the impact on distribution networks, increase the network capacity to host more BEVs, and open up the opportunity for demand response.

While most daily driving is within the range of BEVs and most charging requirement can be met where the car is naturally parked for a long period of time (e.g. home and work), a network of fast chargers could help overcome perceived and actual range barriers to the adoption of BEVs.

7.4 Evidence to Support On-Going EV Policy In The UK

The Automated and Electric Vehicles Bill includes power to mandate the provision of sufficient charging infrastructure at strategic sites to cater for long-distance journeys but it does not specify the requirements for fast chargers. Evidence from projects such as RCN described in this work and a look at other country's recent initiatives to support fast charging indicate the importance of this type of infrastructure. There is an urgency to develop a clear governmental strategy on roll-out plans of fast charge infrastructure to ensure a roll-out of an extensive fast charge infrastructure, beyond high demand locations.

The workplace is another strategic location to install chargers. In addition to supporting drivers for whom home charging is not possible or sufficient, extending charging infrastructure to the workplace would enable BEVs to be connected most of the time to the electricity network. This opens up opportunities for demand response programs and support the integration of more renewable energy. The government is already supporting the installation of workplace chargers through the Workplace Charging Scheme. Including powers in the EV Bill to require the installation of workplace charging might be strongly opposed. However, for a wider impact of the available workplace grant, it is suggested that the government could supplement it by a workplace charging challenge scheme, similar to the US DOE initiative, to encourage more employers to pledge to install chargers.

Rolling out an appropriate charging infrastructure requires collaboration between several stakeholders, particularly between transport and energy sectors, and this hasn't been explicitly mentioned in the EV Bill.

Charging infrastructure is connected to distribution networks and network operators should play an active role in supporting its roll-out. The EV Bill could include a clause to require, in the future, network operators to actively support the roll-out of charging infrastructure. While a new clause won't impose requirements, it would send a strong signal to encourage and accelerate the involvement of network operators to play an active role in accommodating what could be the new biggest source of electricity sales.

This might encourage DNOs to adopt a preliminary strategy to manage BEVs charging demand by supporting the roll-out of infrastructure at workplace locations. In addition, if not currently in place, it might strengthen a collaboration of all DNOs with Highways England to identify optimal locations, taking into account electricity network capacity and traffic flows. Coordinating closely with network operators is particularly important when deploying fast chargers, especially with the planned introduction of several 350kW chargers at one location to minimise waiting and charging times. DNOs could advise on sites with adequate grid capacity which would minimise costly and lengthy network upgrades. This could ensure faster and cheaper deployment of national fast charge infrastructure. In preparation for any potential secondary legislation on this topic, all parties involved should follow progress of large scale projects in the US (e.g. California) where regulators are working with utilities to accelerate charging infrastructure roll-out. Similarly, initiatives where network operators are installing national charge infrastructure such as ElaadNL in the Netherlands can provide valuable insights. Evidence from this work demonstrated that an active involvement of DNOs is beneficial. An extensive infrastructure at different locations would spread the charge demand in space and time, support the integration more renewable energy (e.g. from PV installations at workplaces), and alleviate network impacts and mitigate upgrade costs to avoid increasing the customers' energy bill.

Coordination of efforts is important when funding and deploying charging infrastructure. Initiatives such as the ENA Open Networks project and the Low Carbon Vehicle Partnership are bringing together different EV stakeholders. However, as noted in chapter 2, key stakeholders are sometimes not represented in these initiatives. The LCVP's EV Network Group brings together major transport and energy stakeholders; however it is not clear how long this group will operate and what plans it is proposing. Building on OLEV's, ENA and the EV Network Group efforts to bring key stakeholders together, it is recommended that a national platform for electric mobility is established. The platform should develop a national strategy defining how many, where and what type of charging infrastructure is needed. The strategy should also describe how the recommendations and plans would be translated into actions to support the roll-out of an integrated charging infrastructure to support the government's ambitious EV adoption targets of almost all cars zero emission by 2050.

The Automated and Electric Vehicles Bill is a great step towards putting the UK at the forefront of the EV revolution. With additional legislations, supported by existing evidence, the Bill would have wider impact and would set an example worldwide for robust EV support.

Chapter 8. Conclusion

8.1 Key Findings

BEVs could break our dependence on fossil fuels by facilitating the transition to low carbon and efficient transport and power systems. This transition could improve air quality, mitigate anthropogenic climate change, and boost the economy.

Yet, in 2017 in the UK, out of a total of 35.6 million cars and light-duty vans only 134,000 were electric [31], [93]. Clearly, there is a need for a substantial market growth and overcoming the barriers to adoption. While BEVs need to be affordable and available to purchase, it is also fundamental to have an appropriate charging infrastructure in place to support the growth of these ultra-low emission vehicles [31], [40].

The aim of this thesis is to propose charging infrastructure integrating both transport requirements and power system characteristics, to ensure a successful and cost effective BEV transition.

The analysis in this thesis is based on a comprehensive dataset collected from three early, real world demonstrators in the UK on electric vehicles and smart grids. The analysis used data collected from private passenger BEVs. In addition, data collection and analysis was carried out using charging profiles from slow (3.8 kW) chargers installed at locations where people parked for long periods of times and fast (50kW) chargers installed at public locations. Probabilistic methods were used to combine and analyse the datasets to ensure robustness of findings.

This work revealed insights that could inform the planning of an appropriate charging infrastructure to support the transition towards BEVs

For half of the charging events analysed, the batteries were at least half full (SoC >=54%) when the cars were plugged for charging.

The BEV participants had access and used chargers at different locations. This resulted in charging profiles that were spatially and temporally diverse. Consideration in this work of diverse charging demand, real smart meter data and network models has been demonstrated to reduce previously estimated impacts on distribution networks.

The current regulatory environment in the UK does not allow distribution companies to own and operate charging infrastructure as part of their regulated business; yet this work suggests a demand management strategy for DNOs to support the roll-out of charging infrastructure at locations where cars are routinely parked for a long time (i.e. home and workplace). This preliminary demand management strategy will spatially spread the BEV charging demand. Consequently, this will also spread the demand in time. The benefits of such a strategy are to mitigate the impacts on distribution networks and increase their hosting capacity to accommodate more BEVs.

Workplace charging becomes more than just a top-up location but a key location to enable BEV charging demand management strategies. In addition, rolling out an extensive charging infrastructure at both residential and workplace locations could facilitate the integration of renewable energy (e.g. from PV installations at workplaces). It would also open up opportunities for new demand response schemes to accommodate what could be the new biggest source of electricity demand. Has the race to own and operate this type of infrastructure started already?

The analysis in this work considered different types of electricity distribution networks. This demonstrated that distribution networks are not a homogenous group with a variation of capabilities to accommodate BEVs. Similarly, consideration of different groups of BEV users highlighted different charging requirements and behaviour. For example, users on the trial who were residing in rural areas had longer trips back home compared to urban users, and consequently a lower SoC when their cars were plugged for charging. The distribution impact study showed that the urban network was able to accommodate BEV penetration 4 times higher compared to the rural network. This is the result of different BEV charging profiles, network topologies and impedances between urban and rural areas. For all 3 networks studied and for all BEV penetration levels considered (up to 60% penetration), voltage magnitude did not drop below statutory limit. In contrast to voltage, transformer loading issues were detected. For the case study urban network, load data (97^{th} percentile) for 60% BEV penetration, loading limits (500 kVA) of the transformer were approached. Loading limits were exceeded at 30% BEV penetration for the urban generic network, and at 15% BEV penetration for the case study rural network.

The analysis confirmed that weather and real driving conditions would impact the energy consumption of BEVs and affect their achievable range. The achievable range of a BEV in real driving conditions is less than their advertised range, which is determined in laboratory conditions.

Most of daily driving is under 150 km. The analysis of daily distances on the BEV trial and on the UK NTS dataset revealed that only 5% of driving days were above 150 km. It is clear then that the majority of daily driving can be met with current BEV models (150 km range circa 2017) on one charge. However, the analysis of real driving and charging data from a group BEV users who had access and used fast chargers demonstrated the importance of this type of infrastructure. Occasional long-distance passenger journeys, above the single-charge range of BEVs, were collected on the RCN trial. Fast charging starts to become more important for journeys that are above 240km per day. These single-day journeys were possible because of the availability and usage of fast chargers. A network of fast chargers could help overcome perceived and actual range barriers to the adoption of BEVs. In 2015, 65% of the 28,000 fast chargers installed worldwide were located in China and Japan while these two countries accounted for 40% of the global BEV stock [215]. The installation of these public chargers in China and Japan was government driven [128]. Fast chargers could encourage customers to opt for a battery electric vehicle and there is a vital need to accelerate the development of fast charge networks.

The patterns of recharging BEVs is different than the pattern of refuelling a conventional vehicle. It is essential to consider a new refuelling paradigm for BEV charging infrastructure and not replicate the liquid-fuel infrastructure where all demand is met a public fuelling stations in a very short period of time. BEVs could be charged where they are naturally parked for long period of times (i.e. home, work) and meet most of the charging needs of drivers. Electric power is available in almost all locations and installing low power-rate (slow) charging infrastructure at residential and work locations could be less expensive and less complicated than rolling-out a ubiquitous fast charging infrastructure to meet all the charging needs. Furthermore, the cost of running the electricity network including building new infrastructure to meet increasing demand for electricity is spread across all customer of the network and there could be an economic benefits to customers from deferral of network reinforcement [245]. As such, ensuring that cars are connected most of the time to the electricity network ensures that charging demand can be managed to support a reliable and efficient operation of the power system to minimise network upgrade costs.

Finally, when slow charging infrastructure is neither available nor practical to meet charging needs, fast chargers can be used to fill in this gap. A network of fast chargers is an important feature of the overall charging infrastructure and fast chargers can be installed at strategic locations to complement home and work charging.

An appropriate infrastructure takes an integrated approach encompassing BEV drivers' requirements and the characteristics of the distribution networks where the BEV charging infrastructure is connected. A non-integrated approach to delivering a charging infrastructure could impede the transition towards electric cars. The findings of this work support planning national charging infrastructure to support the adoption of BEVs in a cost-optimal manner.

8.2 Fulfilment of Research Objectives

This section demonstrates how this work fulfilled the research objectives as set out in section 1.7: Original Contribution to Knowledge.

- Reveal insights on BEV usage patterns by analysing data collected from real world trials. This is linked to **RQ2:** How do people use battery electric vehicles?

This work analysed a comprehensive dataset of real world BEV usage and provided insights on the usage of this new technology in a real world setting. The findings are presented in chapter 4 and the usage patterns were used to carry out additional analyses in chapters 5 and 6. These insights were summarised in section 8.1.

The following two bullet points (contribution to knowledge points) are linked to **RQ3:** What is the impact of BEV charging, using low power-rate chargers (i.e. 3.8 kW), on LV electricity distribution networks? And do realistic charging and driving patterns change the expected impact on these networks?

- Develop a probabilistic method combining real BEV, smart meter and network data, to investigate distribution network impacts of BEV uptake.

In contrast to a deterministic method, a probabilistic method captures the uncertainties related to BEV charging. A probabilistic method based on a Monte Carlo Simulation was used to combine BEV charging patterns, residential smart meter data and local distribution network data to investigate distribution network impacts. The study provides the network operator with results in terms of a probability of encountering technical issues that could be used to further assess whether remedial actions are required. The programming code developed for the MCS is presented in Appendix A.

- Provide recommendations to Distribution Network Operators (DNOs) for preliminary demand management strategy of BEV demand.

The analysis in chapter 5 suggests that a preliminary demand management strategy for DNOs could be to support the roll out of the BEV charging infrastructure to places where cars are routinely parked for a long period of time. This would help spreading the charging demand in space and time and could alleviate distribution network impacts and increase the networks' hosting capacity to accommodate more BEVs. As an example, using charging profiles of BEV users who had access and used charging infrastructure at several locations, the urban network impact assessment did not exhibit technical issues for up to 60% BEV penetration level.

Other findings from this research are of relevance to DNOs. The analysis showed that LV networks are not a homogenous group and have different characteristics, sets of parameters and customer behaviour, which illustrates the importance of bespoke studies.

- Develop a statistical method combining real driving and charging data including fast charge events to examine the impact of fast chargers on driving patterns and investigate their role for the adoption of BEVs. This is linked to **RQ4:** How does BEV usage impact the requirement for charging infrastructure (i.e. low power-rate (slow) and high power-rate (fast) charge infrastructure)?

Multiple regression analysis was carried out to investigate the relationship between daily driving distance and slow and fast charging. The results show that fast charging starts to become more important than slow charging for daily journeys that are above 240 km. The availability and usage of fast chargers made the long-distance journeys collected on RCN possible. Fast chargers can be installed at strategic locations to complement most of the charging demand carried out at locations where cars are parked for long periods of time such as home and work. The regression model and analysis demonstrating the importance of fast chargers for perceived and actual limited driving range of BEVs are presented in chapter 6.

- Provide recommendations to private and public stakeholders planning the roll-out of BEV charging infrastructure. This related to the **aim** of the thesis which is to propose charging infrastructure integrating both transport requirements and power system characteristics, to ensure successful and cost effective BEV transition.

The UK government is investing over £1 billion between 2015 and 2021 to boost the number of EVs on UK roads, including supporting the development of charging infrastructure. The Automated and Electric Vehicles Bill is a key enabler in delivering the charging infrastructure to support the anticipated uptake of EVs. Findings from this work provide empirical evidence to support planning national charging infrastructure and could be used to inform potential new regulations on charging infrastructure. This research may provide insights for regulators and national commissions such as the NIC to formulate and promote policies that could accelerate the development of an integrated charging infrastructure taking into account users' requirements and grid characteristics. In addition, findings from this work could be used by electricity distribution network operators. In particular, the work proposed a preliminary approach to help DNOs optimise the infrastructure they currently have. DNOs could build on the probabilistic analysis conducted to investigate future deployment of additional distributed energy resources and charging control strategies.

Most charging demand could be met at low power-rate charging infrastructure installed where cars are routinely parked for a long period of time and this infrastructure would be complemented by high power-rate chargers installed at public locations. Finally, it is important to avoid deploying a fragmented infrastructure and provide it in a coordinated way, and adopt an approach to ensure future proofing of the infrastructure. Chapter 7 discussed the implications of this research to the development of charging infrastructure and section 8.3 below presents opportunities for further research.

8.3 Further Research

The work in this thesis is not investigating all the criteria required to set up national charging infrastructure and there remain many areas for future research.

While this work provided evidence on the importance of fast chargers, areas for future research include assessing the impact on electricity networks from clusters of super-fast chargers and devising cost-effective strategies to connect them to the electricity network.

Moreover, questions remain on the extent of battery degradation from the use of fast and ultra-fast chargers. More research, based on extensive real world datasets, is required to properly understand the impacts of fast charging on battery degradation. In addition, significant more research is required to develop next generation batteries for the automotive industry. Among other requirements such as lighter and cheaper batteries, these new technologies could better accommodate the electrochemical and thermal demands of ultra-fast charging. Improvement of battery technology could also enable car companies to produce affordable electric vehicles at scale to transition from 130,000 EVs in 2017 to the ambitious target of tens of millions EVs in 2040.

Working on city and regional levels to take into account population and household characteristics, tools can be developed to estimate the required number of residential, workplace, residential on-street, and urban fast chargers filling stations. An EV infrastructure projection tool is currently being developed by NREL and could constitute a starting point for a UK based tool [296]. Such a tool could support local authorities and network operators prepare for the anticipated growth of EVs.

The results of the network impact study in chapter 5 are based on average hourly load profiles and the focus of future work could be on collecting and using load data at higher resolution (e.g. 10-minute average data). This would be more consistent with the BS EN 50160 standard where the LV voltage compliance is established at 10-minute average values. Additionally, the impact analysis was undertaken at a single voltage level (LV) and future work could take into account the interdependencies with other voltage levels (e.g. MV or HV).

Furthermore, car companies have already introduced BEVs with larger battery capacity and higher power-rate on-board charger. For example, the 2018 Nissan LEAF has a 40kWh battery (an increase from 24kWh and 30kWh) and a 6.6 kW on-board charger (an increase from 3.3 kW). Currently (circa 2018), most of residential charging stations available on the market are rated at 3.8 kW. However, the introduction of BEVs with a larger battery capacities and on-board chargers would encourage the development and deployment of higher power-rate residential chargers (e.g. 7 kW). Consequently, future research could analyse the usage patterns of higher power-rate charging (e.g. 7kW) at residential locations and their impact on distribution networks. The findings could be then compared to studies focusing on currently typical 3.8 kW chargers. As a speculation, charging profiles using 7kW chargers could be similar to using chargers of lower power-rate. This is because these new domestic 7kW chargers are very likely to be introduced as smart controllable chargers to take into account the recommendation of the EV bill. Consequently, charging rates could be limited to less than 7kW to mitigate network problems.

This work suggested that DNOs could support the roll-out of charging infrastructure (e.g. workplace charging) as a preliminary strategy for BEV demand management by spreading the demand in space and time. Current regulation don’t allow DNOs to own equipment behind the meter (i.e. charging infrastructure). If regulation change, similarly to what is happening in some U.S. states, and DNOs in the UK are able and interested in providing BEV charging infrastructure as part of their regulated business, it will be important to calculate the cost and benefits of such a strategy.

It is important to carry out robust quantification of the network reinforcement costs associated with BEV uptake and how this cost would vary with the consideration of different demand management strategies. Several projects provided a range of estimates (e.g. Low Carbon London and My Electric Avenue projects). BEVs and charging infrastructure technologies are evolving fast and it would be important to update these costs taking into account more recent BEV usage data, from a larger sample of users, and across different types of networks.

The real world data and probabilistic method developed in this work could be adapted to develop charging control strategies to further increase BEV penetration level on distribution networks. For example, thermal overloads were detected at 15% BEV penetration at the case-study rural network and charging control strategies could be developed to increase the BEV hosting capacity of the rural network.

Advanced BEV charging control strategies, which could delay charging, control charging rate and enable bi-directional power flows, require advanced sensing, communication and control infrastructure that is not typical of a distribution network. Additional research and real world demonstrators are required to provide evidence on the scalability, reliability, and responsiveness of these methods to support network operation and maintain acceptable level of reliability and quality of supply at an economic cost. Evidence on the suitability of these methods is necessary if DNOs are to invest in the required infrastructure and adopt them when operating their networks to transition from conventional passive network reinforcement towards active network management.

The probabilistic method developed in chapter 5 could be applied to additional low carbon technologies in combination with BEVs. This would include investigating the impact on LV distribution networks with the introduction of BEVs, PVs, stationary storage solutions, and other smart grid technologies. Low carbon technologies would introduce further uncertainties to the operation of distribution networks and it becomes vital for network operators to understand the impacts of several LCTs combined.

To encourage the collaboration between the transport and energy sectors, the government dedicated £30M to co-fund 21 projects including real world demonstrators on vehicle-to-grid (V2G) technology, which enable bidirectional power flow [102]. Based on real world data, future work could investigate the flexibility potential of BEVs and examine how the cars could support the power system with the introduction of bidirectional chargers. In return for financial incentives for the BEV users, bidirectional chargers allow the cars to be charged and discharged in response to a control signal aiming at meeting BEV users' needs, minimising battery degradation and optimising the operation of the power system [7], [96], [97]. The probabilistic approach developed in this work could be applied to future projects on V2G technology, which will increase the uncertainty and complexity of managing distribution networks. In addition, future research could investigate potential electricity market and regulatory changes required to facilitate large scale adoption of controllable chargers; cyber security issues and customer willingness to use this new technology.

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Appendices

Appendix A- R code for Monte Carlo Simulation

```
#generic_urban_loadsample_feeder1_voltage.R

# R code- Generic network loadShapes-Monte Carlo Simulation- BEV and smart
meter data

#Loading the Urban BEV profiles
urbanprofiles=read.csv("H:/!Docs/Data/ISGT/urbanprofiles.csv")
urbanprofiles=urbanprofiles[-1] # the first column is 1:24, to be removed.
urban=data.frame(urbanprofiles)

#Loading the smart meter  database
book1=read.csv("H:/!Docs/Data/ISGT/domestic load/urban/Book1_uss19.csv")
book1=book1[-1]

book2=read.csv("H:/!Docs/Data/ISGT/domestic load/urban/Book2_uss24.csv")
book2=book2[-1]

book3=read.csv("H:/!Docs/Data/ISGT/domestic load/urban/Book3_uss14.csv")
book3=book3[-1]
book3=book3[-1,]

book4=read.csv("H:/!Docs/Data/ISGT/domestic load/urban/Book4_uss18.csv")
book4=book4[-1]

book5=read.csv("H:/!Docs/Data/ISGT/domestic load/urban/Book5_uss2.csv")
book5=book5[-1]

book6=read.csv("H:/!Docs/Data/ISGT/domestic load/urban/Book6_uss2.csv")
book6=book6[-1]

# structure for generic netowrk
#8 BEV+smart meter users *12

evuptake=read.csv("H:/!Docs/Data/Grid Paper/EV levels per intake_R.csv",he
ader=F)

#for (j in 1: length(evuptake[1,]) ) {

seg1_r_vec=NULL
seg1_y_vec=NULL
seg1_b_vec=NULL
seg2_r_vec=NULL
seg2_y_vec=NULL
seg2_b_vec=NULL
seg3_r_vec=NULL
seg3_y_vec=NULL
seg3_b_vec=NULL
seg4_r_vec=NULL
seg4_y_vec=NULL
seg4_b_vec=NULL
```

```
x=NULL

#1,000 iteration for MCS

for (i in 1:1000) {

x<-c(x,1:24)

#smart meter load
#Randomly sampled 96 smart meter profiles- following the demographic propo
rtions 25;32;15;19;2;3 (=96)

h1=sample(book1,25,replace=T)
h2=sample(book2,32,replace=T)
h3=sample(book3,15,replace=T)
h4=sample(book4,19,replace=T)
h5=sample(book5,2,replace=T)
h6=sample(book6,3,replace=T)

sm96_feeder1=cbind(h1,h2,h3,h4,h5,h6)
rownames(sm96_feeder1)=1:nrow(sm96_feeder1)

# randomly add EV data
### Feeder 1   12*8
#96 customers: 60% penetration: 86% vehicle ownership
#96*0.6*0.86= 49.536. Approx 50 EVs

#s<-sample(1:96,evuptake[3,j],replace=F) # this is creating the randomness
of assigning.
# evuptake[3,12]=50. 12th column is for the 60% uptake. 50 EVs.

s<-sample(1:96,50,replace=F) # this is creating the randomness of assignin
g.

homeforEV=sm96_feeder1[,s] # choosing random loads (i.e. houses) (with ind
exes determined by s)
#to be combined with an EV load

homenoEV=sm96_feeder1[,-s] # this is the rest of the homes with no EVs

#EVload=sample(urban,evuptake[3,j],replace=T)   # sampling 50 EV profiles
from the EV population
EVload=sample(urban,50,replace=T)

combined_load=homeforEV+EVload    # forming the combined load

df=data.frame(combined_load,homenoEV)

#Feeder1: 12 rows* 8 users each   (96 users)
#always 60% , reorded

s2<-sample(1:96,96,replace=F)
file=df[,s2]   # re-arranged df
```

```
seg1_r=file[1:8]  #8
seg1_rt=apply(seg1_r,1,sum)
seg1_r_vec=c(seg1_r_vec,seg1_rt)

seg1_y=file[9:16]
seg1_yt=apply(seg1_y,1,sum)
seg1_y_vec=c(seg1_y_vec,seg1_yt)

seg1_b=file[17:24]
seg1_bt=apply(seg1_b,1,sum)
seg1_b_vec=c(seg1_b_vec,seg1_bt)

seg2_r=file[25:32]
seg2_rt=apply(seg2_r,1,sum)
seg2_r_vec=c(seg2_r_vec,seg2_rt)

seg2_y=file[33:40]
seg2_yt=apply(seg2_y,1,sum)
seg2_y_vec=c(seg2_y_vec,seg2_yt)

seg2_b=file[41:48]
seg2_bt=apply(seg2_b,1,sum)
seg2_b_vec=c(seg2_b_vec,seg2_bt)

seg3_r=file[49:56]
seg3_rt=apply(seg3_r,1,sum)
seg3_r_vec=c(seg3_r_vec,seg3_rt)

seg3_y=file[57:64]
seg3_yt=apply(seg3_y,1,sum)
seg3_y_vec=c(seg3_y_vec,seg3_yt)

seg3_b=file[65:72]
seg3_bt=apply(seg3_b,1,sum)
seg3_b_vec=c(seg3_b_vec,seg3_bt)

seg4_r=file[73:80]
seg4_rt=apply(seg4_r,1,sum)
seg4_r_vec=c(seg4_r_vec,seg4_rt)

seg4_y=file[81:88]
seg4_yt=apply(seg4_y,1,sum)
seg4_y_vec=c(seg4_y_vec,seg4_yt)

seg4_b=file[89:96]
seg4_bt=apply(seg4_b,1,sum)
seg4_b_vec=c(seg4_b_vec,seg4_bt)
}

#create the 97.5% data bound at each point
ymax_seg1_r<-by(seg1_r_vec,x,function(x)quantile(x,probs=(0.975)))
ymax_seg1_y<-by(seg1_y_vec,x,function(x)quantile(x,probs=(0.975)))
ymax_seg1_b<-by(seg1_b_vec,x,function(x)quantile(x,probs=(0.975)))

ymax_seg2_r<-by(seg2_r_vec,x,function(x)quantile(x,probs=(0.975)))
```

```
ymax_seg2_y<-by(seg2_y_vec,x,function(x)quantile(x,probs=(0.975)))
ymax_seg2_b<-by(seg2_b_vec,x,function(x)quantile(x,probs=(0.975)))


ymax_seg3_r<-by(seg3_r_vec,x,function(x)quantile(x,probs=(0.975)))
ymax_seg3_y<-by(seg3_y_vec,x,function(x)quantile(x,probs=(0.975)))
ymax_seg3_b<-by(seg3_b_vec,x,function(x)quantile(x,probs=(0.975)))


ymax_seg4_r<-by(seg4_r_vec,x,function(x)quantile(x,probs=(0.975)))
ymax_seg4_y<-by(seg4_y_vec,x,function(x)quantile(x,probs=(0.975)))
ymax_seg4_b<-by(seg4_b_vec,x,function(x)quantile(x,probs=(0.975)))

#}

#cannot coerce class ""by"" to a data.frame. use as.numeric
generic_max=data.frame(as.numeric(ymax_seg1_r),as.numeric(ymax_seg1_y),as.
numeric(ymax_seg1_b),as.numeric(ymax_seg2_r),
                       as.numeric(ymax_seg2_y),as.numeric(ymax_seg2_b),as.
numeric(ymax_seg3_r),
                       as.numeric(ymax_seg3_y),as.numeric(ymax_seg3_b),as.
numeric(ymax_seg4_r),
                       as.numeric(ymax_seg4_y),as.numeric(ymax_seg4_b))

write.csv(generic_max,"C:/nmn26/OpenDSS_working_directory/openDSS_wd_thesi
s/simulation_feeder_max_0.6/DSS_feeder_analysis_12times8cust_max_0.6.csv")
```

Appendix B- Description of the power flow solution in OpenDSS

OpenDSS is an open-source software for the simulation of distribution networks. It is developed by the Electric Power Research Institute (EPRI) and designed for the unbalanced multi-phase distribution systems [240], [241]. OpenDSS allows 4-wire representation and simulation of networks.

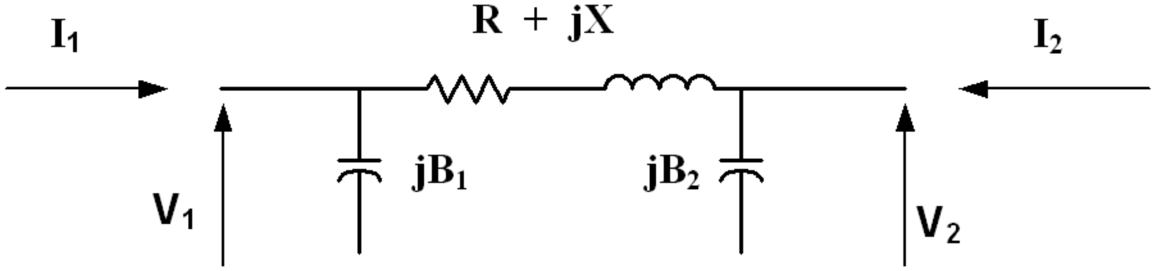
The mathematical methods commonly used in power flow (e.g. Gauss-Seidel, Newton Raphson) are not the only iterative techniques that could be used to solve for the power flow [297], [298].

The method used in OpenDSS is based on a straightforward application of the nodal admittance (Y matrix) formulation method of representing networks. The default power flow solution method solves the set of nodal admittance equations using a Fixed-Point iteration technique [241].

First, the modelling of the circuit elements in OpenDSS is described; then the representation of the network model and iterative solution are presented.

Definition of circuit elements (power delivery and power conversion elements) in OpenDSS

The power delivery elements (e.g. lines, transformers) are generally completely defined by their impedances. Thus, they can be represented fully by their primitive admittance matrix ($\mathbf{Y}_{prim}$). Figure 41 shows the $\mathbf{Y}_{prim}$ of a line model in OpenDSS.



$$\begin{bmatrix} I_1 \\ I_2 \end{bmatrix} = \underbrace{\begin{bmatrix} (R+jX)^{-1} + jB_1 & -(R+jX)^{-1} \\ -(R+jX)^{-1} & (R+jX)^{-1} + jB_2 \end{bmatrix}}_{Y_{prim}} \begin{bmatrix} V_1 \\ V_2 \end{bmatrix}$$

Figure 41. Yprim of a line model [240].

Non-linear power conversion elements (e.g. loads, generators) are modelled by Norton equivalents in OpenDSS, with a constant $\mathbf{Y}_{prim}$ and a compensation current (injection current) that compensates for the non-linear portion of the element (Figure 42). The current source is modified at each iteration to compensate for the nonlinear effect. $\mathbf{Y}_{prim}$ is added to the system admittance matrix ($\mathbf{Y}_{system}$) and the compensation current is added into the injection current vector $\mathbf{I}_{inj}$. When defining the circuit elements in the OpenDSS script files, the loads were defined with Volts, real and reactive powers. OpenDSS linearize these defined loads to a Norton equivalent based on nominal 100% rated voltage (so OpenDSS determines a $\mathbf{Y}_{prim}$ and $\mathbf{I}_L$ for the load). Modelling the loads as a Norton equivalent allows the representation a wide range of models of loads with non-linear variation of the current with respect to voltage [240], [241].

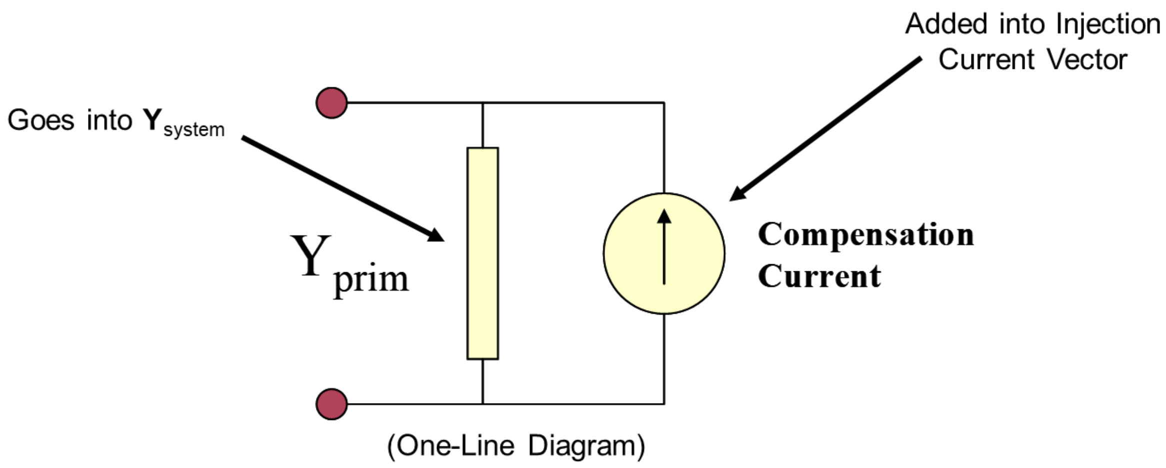


Figure 42: Modelling of most power conversion elements (e.g. loads) in OpenDSS as Norton Equivalent [241].

Representation of the network model in OpenDSS

Figure 43 is a representation of the interconnection of the circuit elements. It can be noted that the voltage source is transformed to its current source equivalent. The power delivery elements are shown in the blue circle (lines and transformers) connecting the power conversion elements (voltage source and loads).

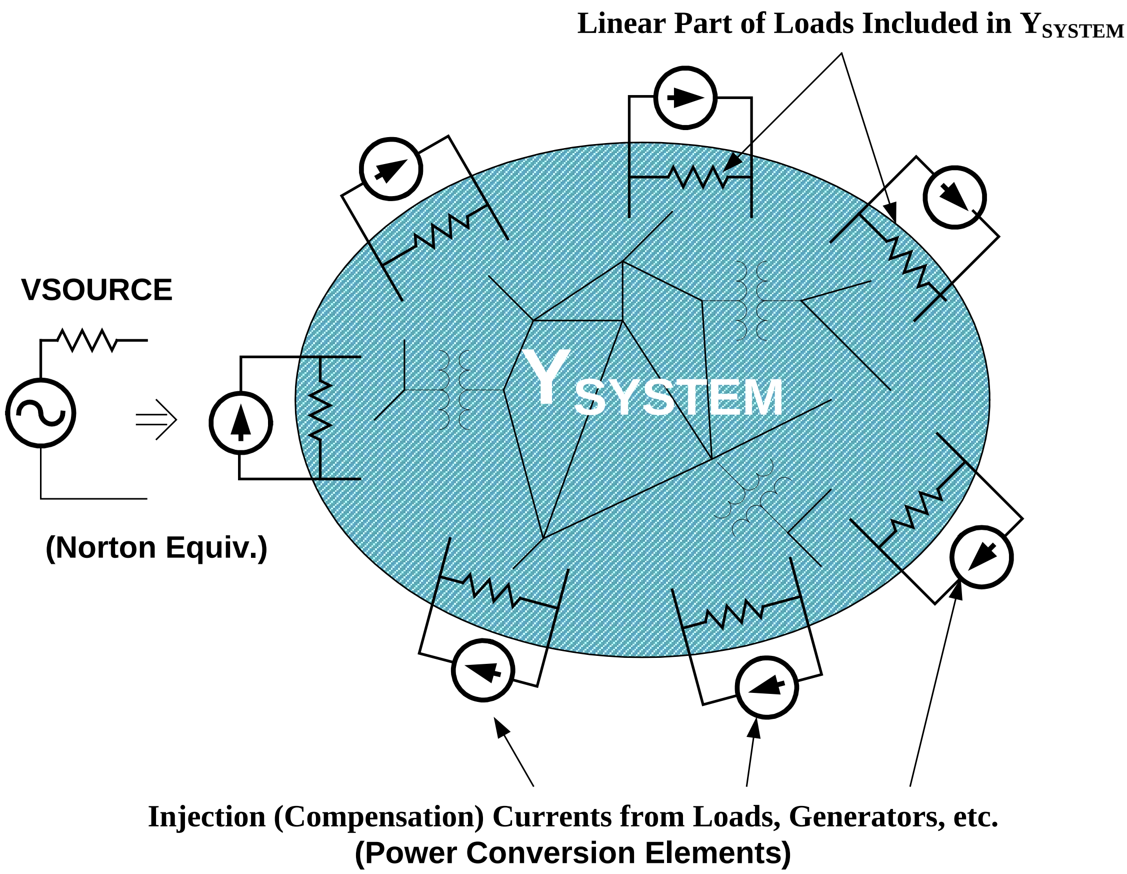


Figure 43: Representation of the circuit elements [240].

A simple iterative solution for solving the power flow

There is a difference in the definition of buses in OpenDSS that should be noted. In OpenDSS, a bus is a container of node objects, this means a bus has nodes. This is different than in many power system analysis programs where bus and node are nearly synonymous. In OpenDSS, there is a nodal admittance equation written for every node (i.e., the current is summed at each node). This dictates the size of the problem that must be solved. The size of the $\mathbf{Y}_{\text{system}}$ is N*N where N is the number of nodes in the system (excluding the reference node), not the number of buses. An advantage of OpenDSS is that it does not need to use a single-phase model nor assume balanced phase conditions.

The power flow solution is illustrated in Figure 44. The nodal admittance equations are in the form:

$$\mathbf{I}_{\text{inj}} = \mathbf{Y}_{\text{system}}\mathbf{V}$$

OpenDSS creates the $\mathbf{Y}_{\text{prim}}$ matrices for each element in the circuit, then these are fed to the sparse matrix solver, which constructs the system admittance matrix ($\mathbf{Y}_{\text{system}}$).

The fixed-point iteration method employed by OpenDSS solves for the node voltages $\mathbf{V}$. An initial guess at the voltages is obtained by performing a zero load power flow by disconnecting all shunt elements and considering only the series power delivery elements [241].

The iteration cycle begins by obtaining the injection currents from all the power conversion elements in the system and adding them to the appropriate slot in the $\mathbf{I}_{\text{inj}}$ vector [241]. To obtain these currents, the program applies the voltages to the individual, independent circuit elements (e.g. lines, transformers, loads) and the element's algorithm returns the terminal currents.

Then, the sparse set is solved for the following voltages guess. The cycle repeats until the voltages converge to a default tolerance. The convergence is based on change in per unit voltage magnitude (default tolerance = 0.0001 pu).

The “ShowMismatch” command sums currents at each node. This command can be used to verify convergence and that a good solution has been achieved. A good solution is achieved when the sum of the currents at each node is zero or very close to zero- meeting Kirchhoff's current law (KCL) [297], [298].

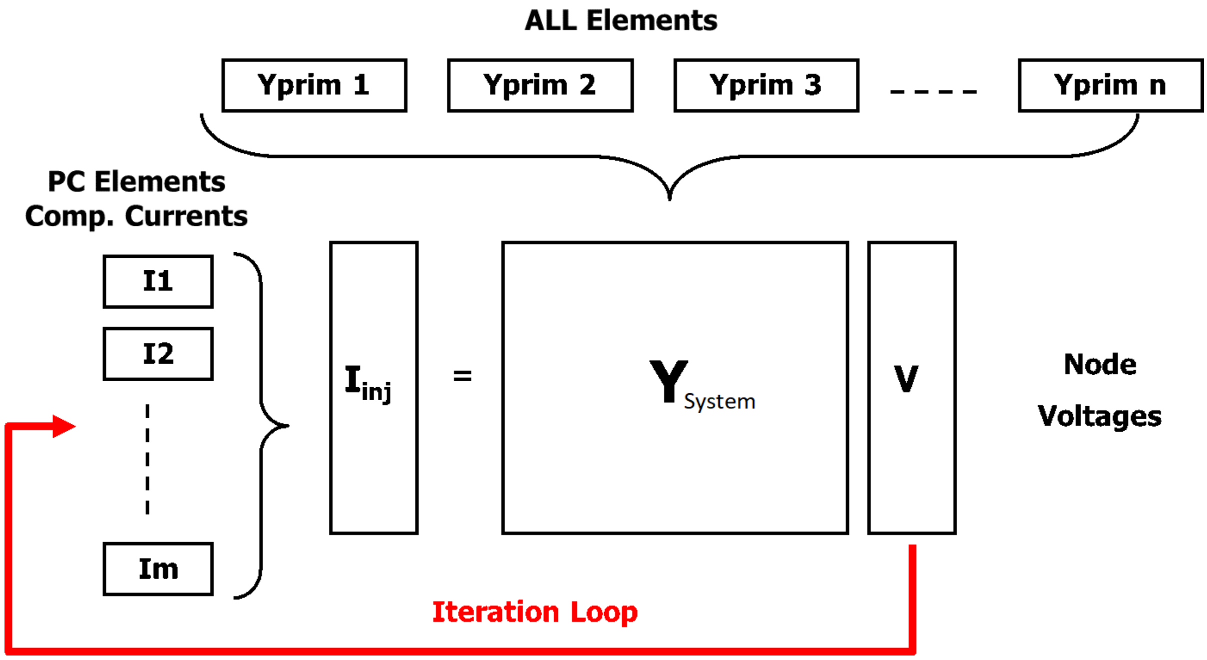


Figure 44: Power flow solution in OpenDSS [241].

The following equation is a concise form of the fixed-point solution:

$$\mathbf{V}_{n+1} = \left[\mathbf{Y}_{\mathrm{system}}\right]^{-1} * \mathbf{I}_{\mathrm{PC\_V_n}} \quad n = 0,1,2,3, \ldots \text{until converged}$$

where

$\mathbf{I}_{\mathrm{PC\_V_n}}$ = compensation currents from the power conversion (PC) elements in the circuit as a function of voltage.

Appendix C- Generic network modelling and simulation in OpenDSS

In OpenDSS the models are constructed using a series of text files. These text files define the circuits and the circuits' elements, control the solution of circuits and specify outputs [240], [299].

The script files developed to model a feeder and investigate voltage drops for 60% BEV penetration are presented below.

OpenDSS script structure

1. Run_the_Master.dss
    a. Master.dss
        i. Linecodes.dss
        ii. Loadshape.dss
        iii. Transformers.dss
        iv. Lines.dss
        v. Loads.dss
        vi. Monitors.dss

Run.dss

```
compile
(C:\nmn26\OpenDSS_working_directory\openDSS_wd_thesis\simulation_feeder_max_0.6\thesis_feeder_Master.dss)

Set Maxiterations=20

Solve

energymeter.LVbusbar.action=take

energymeter.source.action=take

energymeter.feeder_end.action=take

!Exporting the data

export monitors MVside_PQ

export monitors MVside_VI

export monitors LVbusbar_PQ

export monitors LVbusbar_VI

export monitors A_PQ

export monitors A_VI

export monitors B_PQ

export monitors B_VI

export monitors C_PQ
```

```
export monitors C_VI

export monitors D_t1_PQ

export monitors D_t1_VI

export monitors D_PQ

export monitors D_VI


export monitors seg1R_PQ

export monitors seg1R_VI


export monitors seg4R_PQ

export monitors seg4R_VI

export monitors seg4Y_PQ

export monitors seg4Y_VI

export monitors seg4B_PQ

export monitors seg4B_VI

export meters

export voltages

!export Y
```

Master.dss

```
clear

set datapath= "C:\nmn26\OpenDSS_working_directory\openDSS_wd_thesis\simulation_feeder_max_0.6"

new circuit.LV_generic basekv=11 pu=1.0 angle=0 frequency=50 phases=3

!Library Files

Redirect thesis_feeder_Linecode.dss

Redirect thesis_feeder_Loadshape_max_0.6.dss

!Circuit element descriptions

Redirect thesis_feeder_Transformers.dss

Redirect thesis_feeder_Lines.dss

Redirect thesis_feeder_Monitors.dss

Redirect thesis_feeder_Loads.dss


set controlmode=STATIC

set mode=daily stepsize=1h number=24

set voltagebases=[11 0.4]
```

calcvoltagebases

set normvminpu=0.94

set normvmaxpu=1.1

Linecodes.dss

New Linecode.feeder_cable_185mm2CNE nphases=4 R1=0.164 X1=0.074 R0=0.164 X0=0.014 C1=0 C0=0 Units=km

New Linecode.feeder_cable_95mm2CNE nphases=4 R1=0.32 X1=0.075 R0=0.32 X0=0.016 C1=0 C0=0 Units=km

New Linecode.service_cable_35mm2CNE nphases=2 R1=0.851 X1=0.041 R0=0.9 X0=0.041 C1=0 C0=0 Units=km

Loadshapes.dss

!defining the OpenDSS loadshape class

New Loadshape.seg1_R npts=24 interval=1 mult=[file=DSS_feeder_analysis_12times8cust_max_0.6.csv, column=1, header=yes]

New Loadshape.seg1_Y npts=24 interval=1 mult=[file=DSS_feeder_analysis_12times8cust_max_0.6.csv, column=2, header=yes]

New Loadshape.seg1_B npts=24 interval=1 mult=[file=DSS_feeder_analysis_12times8cust_max_0.6.csv, column=3, header=yes]

New Loadshape.seg2_R npts=24 interval=1 mult=[file=DSS_feeder_analysis_12times8cust_max_0.6.csv, column=4, header=yes]

New Loadshape.seg2_Y npts=24 interval=1 mult=[file=DSS_feeder_analysis_12times8cust_max_0.6.csv, column=5, header=yes]

New Loadshape.seg2_B npts=24 interval=1 mult=[file=DSS_feeder_analysis_12times8cust_max_0.6.csv, column=6, header=yes]

New Loadshape.seg3_R npts=24 interval=1 mult=[file=DSS_feeder_analysis_12times8cust_max_0.6.csv, column=7, header=yes]

New Loadshape.seg3_Y npts=24 interval=1 mult=[file=DSS_feeder_analysis_12times8cust_max_0.6.csv, column=8, header=yes]

New Loadshape.seg3_B npts=24 interval=1 mult=[file=DSS_feeder_analysis_12times8cust_max_0.6.csv, column=9, header=yes]

New Loadshape.seg4_R npts=24 interval=1 mult=[file=DSS_feeder_analysis_12times8cust_max_0.6.csv, column=10, header=yes]

New Loadshape.seg4_Y npts=24 interval=1 mult=[file=DSS_feeder_analysis_12times8cust_max_0.6.csv, column=11, header=yes]

New Loadshape.seg4_B npts=24 interval=1 mult=[file=DSS_feeder_analysis_12times8cust_max_0.6.csv, column=12, header=yes]

Transformers.dss

new transformer.TR1 windings=2 buses=(Sourcebus,LVbus.1.2.3.4) conns=(delta, wye) kvs=(11, 0.433) kvas=(500, 500) %loadloss=0 xhl=5

Lines.dss

!Feeder and service cables definition

!Feeders definition

!Feeder cable segment 1. length= 75 meters. phases=4 to account for 3 phases+neutral.

New Line.feederA bus1=LVbus.1.2.3.4 bus2=busA.1.2.3.4 length=0.075 phases=4 units=km linecode=feeder_cable_185mm2CNE

!Feeder cable Segment 2. length= 75 meters. phases=4 to account for 3 phases+neutral.

New Line.feederB bus1=busA.1.2.3.4 bus2=busB.1.2.3.4 length=0.075 phases=4 units=km linecode=feeder_cable_185mm2CNE

!Feeder cable Segment 3. length= 75 meters. phases=4 to account for 3 phases+neutral.

New Line.feederC bus1=busB.1.2.3.4 bus2=busC.1.2.3.4 length=0.075 phases=4 units=km linecode=feeder_cable_95mm2CNE

!Feeder cable Segment 4. length= 75 meters. phases=4 to account for 3 phases+neutral.

New Line.feederD bus1=busC.1.2.3.4 bus2=busD.1.2.3.4 length=0.075 phases=4 units=km linecode=feeder_cable_95mm2CNE

!Service cables definition

!Service Cables Segment1. Total=30 meters. 10 meters for each phase serving 8 loads. phases=2 to account for neutral

New Line.cable_seg1R bus1=busA.1.4 bus2=seg1R.1.4 length=0.01 phases=2 units=km linecode=service_cable_35mm2CNE

New Line.cable_seg1Y bus1=busA.2.4 bus2=seg1Y.2.4 length=0.01 phases=2 units=km linecode=service_cable_35mm2CNE

New Line.cable_seg1B bus1=busA.3.4 bus2=seg1B.3.4 length=0.01 phases=2 units=km linecode=service_cable_35mm2CNE

!Service Cables Segment 2. Total=30 meters. 10 meters for each phase serving 8 loads. phases=2 to account for neutral

New Line.cable_seg2R bus1=busB.1.4 bus2=seg2R.1.4 length=0.01 phases=2 units=km linecode=service_cable_35mm2CNE

New Line.cable_seg2Y bus1=busB.2.4 bus2=seg2Y.2.4 length=0.01 phases=2 units=km linecode=service_cable_35mm2CNE

New Line.cable_seg2B bus1=busB.3.4 bus2=seg2B.3.4 length=0.01 phases=2 units=km linecode=service_cable_35mm2CNE

!Service Cables Segment 3. Total=30 meters. 10 meters for each phase serving 8 loads. phases=2 to account for neutral

New Line.cable_seg3R bus1=busC.1.4 bus2=seg3R.1.4 length=0.01 phases=2 units=km linecode=service_cable_35mm2CNE

New Line.cable_seg3Y bus1=busC.2.4 bus2=seg3Y.2.4 length=0.01 phases=2 units=km linecode=service_cable_35mm2CNE

New Line.cable_seg3B bus1=busC.3.4 bus2=seg3B.3.4 length=0.01 phases=2 units=km linecode=service_cable_35mm2CNE

!Service Cables Segment 4. Total=30 meters. 10 meters for each phase serving 8 loads. phases=2 to account for neutral

New Line.cable_seg4R bus1=busD.1.4 bus2=seg4R.1.4 length=0.01 phases=2 units=km linecode=service_cable_35mm2CNE

New Line.cable_seg4Y bus1=busD.2.4 bus2=seg4Y.2.4 length=0.01 phases=2 units=km linecode=service_cable_35mm2CNE

New Line.cable_seg4B bus1=busD.3.4 bus2=seg4B.3.4 length=0.01 phases=2 units=km linecode=service_cable_35mm2CNE

Loads.dss

!Loads definition

!Segment 1 Loads. 24 loads in total. 8 loads per phase

new Load.seg1R bus1=seg1R.1.4 phases=1 kV=(0.4 3 sqrt /) kW=1 pf=0.988 model=1 conn=wye status=variable daily=seg1_R !Vminpu=0.94

new Load.seg1Y bus1=seg1Y.2.4 phases=1 kV=(0.4 3 sqrt /) kW=1 pf=0.988 model=1 conn=wye status=variable daily=seg1_Y

new Load.seg1B bus1=seg1B.3.4 phases=1 kV=(0.4 3 sqrt /) kW=1 pf=0.988 model=1 conn=wye status=variable daily=seg1_B

!Segment 2 Loads. 24 loads in total. 8 loads per phase

new Load.seg2R bus1=seg2R.1.4 phases=1 kV=(0.4 3 sqrt /) kW=1 pf=0.988 model=1 conn=wye status=variable daily=seg2_R

new Load.seg2Y bus1=seg2Y.2.4 phases=1 kV=(0.4 3 sqrt /) kW=1 pf=0.988 model=1 conn=wye status=variable daily=seg2_Y

new Load.seg2B bus1=seg2B.3.4 phases=1 kV=(0.4 3 sqrt /) kW=1 pf=0.988 model=1 conn=wye status=variable daily=seg2_B

!Segment 3 Loads. 24 loads in total. 8 loads per phase

new Load.seg3R bus1=seg3R.1.4 phases=1 kV=(0.4 3 sqrt /) kW=1 pf=0.988 model=1 conn=wye status=variable daily=seg3_R

new Load.seg3Y bus1=seg3Y.2.4 phases=1 kV=(0.4 3 sqrt /) kW=1 pf=0.988 model=1 conn=wye status=variable daily=seg3_Y

new Load.seg3B bus1=seg3B.3.4 phases=1 kV=(0.4 3 sqrt /) kW=1 pf=0.988 model=1 conn=wye status=variable daily=seg3_B

!Segment 4 Loads. 24 loads in total. 8 loads per phase

new Load.seg4R bus1=seg4R.1.4 phases=1 kV=(0.4 3 sqrt /) kW=1 pf=0.988 model=1 conn=wye status=variable daily=seg4_R

new Load.seg4Y bus1=seg4Y.2.4 phases=1 kV=(0.4 3 sqrt /) kW=1 pf=0.988 model=1 conn=wye status=variable daily=seg4_Y

new Load.seg4B bus1=seg4B.3.4 phases=1 kV=(0.4 3 sqrt /) kW=1 pf=0.988 model=1 conn=wye status=variable daily=seg4_B

Monitors.DSS

!Monitors.dss

!A monitor records the time and the complex vaues of voltage and current, or power, at all phases. other quantities may be saved (e.g. transformer taps)

! A meter object simulates the behaviour of an actual energy meter. It measures power and energy values at its location amd losses and overload values within a defined region of the circuit.

!A meter can be used in power delivery elements (transformers, lines). to add a meter to a load, we need to add a line object (use vert low values of R and X=0 for these fictious lines).

!monitoring the transformer

new monitor.MVside_PQ element=transformer.TR1 terminal=1 mode=1 ppolar=no !Active and reactive power

new monitor.MVside_VI element=transformer.TR1 terminal=1 mode=0 !Voltages and currents

new monitor.LVbusbar_PQ element=transformer.TR1 terminal=2 mode=1 ppolar=no

new monitor.LVbusbar_VI element=transformer.TR1 terminal=2 mode=0

!Monotoring the feeders

```
new monitor.A_PQ element=Line.feederA terminal=2 mode=1 ppolar=no

new monitor.A_VI element=Line.feederA terminal=2 mode=0

new monitor.B_PQ element=Line.feederB terminal=2 mode=1 ppolar=no

new monitor.B_VI element=Line.feederB terminal=2 mode=0

new monitor.C_PQ element=Line.feederC terminal=2 mode=1 ppolar=no

new monitor.C_VI element=Line.feederC terminal=2 mode=0

new monitor.D_t1_PQ element=Line.feederD terminal=1 mode=1 ppolar=no

new monitor.D_t1_VI element=Line.feederD terminal=1 mode=0

new monitor.D_PQ element=Line.feederD terminal=2 mode=1 ppolar=no

new monitor.D_VI element=Line.feederD terminal=2 mode=0


new monitor.seg1R_PQ element=Line.cable_seg1R terminal=2 mode=1 ppolar=no

new monitor.seg1R_VI element=Line.cable_seg1R terminal=2 mode=0

new monitor.seg4R_PQ element=Line.cable_seg4R terminal=2 mode=1 ppolar=no

new monitor.seg4R_VI element=Line.cable_seg4R terminal=2 mode=0

new monitor.seg4Y_PQ element=Line.cable_seg4Y terminal=2 mode=1 ppolar=no

new monitor.seg4Y_VI element=Line.cable_seg4Y terminal=2 mode=0

new monitor.seg4B_PQ element=Line.cable_seg4B terminal=2 mode=1 ppolar=no

new monitor.seg4B_VI element=Line.cable_seg4B terminal=2 mode=0


! Meters( to check energy exports/imports, losses)

new energymeter.source element=transformer.TR1 terminal=1

new energymeter.feeder_end element=Line.feederD terminal=2

! Energy meter at the head of the feeder

new energymeter.LVbusbar element=Line.feederA terminal=1
```

Appendix D- Awards

1st prize talk at Newcastle University's postgraduate conference in July 2016.

1st prize poster at Newcastle University's postgraduate conference in July 2015.

2nd prize at The Chartered Institution of Highways & Transportation (CIHT) conference in 2012.

Appendix E- Published Journal Papers

1. Neaimeh M, Hill GA, Hübner Y, Blythe PT. "Routing systems to extend the driving range of electric vehicles." *IET Intelligent Transport Systems* 2013, 7(3), 327-336.
2. Neaimeh M, Wardle R, Jenkins A, Hill GA, Lyons P, Yi J, Huebner Y, Blythe PT, Taylor P. "A probabilistic approach to combining smart meter and electric vehicle charging data to investigate distribution network impacts." *Applied Energy* 2015, 157, 688-698.
3. Neaimeh M, Salisbury SD, Hill GA, Blythe PT, Scoffield DR, Francfort JE. "Analysing the usage and evidencing the importance of fast chargers for the adoption of battery electric vehicles." *Energy Policy* 2017**,** 108**,** 474-486.

Published in IET Intelligent Transport Systems
Received on 2nd July 2013
Revised on 24th July 2013
Accepted on 25th July 2013
doi: 10.1049/iet-its.2013.0122

ISSN 1751-956X

Routing systems to extend the driving range of electric vehicles

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Abstract: This study develops a more accurate range prediction for electric vehicles (EVs) resulting in a routing system that could extend the driving range of EVs through calculating the minimum energy route to a destination, based on topography and traffic conditions of the road network. Energy expenditure of EVs under different conditions is derived using high-resolution real-world data from the SwitchEV trial. The SwitchEV trial has recorded the second-by-second driving events of 44 all-electric vehicles covering a distance of over 400 000 miles across the North East of England, between March 2010 and May 2013. Linear models are used to determine the energy expenditure equations and Dijkstra's graph search algorithm is used to find the route minimising energy consumption. The results from this study are being used to better inform the decisions of the smart navigation and eco-driving assist systems in EVs, thus improving the intelligent transport systems provisions for EV drivers. The outputs of the research are twofold: providing more accurate estimations of available range and supporting drivers' optimisation of energy consumption and as a result extending their driving range. Both outputs could help mitigate range anxiety and make EVs a more attractive proposition to potential customers.

1 Introduction

The North East of England is one of the pioneers of wide-scale demonstration projects of electric vehicles (EVs) in the United Kingdom (UK). The SwitchEV trial is one of only eight projects across the UK to have won funding through the Technology Strategy Board's (TSB's), ultra-low carbon vehicle demonstrator programme. As part of the 3-year trial, 44 all-electric production vehicles have been equipped with data loggers. The data collected from the loggers and charging network are correlated with attitudinal data from questionnaires and focus groups to understand the behaviour and attitudes of the participants on driving range and to understand what new intelligent transport systems (ITS) and services are required to support the roll-out of EVs and their associated charging infrastructure. With more than 90 000 recorded journeys and over 400 000 miles driven (as well as over 20 000 re-charging events recorded), the SwitchEV project has created a unique dataset on the driving behaviour of EV users. The real-life driving behaviour of the users, their energy use and re-charging behaviour has been charted and analysed to identify barriers to the introduction of EVs and to inform future policies on electric transport. Utilising the data from tens of thousands of recorded driving events, an understanding of the real battery performance and real range of EVs has been developed. Using this as a 'ground truth', a series of equations have been derived to calculate the range available to an EV based upon the traffic conditions and topology of the road. This enables, for the first time, the ability to predict more accurately the available range of the vehicle and in addition to provide advice on selecting the most efficient route for an EV for a particular journey.

2 Range of EVs

2.1 Background

The Stern review [1] highlighted the potential future economic costs because of climate change. It recommended cutting greenhouse gas emissions by 60–80% by 2050, relative to 1990 levels. As a response to the Stern Report, the UK government passed the Climate Change Act [2] that set the legally binding target of cutting 2050 greenhouse gas emissions by 80%. In 2011, the UK Government published the Carbon Plan [3], which sets out how the UK will achieve decarbonisation targets across all sectors. It anticipated that the average carbon emissions of new cars will fall by one third because of new legislation on European Union (EU) vehicle emissions standards. However, to meet long-term climate change targets, the private vehicle fleet will have to ultimately be converted into ultra-low emission vehicles such as full electric cars and plug-in hybrids recharged using renewable energy sources, as well as hydrogen fuelled cars [4, 5]. Yet, the real uptake of EVs is falling short of Government and industry expectations despite Government efforts to promote the uptake of EVs [4, 6, 7]. According to the Society of Motor Manufacturers and Traders (SMMT), new full-electric car registrations were 1262 units in 2012 and a total of 2237 plug-in-car grants of up to £5000 each were awarded [8]. The main reason is that the public still see a large number of barriers to the uptake of EVs such as limited range, insufficient availability of public charging infrastructure and the high purchasing cost of EVs [9–13]. Franke and Krems [14] argue that drivers are only comfortable utilising between 75 and 80% of the available range of electric cars. The authors discuss that driving an electric car on a daily basis has a positive effect on the driver's comfortable (the preferred range safety margin that an EV driver likes to have at the end of a journey) and competent range (the maximum range utilised by an EV driver throughout the trials) and that feedback should be given to drivers in order to help them expand their range. ITS could therefore provide the driver with optimised route choice to minimise energy expenditure and more accurate range predictions based on their journey information, topography, traffic conditions, temperature as well as the location and availability of charging points along their chosen route. All of which will provide the driver with more confidence in their available range.

2.2 ITS for EVs

The importance of accurate range prediction has been highlighted by the ITS industry. In 2012, European Road Transport Telematics Implementation Co-ordination Organisation (ERTICO) published a roadmap on ITS for ElectroMobility [15], which highlighted the limited range as one of the key challenges to be addressed through ITS services. The roadmap covered the development of ITS services and applications that were relevant for the mass deployment of EVs. The roadmap had been developed by the ERTICO Task Force 'ITS for ElectroMobility', which included representatives of the automotive industry, ITS sector, research sector and service provision sector. Table 1 shows the priorities for ITS developments for EVs. It can be seen that three of the top five priorities refer to accurate range and optimised driving and route planning to maximise the range of the electric cars.

Most electric cars have a range estimator on board. However, these calculate the range of the vehicle based on the driving style of the previous trips and do not take into account a number of factors affecting the vehicle's energy consumption and remaining range. These factors include traffic conditions, road types and topography, weight and weather conditions. A lot of work has been done to develop eco-driving algorithms for ICE vehicles [16–18]. For example, previous work has shown how energy management systems and route-based control systems can overcome some of the negative impacts of road gradients on fuel consumption of heavy duty vehicles [19] and hybrid electric cars [20]. However, little work has been done to estimate energy expenditure and driving range specifically for EVs. Moreover, satellite navigation systems specifically designed for EVs would be more relevant if, instead of optimising distance or travel times, the routing was based on optimising energy expenditure for a given journey. This would then optimise a key factor for EVs suitability, the driving range.

Table 1 Priorities for the development of ITS services for electric vehicles [15]

Priority	Service
1	electric vehicle charging management and services
2	new traffic management tools for large-scale introduction of EVs into the road network
3	accurate range prediction
4	EV route guidance and EV navigation
5	EV eco-driving

3 Methodology

3.1 Electric vehicles

This study only analysed the range of full EVs and does not refer to conventional engine cars. The vehicles used in the SwitchEV trial were Nissan LEAF, Peugeot iOn, Avid Cue-V, Liberty electric cars eRange, and the Smith Electric Vehicle Edison Minibus. For the purpose of the research reported in this paper, only data from the Leaf and iOn vehicles performance were used. Table 2 summarises the key vehicle specifications.

3.2 Driver recruitment

A 86% of vehicles were leased by organisations and 14% by private individuals. Of the vehicles leased to organisations, 51% were used by single users and 49% were designated pool vehicles. In order to understand the behaviour of the SwitchEV triallists and whether there are some specific traits and choices associated with age, gender or demographics, a pre-trial questionnaire included questions to profile the participants. From this, it was summarised that the majority of trial candidates were men with 72% of drivers being male and 28% being female. Only 5% of drivers were 17–25 years old, 16% of drivers were 26–35 years old, 31% of drivers were 36–45 years old. The largest groups with 38% were 46–55 years old and a further 10% were 56–65 years old. 90% of respondents were in full-time employment, 6% in part-time employment, 3% self-employed and 1% full-time students. This bias towards older male drivers is due to two characteristics of the trial; the first being that many of the vehicles were leased to triallists to use at work (either being an organisation single-user vehicle, or an organisation pool vehicle shared by a number of workplace colleagues), and the age profile (particularly of the single users) was quite high – this is largely correlated with the actual costs of leasing the EVs. Further research showed that the profile of the SwitchEV drivers fits well into the general EV purchasing behaviour.

Table 2 Vehicle characteristics [21]

	Peugeot iOn	Nissan LEAF
driving range	93 miles (150 km)	109 miles (175 km)
max speed	81 mph	90 mph (over 145 km/h)
battery type	lithium manganese oxide	laminated lithium-ion battery
battery capacity	16 kWh	24 kWh
battery layout	under seats and floor	under seat and floor
length	3474 mm	4445 mm
width	1792 mm	1770 mm
height	1608 mm	1550 mm
seating capacity	4 adults	5 adults
max engine power	47 kW	80 kW
max engine torque	180 Nm	280 Nm
number of vehicles on trial	20	15

doi: 10.1049/iet-its.2013.0122

According to the DfT, 87% of recipients of the Plugged in car grant were males, working full time (in senior roles or self-employed) or retired and aged 40 years and above [22].

3.3 Soft data collection

Attitudinal data were collected through online pre- and post-driving questionnaires and focus groups. The analysis is based on three six-month trial periods between March 2011 and October 2012. Over the course of the SwitchEV project, 192 participants provided answers to the pre-trial questionnaire, 101 answers to the post-trial questionnaire and 30 answers to fast charger questionnaire. A 60 participants attended 12 focus groups, with 12 individual exit interviews and 10 pre-trial interviews conducted in order to understand drivers' attitudes towards EVs and their charging infrastructure. The number of drivers exceeds the number of vehicles because some of the vehicles are used as pool and fleet vehicles and multiple drivers have access to those vehicles.

Some direct quotes from individual SwitchEV drivers that have been provided in the results section were reproduced from their questionnaire responses or captured from oral records of the focus groups. All quotes are unedited and are presented in quotes: '…'.

3.4 Data logging

The research presented in this paper is based on driving data from EVs over 18 months, monitored using on board vehicle data loggers throughout the North East of England as part of the SwitchEV trial. The driving performance and remaining range of the EV are analysed based upon a number of dynamic parameters rather than just the state of charge of the EV battery. The raw data collected monitors all aspects of vehicle usage. The loggers enable the collection of real-time second by second driving data by connecting to the controller area network (CAN) bus through the vehicles on-board diagnostics port (OBD). In addition, the loggers record GPS and time-stamp as well as analogue inputs from current-clamps attached to various electrical systems of the vehicle [23].

3.5 EV-specific models

Linear models derived from real-life driving data are used to determine the energy expenditure of EVs for different topography and driving speed. The driving speed is used as a proxy for the road network capacity or traffic conditions. The driving data include the altitude, speed and corresponding energy consumption or regeneration derived from the raw battery data. Energy regeneration occurs due to breaking and deceleration of the vehicle. The data collected from the vehicles was aggregated into 100 m 'blocks'. Afterwards, a linear model was used to determine the slopes from the altitude data for every 100 m block. Furthermore, additional linear models were used to determine the corresponding energy use of the vehicle per km, for the different slopes and different average driving speeds. A multiple regression model was constructed to justify this work. It was demonstrated that the accuracy of range prediction is greatly improved by incorporating variables such as topography and average speeds in addition to historical data about driving conditions. Finally, based on the energy expenditure equations, a case study in the later parts of this paper has illustrated optimum routes for an EV journey.

4 Results

4.1 Attitudinal evidence from SwitchEV trials

Overall, 80% of drivers of the SwitchEV trial thought that the experience of driving an EV was either the same or better than driving an internal combustion engine (ICE) car. However, 20% of drivers thought that driving an EV was still worse than driving an ICE car. One driver explained in the focus group: 'I would say that the range must be probably the biggest barrier. If it's your only mode of transport then it probably is a problem, but not if it's for use as a second vehicle.'

Most drivers reported that they did not change their driving behaviour for most of their journeys. Many drivers reported however that they changed their driving style or their chosen routes if they wanted to go on longer journeys: 'If I was on the rare occasion going on a long journey then definitely I made the most of the regenerative braking and tried to keep the battery life but apart from that I think I probably drove a little bit faster than I would in a normal car just to try and push it and just to see what it could do really and because I did not have to worry about range then that was something that I could do was just see what it actually performed like but if it was a long journey then I would definitely change my driving style just because I was aware of the battery life.' Another driver explained their observations when asked about the key barriers to the uptake of EVs: 'the range and the battery drain. The drain is related to the topography of the roads round here and potentially how you drive it, but the range is limited and its drain is the topography. However, you do maybe change your route to take that into account. For example, to [a location] which is 30 miles I went up [one road] and deliberately chose to not come back that way because of the hills, and instead came back via the rural road where it is quite comfortable going along at 40 mph.' Other drivers also reported that they changed the routes they took when driving an EV: 'I find I did not change my driving style; but I did change my routes. When I came down a [dual-carriageway A road] and the range went down very quickly whereas when I went down the [single carriage way A road] which is exactly the same route, I ended up at the same place and I found the range did not go down that far because we were in traffic stop starting all the way through so I would use that route. I lost about five minutes but gained all the regenerative braking.' A 32% of drivers reported that they reduced the number of trips on the motorways. This anecdotal evidence shows how important it is to give EV drivers relevant information affecting the range.

4.2 EV-specific driving efficiency models

The driving events were separated into 100 m data 'blocks' then the slope, average speed and corresponding energy expenditure were calculated for each data block. By aggregating the driving data collected from the vehicles into 100 m blocks, it is thought that a balance is struck between capturing altitudinal changes in the vehicle's position while reducing the noise inherent in the higher resolution recording. By dividing the driving data into blocks in this way, it is possible to model the altitude change between the start and end point of that driving event as linear or

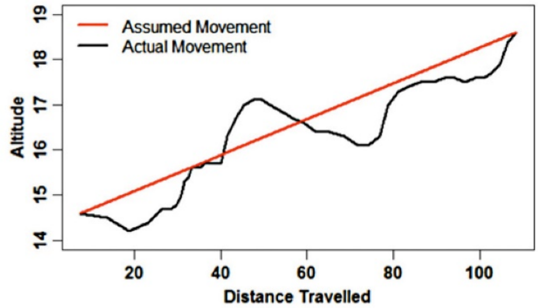

Fig. 1 *Nonlinear altitude change*

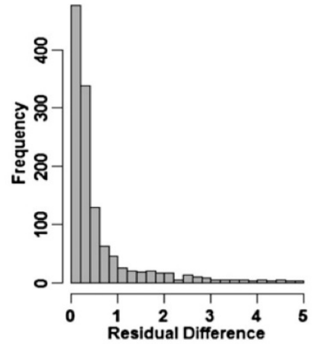

Fig. 2 *Distribution of the linearity check*

continuous (i.e. assuming the car is only moving up or down for the 100 m). However, Fig. 1 illustrates an example where an individual data block exhibits non-linear altitude change between the start and end point over the 100 m, as opposed to the assumed linear altitude change.

To validate that the altitude change would mostly be linear and cases similar to Fig. 1 are an exception, the actual altitude variation was compared to the modelled altitude change over the 100 m for the data blocks. To achieve this, the residual variation between the created linear regression model and the actual data was calculated. Then the average of the absolute values of the residuals (difference between the observed values and modelled values) was taken for every 100 m section. If the altitude change is continuous then the values calculated above should be zero.

Fig. 2 shows that the majority of the linearity check values are within 1 m of zero which confirms that the altitude change in the vast majority of the data blocks varies only slightly away from linearity. Hence, the 100 m path can be used as an accurate approximation for the overall altitude change. More details on the model were introduced in [23].

At this stage of the analysis, the different slopes for the driving data and the related energy consumption per km for every slope were calculated (Fig. 3*a*). Fig. 3*b* confirms that the majority of the slope values in the data are in the range of –6 to +6° with ~99% of the data lying within ±6°. The significant reduction in data outside the ±6° range leads to an increasing uncertainty about the efficiency in these ranges and as such it is not possible to empirically derive EV performance values for gradients greater than ±6° with confidence. This is reflected in the increasing variance outside the ±6° shown in the grey area in Fig. 3*a*.

To overcome the small number of data outside the ±6° range, regression analysis was used to fit a linear model to the robust set of data (corresponding to low slope) to determine the driving efficiency for the rest of the slopes. Fig. 4 illustrates fitting a linear model to low slope values and the linear model equation is represented in the following equation

$$y = a + bx \tag{1}$$

where y is efficiency (kWh per km), x is slope (deg.), a is first coefficient from the linear regression (intercept) and b is second coefficient from the linear regression.

Standardised residuals between the fitted and observed values were calculated to test if the model assumptions are correct. Fig. 5 illustrates that the model assumptions are correct where the plots of the residuals against the predictor variables are randomly scattered (Fig. 5*a*) and the residuals lie on a straight line (Fig. 5*b*).

It is believed that fitting a linear model to determine the efficiency for higher slope values is justified due to the basic physics behind power consumption in an EV [24]. When moving on a gradient, a proportion of the vehicle's power is used to move the car up an incline; in addition to the power needed to overcome friction and to supply any

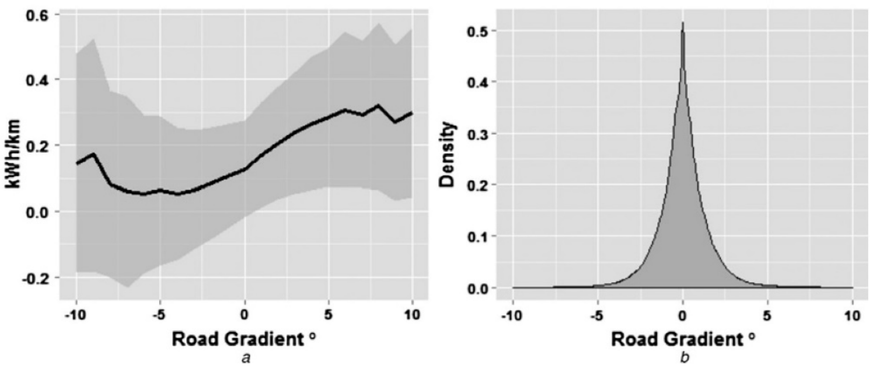

Fig. 3 *Different slopes for the driving data and the related energy consumption per km*

a Overall driving efficiency
b Distribution of slope values

doi: 10.1049/iet-its.2013.0122

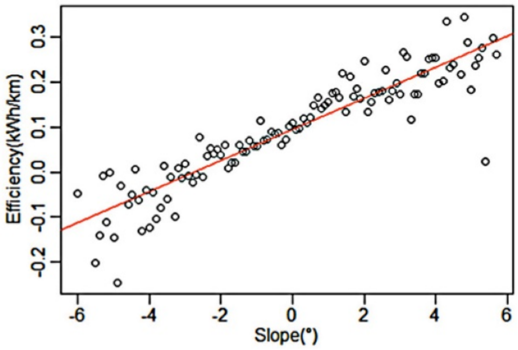

Fig. 4 *Fitting a linear model*

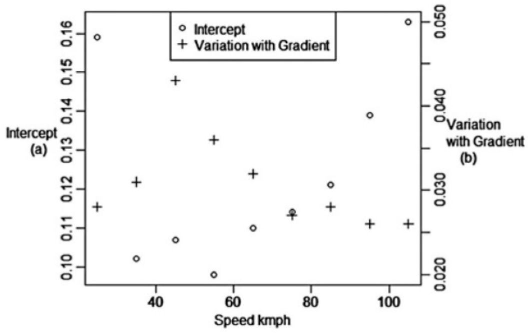

Fig. 6 *Linear models used for efficiency calculation*

acceleration. The general formula for this is given by

$$\text{Power} = mv\big(a + g\big(\mu + \sin(\alpha)\big)\big) \tag{2}$$

where m is the mass, v is the velocity, a is the acceleration, g is the standard gravitational acceleration, μ is the coefficient of friction, and α is the angle of slope. Wind resistance has not been included in this equation but it is not dependent on gradient. For small values of α

$$\sin(\alpha) \simeq \alpha \tag{3}$$

Equation (2) may be then reduced to the form

$$\text{Power} = a + b\,\alpha \tag{4}$$

Equation (4) is then equivalent to the linear model equation shown in (1). By extending the data through the use of a physically valid (4), rather than using the increasingly scarce data beyond the $\pm 6°$ range, there will be a more accurate estimate for power consumption (and thus efficiency) on a gradient.

Although power is linearly dependent on the gradient, it is also dependent on the speed of the vehicle (mass has not been taken into consideration in this study); the coefficient for the dependence of power on the gradient, b in (4), varies with speed. The two coefficients for the power equation (a and b) were calculated for a variety of different speed regimes. Fig. 6 shows the variation of the coefficients of the linear regression analysis used to model the effect of gradient.

The linear models show that for a road with no inclination, that is, a road where the efficiency is purely driven by the intercept (a) on Fig. 6, 50–60 kmph is the most efficient speed. The effect of gradient on the typical speed–efficiency curve can be directly observed in Fig. 7.

In Fig. 7 it can be seen that for the 50–70 kmph regime, there is greater variation in efficiency with respect to the gradient. In addition, it can be seen that at low speeds there is comparatively little variation in efficiency with respect to gradient. One implication of this is that the gradient in inner city areas, for example, is of less importance than that where greater speeds could be expected.

4.3 Justification of the work

In general, it is to be expected that the efficiency of a vehicle over a given distance will be a product of multiple different variables, with the total energy needed to complete a full journey in an EV is governed by multiple different factors such as the loading of the vehicle or the road type. Some of these variables are not predictable, or at least not easily measurable, across the whole of the journey. To successively achieve this, a multiple linear regression model was constructed using data which would either be easily available to any vehicle's on board systems (predicted speed, journey topography etc.) or could be historically derived from data already recorded by the vehicle, for

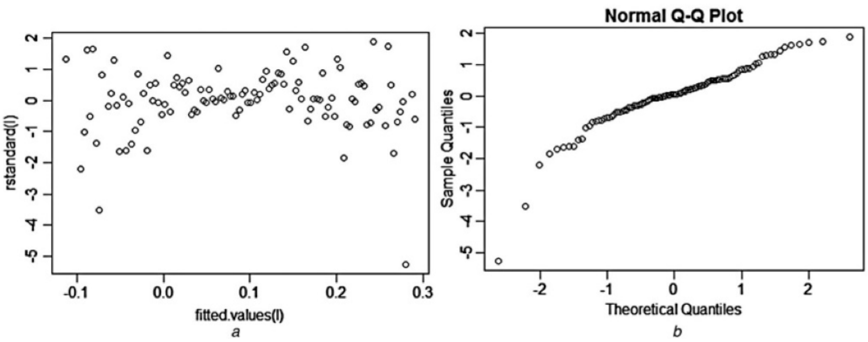

Fig. 5 *Plot of the residuals*

a Plot of the residuals against the fitted values
b *Q–Q* plot of the residuals

doi: 10.1049/iet-its.2013.0122

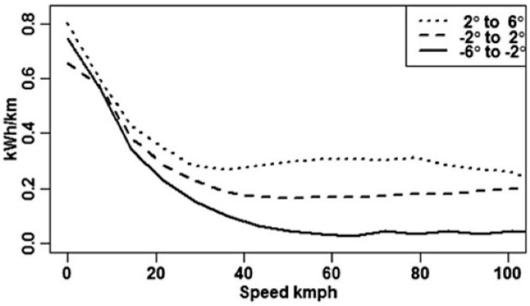

Fig. 7 *Variation in efficiency with speed as the gradient also varies is shown here*

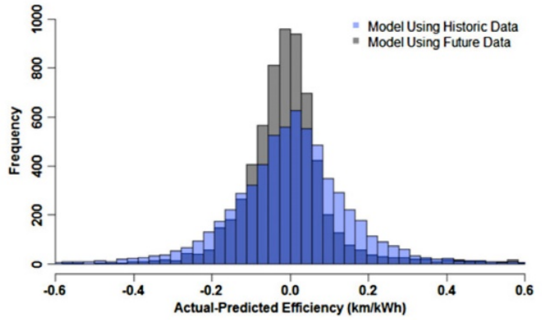

Fig. 8 *Marked improvement in predicting the efficiency of any future journey is shown here*

example, the previous efficiency recorded.

$$\mathrm{Eff}(x) = f(\text{speed, accel, gradient, previous})$$

This equation will be typically composed of multiple different interrelated variables as the effects of, for example, speed vary as the gradient varies, as demonstrated in Section 4.2. Although the specific form of this equation will be the same for each vehicle, as the vehicles rely on the same basic physical underpinnings, there will be varying coefficients because of slight differences between the vehicles.

To illustrate this, referring back to Fig. 7 it can be seen that the efficiency variation of the vehicle with respect to speed is non-linear and can be broken down into two main sections. After 35–40 kmph there is very little variation with respect to speed compared to the strong efficiency variation with speeds below 35 kmph. To improve the model (and remove multiple non-linear terms from the regression equation) it was decided to examine the two sections of data separately.

To assess the importance of each variable in predicting the efficiency, the models were systematically varied and the explanatory power of each variable derived.

Table 3 shows that the faster sections are more predictable than the slower speeds. Qualitatively this makes sense as a great deal of the energy variation at lower speeds is because of variations in hotel loads (lights, radio and air conditioning/heater etc.) rather than actual driving-related power usage. In addition, the speed forms a greater proportion of the explanatory power at lower speeds, which is expected because of the observed strong variation in speed, at lower speeds.

An example is shown in Fig. 8 where there are two distributions: one represents the difference between the actual energy efficiency of a journey and the predicted energy efficiency of that journey where the predicted energy efficiency has been calculated using historical data. The model assumes that the efficiency of a future journey will be the same as the previous journey. This is a system similar to that found in EVs today. In the second distribution, the predicted energy efficiency has been calculated using a combination of historic and available data for the future trip. At this instance, it is assumed that both the topography and the speed of the future journey will be known but it would also be possible to include traffic parameters, such as congestion, or metrological data, such as temperature.

It can be seen that the predicted future efficiency, and hence the accuracy of any predicted future range for the EV is greatly improved through the use of not only historic data,

Table 4 Route planner components of the case study

Input component	Description
ordnance survey integrated transport network (ITN) GIS dataset	digitisation of the UK road network and holds within it information about the road class (a road etc.) and road type (single carriageway etc.)
ordnance survey land-form PANORAMA GIS dataset	dataset provides altitude information across the UK
department for transport COBA manual	average speeds for the road network under different levels of capacities, i.e. capacity 15 (cap 15) indicating free flow
energy cost based on Switch EV data to travel on a road in the network depending on the topography and the capacity level of that road (three capacity levels were used for this work, i.e. cap 15,60,90)	energy cost for travelling 100 m was determined for different slopes and speeds (as a proxy for the road network capacity or congestion level) using the thousands of driving data collected in the trial. These values were then used to define the energy cost of real-world driving on roads with corresponding slope and average speeds (that would match a certain road capacity level)
ArcGis network analyst extension based on Dijkstra's graph search algorithm	finds the least cost route between a chosen start and end point

Table 3 Individual and total explanatory power of each variable is shown here

		All variables, %	Variable removed			
			Speed, %	Gradient, %	Acceleration, %	Previous data, %
% of efficiency explained	<35 kmph	28.5	5.1	4.0	18.5	1.9
	>35 kmph	60.1	3.1	16.6	40.1	3.2

doi: 10.1049/iet-its.2013.0122

but also variables which will affect the car in the future. If it were possible to predict driving patterns, including acceleration, then it would possible to improve this still further.

5 Case study: determining the minimum energy route using EV-specific energy expenditure values

EV-specific energy consumption for different topographical and traffic conditions was determined in Section 4.2. This section will visualise the route choice minimising energy consumption for a given journey on an actual road network. Two steps are needed for this visualisation. First, all the routes on a road network were assigned an EV energy cost value, depending on their topography and for various traffic levels that indicate the EV energy consumption of driving on the roads within the network. Second, Dijkstra's graph search algorithm [25] was used to find the path with the lowest cost (i.e. the path minimising energy consumption) for a given journey. Table 4 shows the input components for this case study that will be detailed in the following sections.

5.1 Modelling a road network

High accuracy road grade or topographical information is not currently widely available [19]. This paper develops a simplified road network topography and capacity level model. The base road network in this work was created

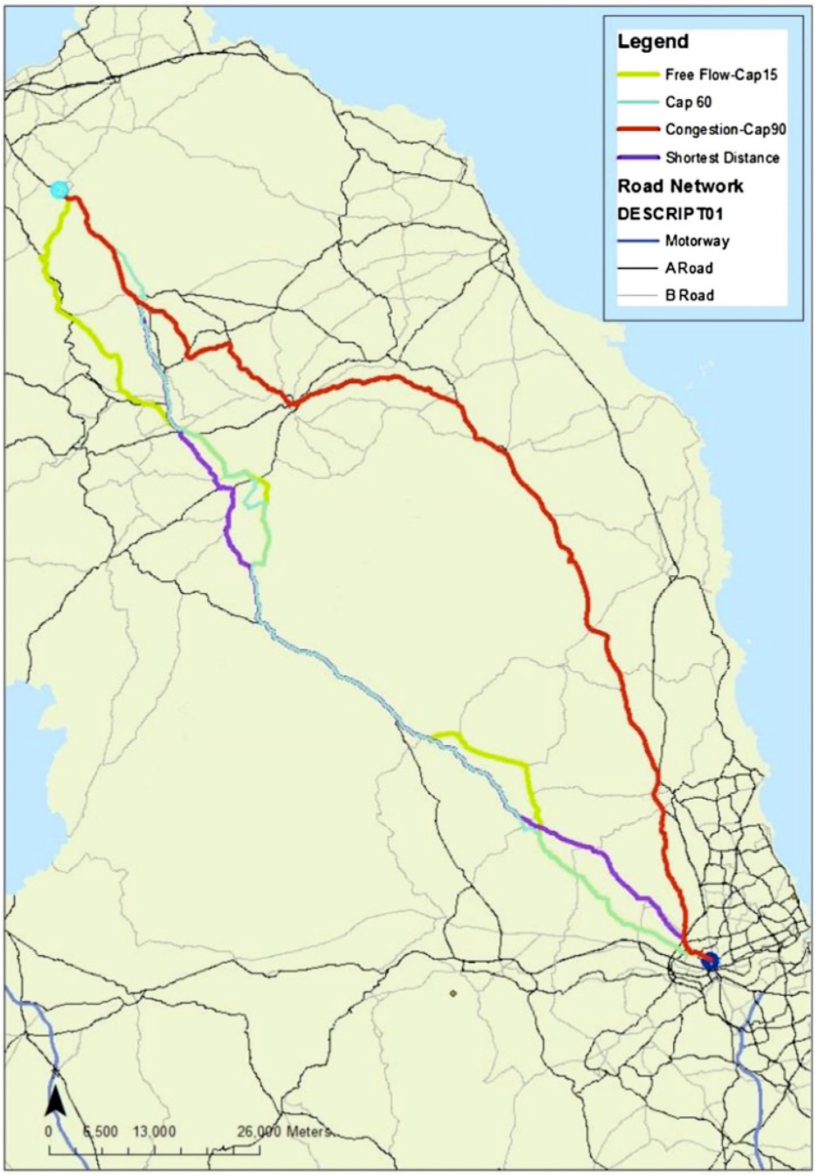

Fig. 9 *Routing to minimise energy consumption under different levels of network capacity*

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through manipulation of the Ordnance Survey Integrated Transport Network (ITN) geographic information system (GIS) dataset [26] for the study area. The ITN dataset is a digitisation of the UK road network and holds within it information about the road class (a road etc.) and road type (single carriageway etc.).

5.1.1 Adding topographical information to the road network: In order to determine the slope of a road segment, the ITN road network was split into start and end points for each road segment. These points were then assigned altitude information from the Ordnance Survey Land-Form PANORAMA dataset. The Open Source dataset provides, if downloaded as a Digital Terrain Model (DTM), a continuous raster surface of heights across the UK. The DTM altitude information assigned to the start and end points of the road segment, combined with the length between the points are used to determine the slope of the road segment using standard trigonometric methods. There is an inherent assumption that the road segment connecting these two points is of a constant gradient over its measured length.

5.1.2 Creating bi-directional links: Originally, the network dataset only exhibits link geometry in the direction they were initially digitised and this is, for all intents and purposes, random. Using the Unique identifier within the dataset, for each original feature, the original digitised geometry direction is termed direction 'A'. A copy of the dataset is then created and the geometry reversed creating

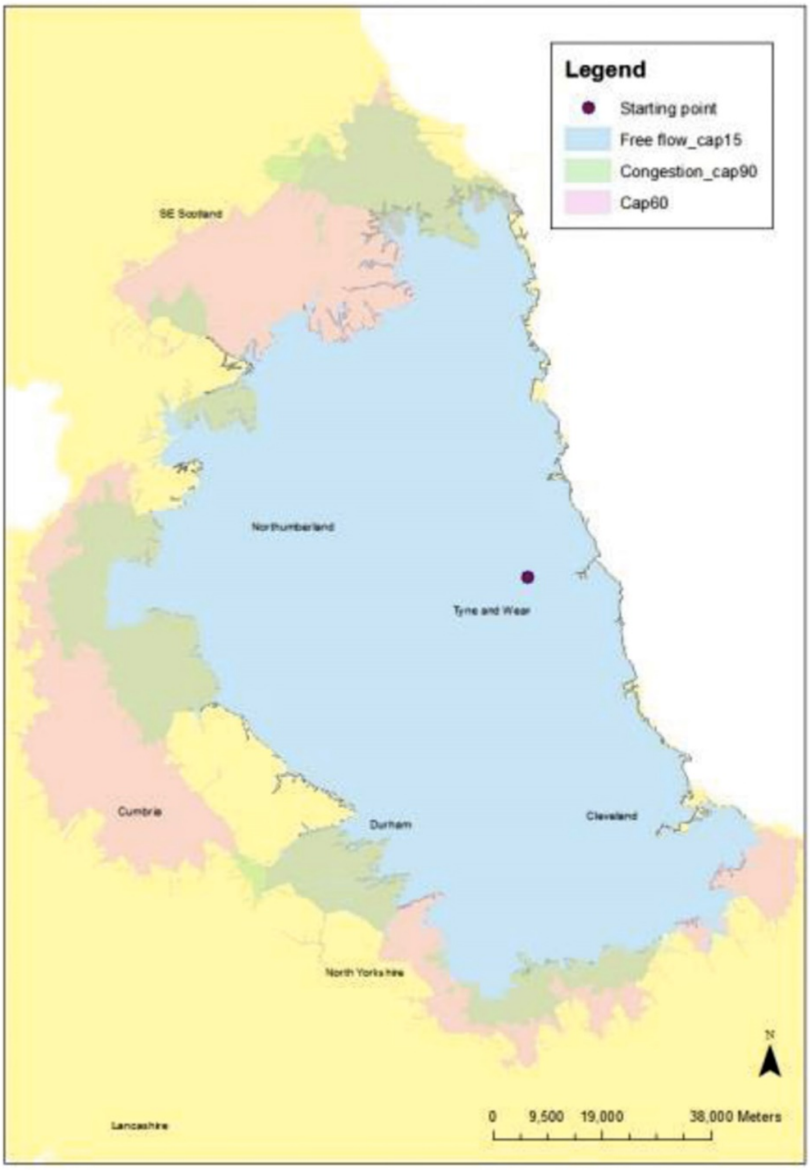

Fig. 10 *Driving range of an EV for different levels of network capacity*

doi: 10.1049/iet-its.2013.0122

direction 'B'. This task is essential so that the bidirectional links can display different impedance values during the network analyst and routing algorithms (i.e. different slope depending on the direction of the travel on that road).

5.1.3 Assigning average speed at predefined COBA capacities: In addition to determining the gradient and direction of the road network in order to visualise the EV data, it is also necessary to prepare the road networks for various levels of traffic capacities. In order to simulate varying levels of congestion, average speeds for different road types at different levels of capacity are determined from the COBA manual. The speed of the roads that make up the ITN network are variable in terms of speed limits, but also in terms of how the speeds of these roads vary when reacting to different levels of network capacity. The capacity conditions range from 15% capacity (essentially free flow speed) to 145% capacity (severe congestion). Each road segment in the ITN dataset was assigned to a COBA link type classification creating a lookup between road type descriptions. Capacities of 15, 60 and 90% (Cap15, Cap60, Cap90) are used for this work.

5.2 Route choice minimising energy consumption

The Network Analyst extension in ArcGis based on Dijkstra's graph search algorithm is used to determine the minimum energy route between an origin and destination. Network Analyst is also used to determine the area of the network that an EV with a certain level of charge could cover. Fig. 9 is an example of finding the route between an origin and destination that minimises energy consumption. It shows the route representing the shortest distance between two points and several energy minimising routing decisions.

The analysis of the routing decisions made under different levels of capacity, and thus average traffic speed, shows that in order to minimise the expenditure of energy, the minimum distance route between the two points can change dramatically. For example, when using Newcastle City Centre and Edinburgh as an origin and destination, two distinctly different routes are chosen; one using predominantly the A1/A697 and the other the A696. The reason for this is that under different capacity levels, the two A Roads react differently in terms of their average speeds. Combining this information, along with topographical changes, the most efficient route is selected. For example, in free flow conditions the chosen route is of a similar distance (159 and 155 km, respectively) to the 90% capacity route; however, there is a noticeable difference in the energy consumption figures (15.95 and 11.75 kWh) which could be related to driving at energy-intensive high speeds. The shortest distance route does not take into consideration the topographical and traffic conditions of the roads; it minimises the distance but not necessarily the energy consumption.

Fig. 10 is an example of finding the area that an EV could cover within the specified network energy cost cut-off. In this work, the energy cost cut-off is the amount of charge on the vehicle. In other words, Fig. 10 shows how far the EV could go from a starting point until it runs out of charge for different levels of network capacity. Comparing the covered area of an EV between free flow conditions, congestion and cap 60, it is found that the driving range of an EV is at its minimum under free flow conditions where average speeds are highest with related high energy consumption as showcased in Fig. 6. Cap 60 (i.e. condition in between congestion and free flow) exhibits the largest range and this is because the average speeds for this road network condition are optimal in terms of energy consumption. The roads are not so heavily congested to have speeds dropping under 35 kmph and they have traffic that could indirectly lead the user to drive in the optimal average speeds (35 to 70 kmph).

6 Conclusion

The analysis presented in this paper shows how understanding the energy consumption of EVs in terms of how they react at certain speeds and how topographical conditions can have a great impact on route choice and thus energy consumption. As an extension of this principle, the paper has also shown that the possible range of an EV fluctuates when these conditions change and that detailed knowledge about future journeys is necessary to accurately predict range. Given that range anxiety is one of the main barriers to EV adoption, this type of information can be input into ITS applications which receive real-time and historic traffic updates to determine the best route available, minimising the energy consumed and thus extending the range. Such information can also help to reduce anxiety effects by giving the driver confidence that the ITS driver aids understand the impacts of these external factors on range, allowing the driver to trust they will be able to reach a destination even on the limit of the stated range. Further work will be done to include other parameters not considered in this paper, such as weight (passengers and baggage) and temperature. A version of this model is going to be used for an eco-driving application that will be demonstrated across four pilot sites in Newcastle upon Tyne, Barcelona, San Sebastian/Bilbao and Reggio Emilia through the SmartCEM project [27] in the first quarter of 2014.

7 Acknowledgments

SwitchEV is a real-world demonstrator trial of electric vehicles co-funded by the UK-Technology Strategy Board and the former regional development agency ONE North East. The authors gratefully acknowledge the contributions and support of the SwitchEV Partners and their funders. The financial support from EPSRC for the project entitled Transforming Utilities' Conversion Points (no. EP/J005649/1) is also gratefully acknowledged.

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doi: 10.1049/iet-its.2013.0122

Applied Energy 157 (2015) 688–698

Contents lists available at ScienceDirect

Applied Energy

journal homepage: www.elsevier.com/locate/apenergy

A probabilistic approach to combining smart meter and electric vehicle charging data to investigate distribution network impacts ☆

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HIGHLIGHTS

- Working with unique datasets of EV charging and smart meter load demand.
- Distribution networks are not a homogenous group with more capabilities to accommodate EVs than previously suggested.
- Spatial and temporal diversity of EV charging demand alleviate the impacts on networks.
- An extensive recharging infrastructure could enable connection of additional EVs on constrained distribution networks.
- Electric utilities could increase the network capability to accommodate EVs by investing in recharging infrastructure.

ARTICLE INFO

Article history:
Received 15 September 2014
Received in revised form 30 January 2015
Accepted 31 January 2015
Available online 13 March 2015

Keywords:
Electric Vehicle (EV)
Smart meter
Load profiles
Spatial–temporal data
Distribution network
User behaviour

ABSTRACT

This work uses a probabilistic method to combine two unique datasets of real world electric vehicle charging profiles and residential smart meter load demand. The data was used to study the impact of the uptake of Electric Vehicles (EVs) on electricity distribution networks. Two real networks representing an urban and rural area, and a generic network representative of a heavily loaded UK distribution network were used. The findings show that distribution networks are not a homogeneous group with a variation of capabilities to accommodate EVs and there is a greater capability than previous studies have suggested. Consideration of the spatial and temporal diversity of EV charging demand has been demonstrated to reduce the estimated impacts on the distribution networks. It is suggested that distribution network operators could collaborate with new market players, such as charging infrastructure operators, to support the roll out of an extensive charging infrastructure in a way that makes the network more robust; create more opportunities for demand side management; and reduce planning uncertainties associated with the stochastic nature of EV charging demand.

1. Introduction

The UK government passed the Climate Change Act which established a legally binding target of cutting the UK's greenhouse gas emissions by at least 80% compared to 1990 levels by 2050 [1]. In order to make the transition to a low carbon economy, the government published the Carbon Plan in 2011 which sets outs a strategy to achieve the decarbonisation target across sectors. A quarter of the UK emissions come from the domestic transport sector which needs to substantially reduce its emissions by 2050. The Carbon Plan emphasizes the need for a move towards a mass market roll-out of ultra-low emission vehicles such as Electric Vehicles (EVs) to achieve the deep cuts required [2]. It would then be important to investigate the potential impact of a significant take up of EVs on the electricity system in the UK; in particular, this work will focus on the impact on electricity distribution networks of residential uncontrolled and clustered charging of EVs.

Several studies have already looked at the impacts of the uncoordinated charging of EVs on distribution networks. The potential impacts on Low Voltage (LV) distribution networks include voltage variations, transformer and thermal limit violations. However, these studies based their work on estimated rather than actual EV charging behaviour and smart meter data. Most of the charging data used in these previous studies was derived from driving patterns collected in national transportation surveys in order to

☆ This paper is included in the Special Issue of Clean Transport edited by Prof. Anthony Roskilly, Dr. Roberto Palacin and Prof. Yan.
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http://dx.doi.org/10.1016/j.apenergy.2015.01.144
0306-2619/© 2015 Published by Elsevier Ltd.

estimate certain aspects of EV usage; such as journey distance and energy used, parking location and time, State-of-Charge (SoC) at the beginning of a charging event and the plug-in time. Some of these studies assumed that the charging starts immediately upon the users' home arrival while others assumed that a large proportion of charging starts from a low SoC. Furthermore, some of the studies considered that users would only charge at home and did not consider the availability of a public charging infrastructure [3–17].

Using the derived charging profiles, the studies demonstrated that the impacts of uncontrolled EV charging in residential areas were detrimental to the operation of distribution networks. Some studies demonstrated thermal limit violations and voltage drops below acceptable limits for EV penetration of 50% [11–13]. One study stated that with 50% EV penetration, there would be significant impacts on the operating conditions of the distribution networks and uncontrolled charging could require major infrastructure upgrades [14]. Another study [15] showed that a 25% penetration of EVs in residential areas would cause considerable voltage dropping below the statutory limit while [16] stated that the distribution network can handle only up to 10% EV penetration without changes in the usual electricity grid operation and planning procedures. One of the studies that focused on British distribution networks found that a 12.5% uptake would cause severe impacts on the transformer and the LV underground cable supplying the households [17]. In this study a probabilistic approach was used to address uncertainties associated with residential loads and EV user behaviour such as plug-in time and SoC. The authors noted that real-world data of EV usage comprising more accurate charge durations, connection times and a reflection on the use of the additional recharging infrastructure (i.e. work, public) could be the focus of further work on the subject and could help improve the probabilistic methods used.

The significance of the present work is that it is based on a unique combination of two comprehensive high resolution spatio-temporal real-world data sets of EV driving and charging patterns and residential smart meter data. The use of real-world data avoids the need to make assumptions about the stochastic nature of vehicle use and would minimise uncertainties associated with simulated charging demand. Based on real-world datasets, this paper demonstrates that distribution networks could accommodate higher EV penetrations than previous studies have suggested.

The EV data is collected from the SwitchEV project which trialled 44 EVs in the North East of England between 2010 and 2013. The cars were fitted with data loggers that captured more than 85,000 EV journeys recorded second by second and over 19,000 recharging events recorded minute by minute at more than 650 public and 260 private charging points [18,19]. The smart meter data was collected via the Customer Led Network Revolution (CLNR) project. This is the UK's largest trial of smart grids and it provided domestic load profiles of half-hourly power consumption data collected from nearly 9000 smart meters. In addition, the CLNR smart meter data set [20] is parameterised by socio-economic variables which allow the selection of representative load profiles appropriate to the network customer population under study. The four-year CLNR project also provided network data and extensively validated network models based on existing local distribution networks operated by the regional distribution network operator (DNO), Northern Powergrid.

This work is an elaboration on [21], extended to include the impacts on a generic distribution network to provide broad value and replicability for the whole of the UK. This is in addition to the urban and rural case study networks. A more comprehensive distribution network impact analysis has been undertaken using IPSA2 (steady-state, balanced three phase network) and PSCAD (Electromagnetic transient analysis for voltage unbalance analysis); and a more extensive results and discussion sections. Section 2 describes the EVs' data, the smart meter data and network models used for this study (including network validation). Section 3 describes our modelling framework to study the impact on the distribution network. The results of the study are presented in Section 4; the discussion and conclusions of this work are presented in Section 5.

2. Data

2.1. Electric vehicles trial – SwitchEV project

High resolution spatial and temporal data of EV driving and charging events were collected, processed and analysed during the SwitchEV project. The dataset gave insight and illustrated the stochastic nature of real world behaviour of EV users. The project recruited different types of users- private and fleet drivers. They had access to an extensive charging infrastructure (home, work, public). The majority of vehicles used in the trial are production vehicles available on the market and were provided by Nissan (LEAF) and Peugeot (iOn). A total of 125 different users were recruited for the duration of the project [19]. As a result, the data collected from the SwitchEV trial captured how people would use an electric car in a real-world context.

2.1.1. The electric vehicle is the primary vehicle

Participants on the trial leased the cars for 6 months which allowed them to get familiar with the vehicle. Shortly after the beginning of their 6-month trial, the participants reported that they had trusted the EV to be their primary car. To verify that the EVs were used in an equivalent fashion to primary vehicles, the authors compared the daily mileage of the Switch EV vehicles collected from the data loggers (Fig. 1) and the National Travel Survey (NTS) mileage data in Great Britain (GB) for conventional cars. The Department for Transport NTS data provides information on personal travel on all mode of transport in GB [22]. Daily average distance travelled was not available; however, according to the NTS the average distance travelled per person per year by car/van drivers is 5207 km. It was assumed that drivers could be using their cars 5 times a week and as such it was estimated that the average distance travelled per person per day by car drivers is 20 km. The average daily mileage of the EV drivers on the trial is 38.9 km, almost the double of the national average, suggesting that the electric vehicles on trial were used as the primary vehicle, as reported by the drivers. Fig. 2 shows the responses collected from the post-trial questionnaires regarding the reasons for driving the electric vehicle.

2.1.2. Real and diverse EV usage profiles (charging and driving)

This work focuses on the charging profile of users. The variables recorded during the recharging events include the time, battery current and voltage along with its State of Charge (SoC). These variables are then used to determine secondary variables such as the duration of a charge event and the energy transferred. However, the driving profile (driving behaviour and driving conditions) is also important because it would determine the SoC of the EV battery before it is plugged in for recharging. The driving profile is briefly described in the two following paragraphs.

The SwitchEV trial recorded trips of varying length ranging from less than 1 km to over 100 km; it also recorded the number of trips between two consecutive charging events. Previous work using the SwitchEV data has demonstrated that driving behaviour of users (i.e. speed) and driving conditions such as the topography of the road network and the network conditions (i.e. free flow, congested)

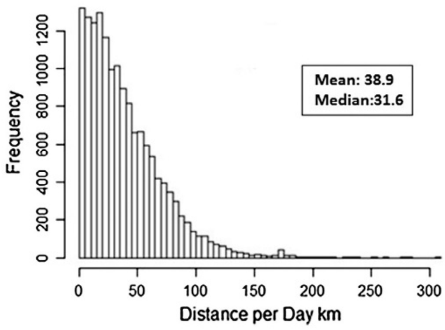

Fig. 1. Distribution of daily mileage of the EV users on the SwitchEV trial.

affects the driving energy efficiency of the vehicle and the residual energy at the end of a driving event [23]. The trial took place over different seasons which enabled the capture of the effects of outside temperature. Temperature affects driving efficiency as lower temperatures would typically lead to the use of the in-car heater fed from the traction battery of the car. This increases the energy used while driving and subsequently further lowers the SoC.

As an example, Fig. 3 illustrates the impact of driving behaviour on energy used for journeys. Different drivers are taking an identical spatial journey as part of an EV trial and their different driving styles result in a different battery drain. At a lower SoC, resulting from an aggressive drive for example, the battery would take more time and energy to return to a level of charge that makes the driver comfortable in using the vehicle again.

The SoC levels recorded during the trial capture the stochastic nature and behavioural diversity of the users. The boxplots in Fig. 4 show the SoC levels of the battery at the beginning of a charging event (left boxplot) and at the end of a charging event (right boxplot). The SoC observations corresponds to the residential charging events recorded during the trial (3332 events). For example, it can be observed that 50% of the charging events started at an SoC $\geqslant$ 53%. These diverse SoC levels would result in a diverse range of charging profiles that were used in this study – moving away from using a fixed energy, static spatio-temporal charging period.

2.1.3. Real and varied charging infrastructure

The SwitchEV trial is distinctive because it collaborated with Charge Your Car (North Ltd) (CYC), the operator of the North East of England's "Plugged in Places" project, which has provided one of the most extensive regional charging networks in Europe with

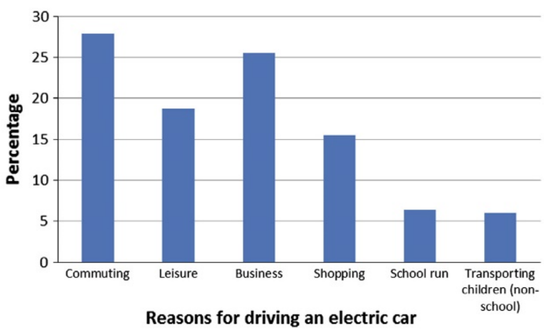

Fig. 2. SwitchEV post-trial questionnaires responses on reasons for driving an EV.

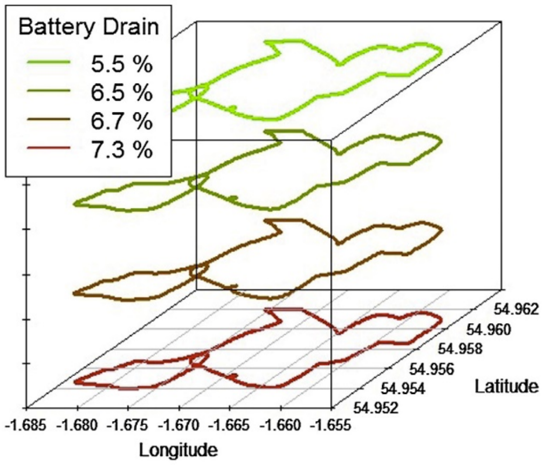

Fig. 3. Illustration of different driving behaviour of four users driving the same route as part of an EV trial. Bottom red journey (7.3% battery drain); top green journey (5.5% battery drain). The colour change denotes the change in driving energy efficiency. The journeys are evenly spaced on the Z-axis to obtain a clearer graph. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

more than 900 charging posts installed in public, work and home locations in the region during the SwitchEV trial. As a consequence, the participants were not limited to one charging location and they had real and varied options about when and where to charge. Their homes and work places could be equipped with charging units; they could access charging posts on-street and in commercial places and public car parks; and there were twelve accessible 50 kW DC Rapid Chargers (RC) installed at strategic locations in the region. The RCs allow a car to recharge from an empty battery (SoC = 0%) to 80% in less than 30 min. The analysis of the dataset collected identified the charging locations used and the energy transferred at each of these locations. This analysis allowed the extraction of home charging events that were used for this study. This extensive and flexible infrastructure was reflected in the charging profiles and was key to the results obtained in this study that will be described in Section 5.

2.1.4. Keepership type and residence setting

The EVs on the trial were leased as private and fleet cars. The charging profiles of private cars were used in this study.

To determine the residence setting (i.e. urban vs rural) of the users on the SwitchEV trial, the Office for National Statistics Postcode Directory (ONSPD) was used. Postcodes on the ONSPD are assigned to urban or rural categories [24]. The postcode of the SwitchEV users were identified in the ONSPD and their residence setting was then determined. It was found that 70% of the SwitchEV users reside in urban areas while 30% reside in rural areas.

Fig. 5 presents an overview of all charging events for the private users at all locations. It shows the percentage of the average energy transferred at different locations per hour of the day for private urban (top figure) and private rural users (lower figure). It can be observed that charging events were recorded at different locations (home, work, public, RC). Urban users in particular used the public infrastructure significantly. Most of the work charging events happened during the day as would be expected. Home charging picks up in the afternoon and a noticeable additional charging peak occurs at midnight for both urban and rural participants. The midnight

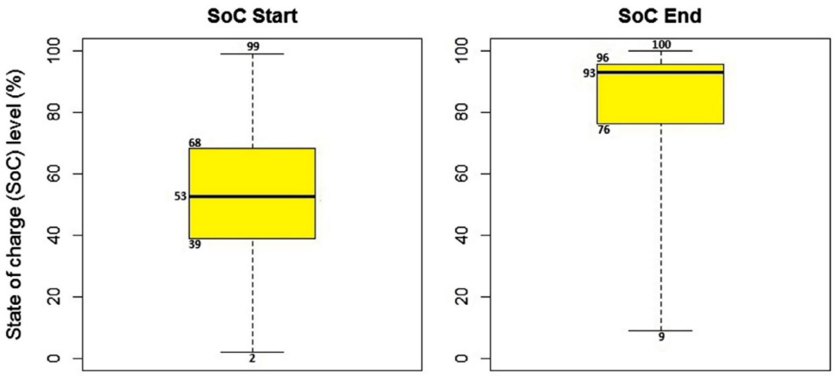

Fig. 4. Boxplots of State of Charge (SoC) of the batteries of the cars on trial. Before charging (left) and after charging (right). The vertical dimension of the boxes display the variation of the data. The bottom of the box is the 25th percentile of the data (SoC value below which 25% of the observations may be found). The top of the box is the 75th percentile of the data. The horizontal bold line inside the box is the median (50th percentile of the data). The end of the whiskers (lines extending vertically from the boxes) can represent several alternative values; for this graph, we chose them to represent the minimum and maximum of all of the observations.

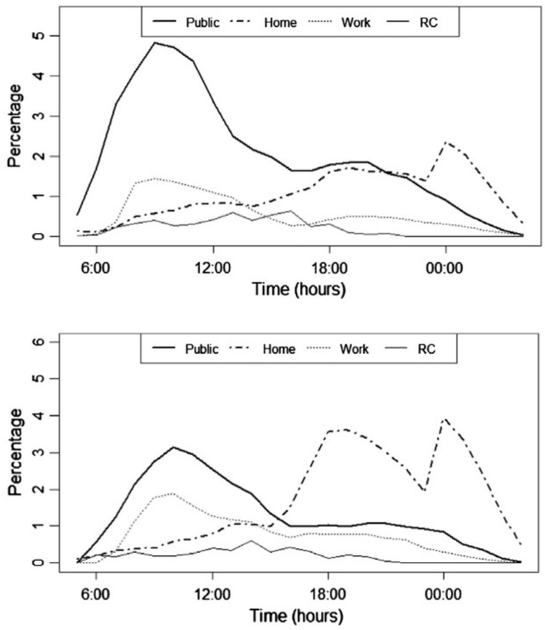

Fig. 5. Percentage energy transferred at each hour of the day for all charging events at different charging locations. Urban users (top figure) and rural users (lower figure).

Table 1
Summary of LV network and population parameters.

	"Urban"	"Rural"
Substation	6.6 kV/400 V 500 kVA	20 kV/400 V 315 kVA
Feeders	4	2
Total LV customers	288	189
Number of customers per LV feeder	A-59, B-66, C-84, D-79	A-123, B-66
Vehicle ownership	86%	74.6%
No. of vehicles in vehicle-owning households	1.7	1.5
ONS morphology code	1 (Urban)	3 (Rural)
House thermal efficiency	Medium	Medium
Percentage households with under 5 s or over 65 s	44%	40%
Equivalent annual income (gross)	60%: >£30 k 35%: £15–£30 k 5%: <£15 k	18%: >£30 k 62%: £15–£30 k 20%: <£15 k
Tenure	Effective 100% home ownership	37% Renting 63% Owned
Household occupancy	97%	97%

peak could be explained by some home chargers equipped with a timer set to start charging at midnight. Finally, rural users rely more on home charging compared to urban users.

2.2. Smart grid trial – Customer Led Network Revolution (CLNR) project

2.2.1. Smart meter data

In order to understand present and emerging load and distributed generation patterns, the CLNR project is conducting monitoring trials using data from over 9000 smart meters placed in residential locations in the UK. The smart meter dataset is classified by household income, presence of under 5 s or over 65 s, tenure, household thermal efficiency and area classification (urban/rural). UK ONS data was used to determine the characteristics of the study areas of this work, which are summarised in Table 1 along with the electricity network characteristics. Using the parameters in Table 1, a representative population of residential load profiles was extracted from the CLNR dataset representing the study areas. Properties in the two regions are mostly mid-20th century semi-detached houses with adjoining off-street parking. Some communal parking facilities are also evident. Vehicle ownership is high and many households own more than one car. Given these observations, these populations are used as model populations of potential future EV owners on their respective networks.

2.2.2. Network models

Previous work suggests that densely-populated urban and sparsely-populated rural LV networks are both likely to be vulnerable to the mass uptake of EVs [7]. As these two network types are estimated to represent approximately 80% of UK

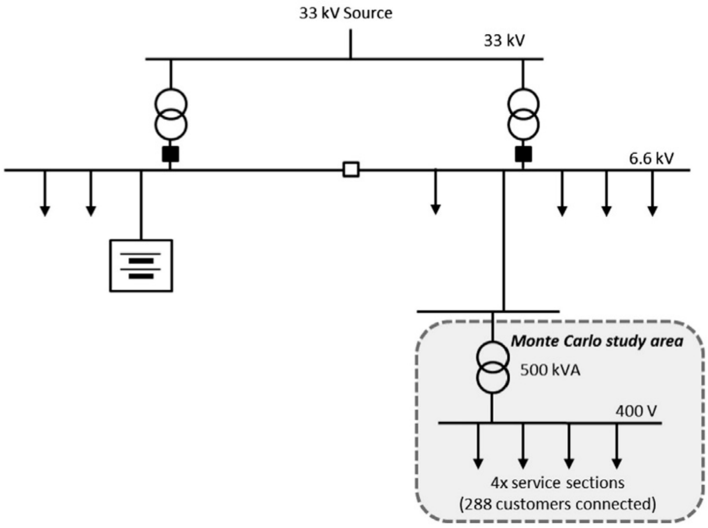

Fig. 6. Diagram of the 6.6 kV case-study urban network used in steady-state IPSA2 study.

networks [3], it is of critical importance to further study these scenarios. The CLNR project is using two real networks within Northern Powergrid's licence area – one rural and one urban – to enable evaluation of questions of load growth and active network management. Models of the trial networks have been developed in IPSA2, a steady-state power system simulation application, and these have been extensively validated with two years of detailed network data and against existing DNO network models (using data provided by Northern Powergrid). This study uses this set of models and data as a foundation for the examination of EV load impacts.

The urban network under study (Fig. 6) is a 6.6 kV network supplying approximately 6000 customers, with a mixed load curve and an early-evening peak. One particular HV/LV substation supplying 288 customers via a 500 kVA transformer and 4 LV feeders is studied in detail as a test case for EV penetration.

Fig. 7 shows the rural network under investigation. This consists of a 20 kV feeder, approximately 40 km long, supplying a number of towns in Northumberland in northern England. Three HV/LV substations supply one of these towns; and this paper focuses on one of these substations which supplies 189 residential properties through two multiply-branched LV feeders.

The LV network sections under study are exclusively residential with no industrial or commercial facilities or public EV charging infrastructure supplied by the HV/LV transformer.

In addition, a third 'generic' network (Fig. 8) based on [25], has been studied. This network has been deemed to be a representative of a heavily loaded UK distribution network by UK DNOs who were involved in specifying and creating it. It consists of a 33 kV source feeding two 15 MVA 33/11 kV transformers. There are six 11 kV feeders, each of which have eight 500 kVA 11/0.4 kV transformers equally spaced along 3 km of underground cable. Downstream of each 500 kVA transformer are 4 LV feeders of 300 m in length with 96 customers spaced equally along each feeder. The population parameters for the 386 customers under study on the generic network were assumed to be the same as the urban network described previously in Table 1.

The rural and urban networks give an indication as to the problems that could be encountered in different types of networks. However, all networks are different and therefore the modelling of a specific system is required to establish if localised problems exist. The generic network has been used in this study in order to draw broad and generalizable conclusions across the UK distribution networks as a whole.

2.2.3. Urban and rural network load modelling validation

Representative power consumption data collected from LV monitoring systems installed on the study networks for two winter (January) peak demand mid-week days for both the urban and rural networks were compared in Fig. 9 with randomised customer group demands (sampled from the smart meter dataset for the peak day). This was done to confirm that the modelled networks and simulated customer groupings approximated the real network loading.

It can be seen that the general customer behaviour adequately represents the real load on the respective networks, particularly total peak loading, and the network and customer models are therefore used as a baseline to evaluate the additional EV loading. It has been found[1] that 50% of secondary distribution transformers operate at approximately 50–60% of their nameplate capacity, therefore the HV/LV transformers under study are not atypical.

3. Methods

3.1. Monte Carlo simulations

Peak consumption of electricity is in winter in the UK. In order to assess the additional impact of EVs during an existing peak loading event, a single peak load test day corresponding to the DNO's system peak load day in January is studied.

Monte Carlo Simulation (MCS) was used to build up a distribution of possible demands on the trial networks. Data for the simulation was produced by sampling the domestic load profile and EV charging profile populations. Households on the LV networks were randomly assigned load profiles in proportion to the local demographic makeup. A defined percentage of these users, corresponding to a level of EV penetration, were further assigned

[1] Information provided by Northern Powergrid.

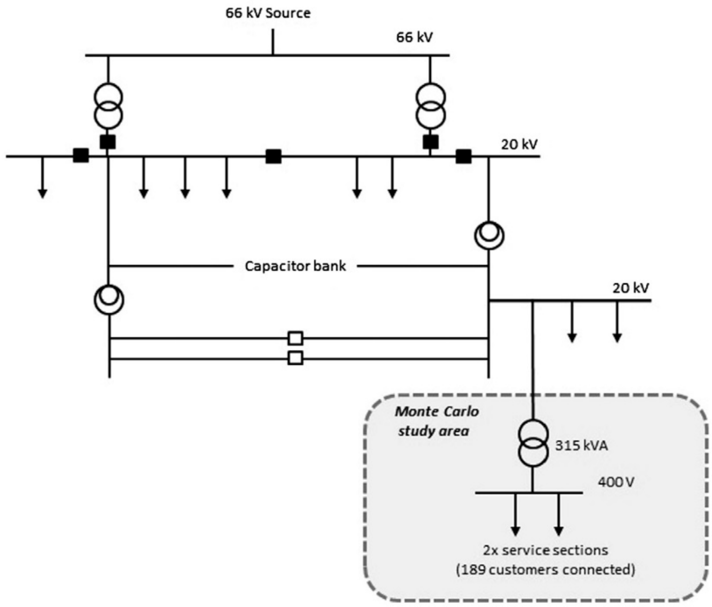

Fig. 7. Diagram of the 20 kV case-study rural network used in steady-state IPSA2 study.

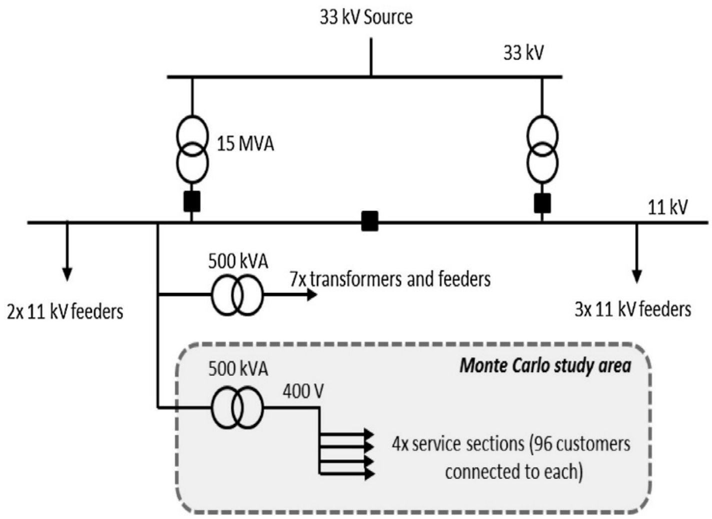

Fig. 8. UK generic network used in steady-state IPSA2 and dynamic PSCAD studies.

an EV load profile which was added to their base domestic profile. EV penetration is defined as the ratio of EVs to the number of vehicle-owning households. For the case of the urban network with 288 customers and a vehicle ownership of 86%; 60% penetration (149 EVs) represents an approximate nominal upper bound on the test networks whereupon all households owning more than one vehicle have an EV as the second vehicle.

1000 simulated peak days (i.e. 1000 simulation runs) were generated to ensure adequate variation of customer behaviour, EV charging profiles and customer location on the network. The generation of multiple random configurations naturally captures any spatial concentration of households with EVs (e.g. at the remote end of the longest feeder) which could cause additional voltage drops. Fig. 10 shows some illustrative examples from the urban profiles population assigned to customers.

A configuration of the urban network with 60% EV penetration at 18.00 on the peak demand day was examined to ensure that stable results had been obtained with 1000 MCS trials. With 1000 trials, the mean transformer demand had converged to a stable 385.8 kVA (standard error 0.29 kVA). The standard deviation

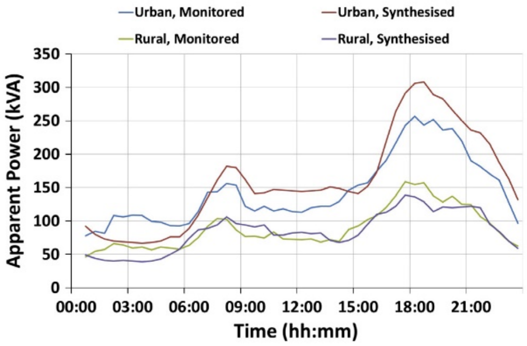

Fig. 9. Comparison of monitored and synthesised load profiles for a rural and urban substation.

of the distribution of transformer demands had also stabilised to 9.1 kVA. Thus the distributions produced by the simulated trials are stable and provide reliable estimators of the simulated demand.

3.2. Steady State, balanced study in IPSA2

Each of the three networks; urban, rural and generic were modelled in IPSA2, version 2.3.1. IPSA2 is a commercial power systems analysis software package developed initially by the University of Manchester Institute of Science and Technology (UMIST) in 1975 and is now supported by TNEI Services Ltd [26]. The IPSA2 load flow algorithm, based on the Fast Decoupled Newton–Raphson algorithm [27], was used to calculate the power flows and voltages throughout the system.

The average hourly load profiles (expected values) of the households on the networks with a defined EV penetration were calculated from the 1000 runs. In addition the 2.5% and 97.5% lower and upper bounds of the data were calculated. Fig. 11 illustrates these calculations for the remote end of the longest feeder on the urban network (10 households connected to that feeder) at 60% EV penetration; the expected values are represented by the black dots and 95% of the data falls within the grey area.

Network simulations in IPSA2 were performed using the average and 97.5% upper bound load data for the EV penetration levels of 15%, 30% and 60%, producing corresponding power flow and voltage drop results for the various configurations of the two networks. Two additional EV penetrations –40% and 50%– were studied for the generic network to consider the thermal loading of the transformer in greater detail.

3.3. Electromagnetic transient, unbalanced study in PSCAD

IPSA2 is unable to calculate voltage unbalance caused by phase concentration of existing load and EVs, and therefore the voltage drop along the feeder calculated by IPSA2 would be an underestimate when the network is unbalanced. In order to overcome these limitations, the network demonstrating the worst case results as calculated by IPSA2, the Generic distribution network (details in Section 4), has also been modelled in PSCAD/EMTDC version 4.2.1. PSCAD/EMTDC is a commercial power systems analysis software package developed by the Manitoba HVDC Research Centre [28] and originally inspired by Dommel [29,30]. It uses time-domain based analysis (as opposed to frequency domain like IPSA2) and was used in this study primarily to evaluate the impact of unbalanced loads on the resultant voltages within the network.

In contrast to the approach of using the average and 97.5% load values in the IPSA2 simulations, each load profile for the 1000 simulated peak days was used in PSCAD and the voltage magnitude and voltage unbalance was assessed once each simulation reached steady-state. This was undertaken for different EV penetration levels ranging from 0% to 100% in 5% steps. To reduce the computational burden in PSCAD, only the worst-case hours of the peak day were assessed. This was 17.00–05.00 based on the IPSA2 results.

The voltage unbalance in a three-phase system is defined in Engineering Recommendation P29 [31] as the ratio (in per cent) between the rms values of the negative sequence component and the positive sequence component of the voltage. This can be approximated for values of voltage unbalance of a few per cent, as was the case for this study, as:

$$\text{Voltage unbalance } (\%) = \frac{\text{Maximum deviation from the average of the three phase voltages}}{\text{Average of the three phase voltages}} \times 100\%$$

4. Results

4.1. Transformer loading

Fig. 12 shows power demand profiles for the urban and rural LV networks on the test day for EV penetration values that produce loading exceeding the transformer thermal limit. Using the 97.5th upper demand bound, the urban network is not compromised even at 60% EV penetration, although at this point the load is approaching the transformer rating (500 kVA). The rural network was compromised at 15% penetration. The generic network was compromised at 40% EV penetration using the 97.5th upper demand bound (Max@ 40%) (Fig. 13).

4.2. Voltage-IPSA2 study

The voltage magnitude in LV networks is required to be within the statutory limits +10%/−6% [32]. Table 2 shows the maximum voltage changes occurring at times of 97.5% of the load for the rural and urban networks. Similarly in Table 3 and 60% EV penetration with 97.5% of the load did not cause voltage problems in the generic LV distribution network.

4.3. Voltage and phase unbalance – PSCAD study

The worst case for voltage drop is at the furthest end of the feeder, and therefore the voltage and its unbalance were measured at the end of the 400 V feeder. Industry planning regulations state that the voltage unbalance should not exceed 2% when assessed over any one minute period, and when sustained the voltage

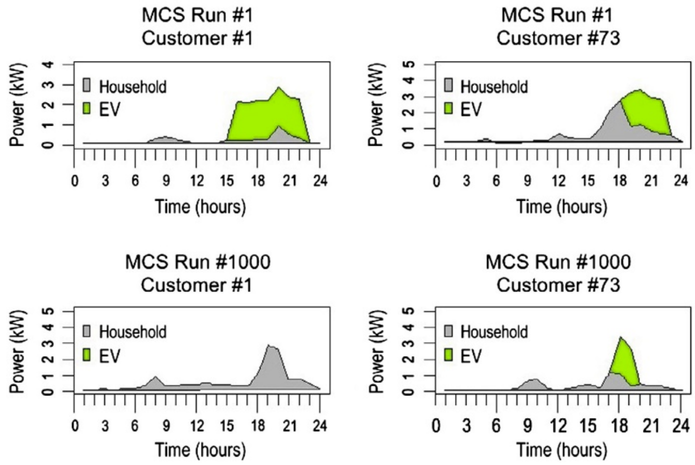

Fig. 10. Example of peak day load profiles for 2 customers (#1 and #73) on the network for 2 different MCS runs (run #1 and 1000). Each MCS run generates a population of customers as defined by the network topology.

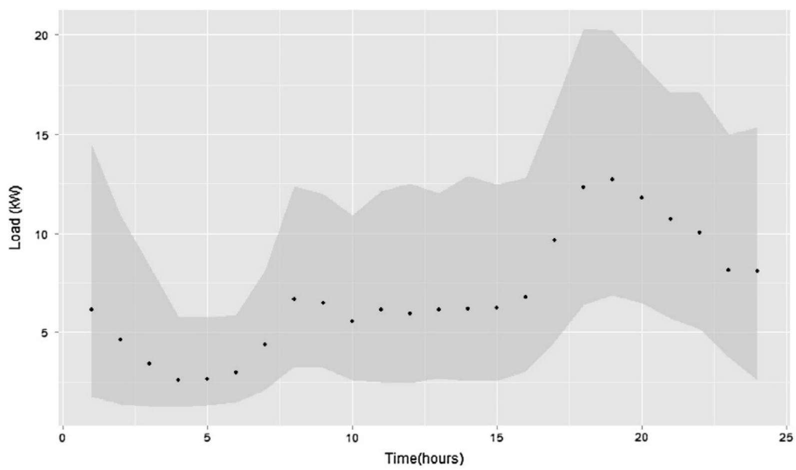

Fig. 11. Remote end of longest feeder-urban 60% EV penetration-average load values (dots) and 95% data bound (grey area).

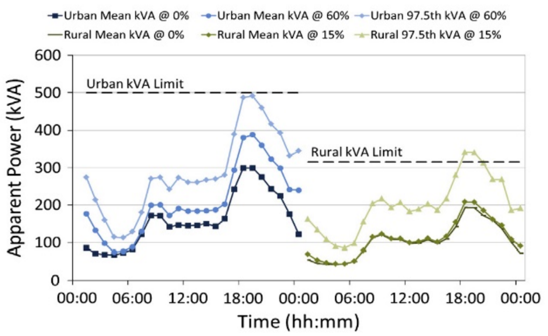

Fig. 12. Test day critical demand for urban and rural network.

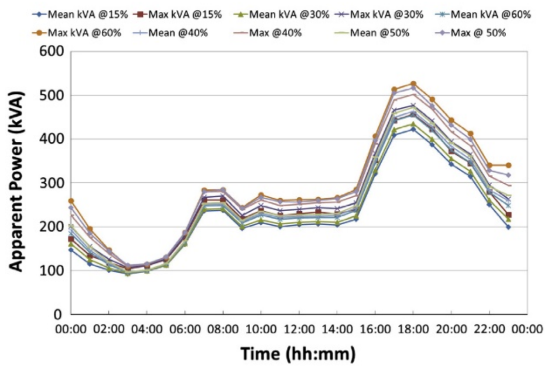

Fig. 13. Test day critical demand for the generic network.

Table 2
Maximum voltage changes on the test networks (negative sign indicates a voltage drop).

	Average Load 0% EVs	Average Load 15% EVs Rural 60% EVs Urban	97.5% Load 15% EVs Rural 60% EVs Urban
ΔV – Rural	−2.33%	−2.52%	−5.39%
ΔV – Urban	−1.40%	−1.72%	−2.90%

Table 3
Maximum voltage changes in the generic LV network (negative sign indicates a voltage drop).

Lowest voltage	15% EVs	30% EVs	60% EVs
ΔV – Mean (%)	−1.58	−1.64	−1.73
ΔV – Max (%)	−2.67	−2.79	−3.02

unbalance should not exceed 1.3% for systems with a nominal voltage below 33 kV [31]. The minimum voltage magnitude experienced for each EV penetration level during all the studies is shown in Fig. 14 and the maximum voltage unbalance during all the studies is shown in Fig. 15. The results for minimum voltage are consistent with the maximum loading condition of the IPSA2 study. The PSCAD results show a marginally lower minimum voltage than IPSA2 results as the unbalance in load and EV connections across the LV network is now modelled. As the penetration of EVs increases the load increases and the minimum voltage experienced reduces, although it does not cause a statutory limit violation even with 100% EV penetration.

Similarly an increase in charging load results in the unbalance of the network increasing. Using the 97.5% percentile, an EV penetration of 60% can be sustained on the generic network before the voltage unbalance would be considered an issue.

CLNR field trials networks, in the authors' experience, have been observed to exhibit a voltage unbalance that frequently approaches

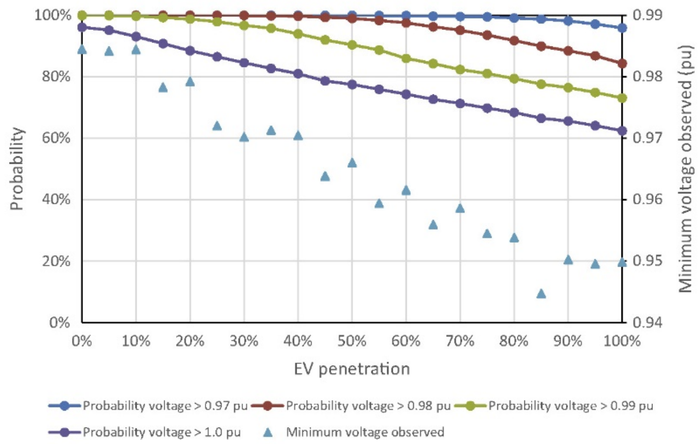

Fig. 14. Minimum voltage magnitude observed for each EV penetration during all studies.

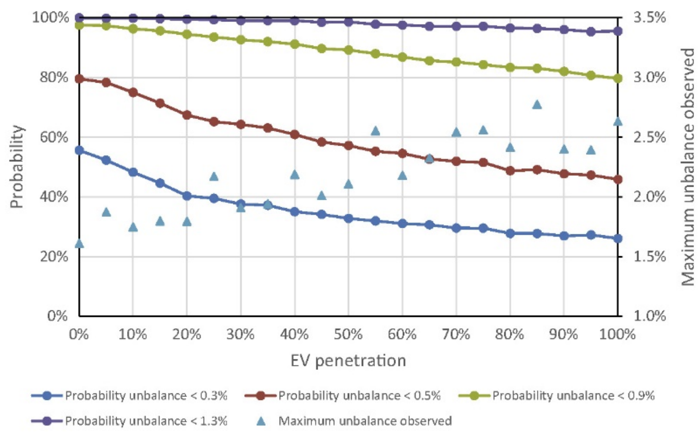

Fig. 15. Maximum voltage unbalance observed for each EV penetration during all the studies.

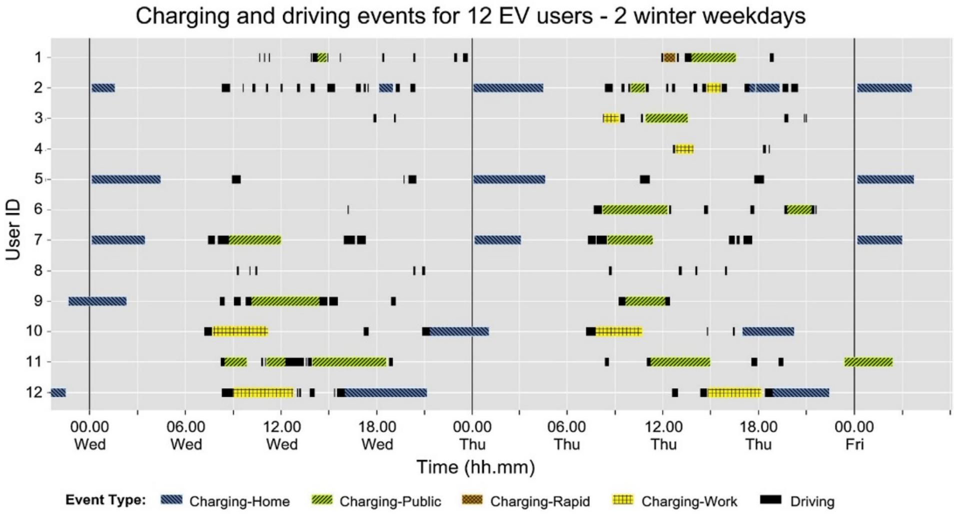

Fig. 16. Spatial and temporal diversity of EV charging demand.

or exceeds the 1.3% limit-with no EVs charging at all. Therefore, the impact of high EV penetrations on unbalance should not be ignored. All networks are different and as EV penetrations increase, the determination of the degree of unbalance will need to be conducted on a network-by-network basis.

5. Discussion and conclusions

This work has used a probabilistic method to combine two unique datasets of real world EV charging profiles and residential smart meter load demand. The datasets were used to study the impact of the uptake of EVs on distribution networks. The study used real, validated networks of an urban and rural area and a generic network, representative of heavily-loaded UK distribution networks. The range of networks used demonstrated that LV networks are not a homogenous group and have different characteristics, sets of parameters and customer behaviour which illustrates the importance of bespoke studies.

5.1. Urban vs rural study

The urban network under study was able to accommodate a much higher EV penetration compared to the rural network. These results stem from the differences in EV charging profiles, network topologies and impedances between the urban and rural areas. The trial data showed that rural users relied on domestic charging more than the urban users who had access to a more extensive public charging infrastructure. In addition, the SoC data indicates that the median SoC start for urban users is 56.3% compared to 47.9% for rural users indicating more energy used for journeys of rural users-suggesting longer trips back home.

5.2. Urban vs generic study

The generic network gives broad and generalisable findings in comparison to more specific findings respective to a specific network (i.e. real urban network). However, the generic network is a heavily loaded network and simulating it using peak day load data at the 97.5th upper demand bound could be considered conservative. Lower EV penetration rates (40%) caused thermal overloads on the generic network compared to the urban network. Working with the heavily-loaded generic network gives insights to future problems on the networks due to a transition to a low carbon economy (i.e. the use of heat pumps, distributed generation and the likely growth in EV battery capacities and charger power). EV loading at different levels erodes the headroom available at peak loading time which implies that the capacity of the network to absorb additional large electrical load (e.g. heat pumps) is reduced and also impacts on voltage unbalance particularly in areas of high PV penetration.

This comparison between the generic and urban networks shows that while currently few networks are likely limited to accommodate EVs, distribution networks in general are more robust than previous work has suggested. The spatio-temporal spread of charging profiles used in this work-moving away from using a fixed energy, static spatio-temporal charging period contributed to these novel findings.

5.3. Spatial and temporal diversity of EV charging demand

Spatial, temporal and behavioural diversity of EV charging demand has been demonstrated to alleviate the impacts on electricity distribution networks. Based on real world trials of EV usage, the results of this study showed that distribution networks could accommodate higher EV penetrations than previous studies have suggested. The diversity of charging demand in time and space was a consequence of an extensive charging infrastructure available to the EV users which gave them multiple options (work, public, rapid and home) and flexibility of when and where to charge. People charged at more than one location and did not rely only on residential charging. Therefore, additional energy was supplied to EVs from non-domestic sources and people arrived home with a higher SoC on their EV batteries than what would have been assumed. Fig. 16 shows an example of the spatial diversity of charging events in addition to the diversity in charging times, duration and frequency, illustrating the stochastic nature of the expected new electricity demand.

The EU Electricity Directive (2009/72/EC) states that the DNOs are legally responsible for ensuring the long-term ability of the system to meet reasonable demand, for the distribution of electricity

[33]. EVs are well suited to meet urban mobility requirements [34] and an uptake of EVs could create a significant new electric demand that the DNOs would need to accommodate [35].

This study demonstrated the benefits of maintaining load diversity by spreading EV charging demand both in space and time. This suggests that it could be beneficial for DNOs to invest in supporting the roll out of the EV recharging infrastructure and work closely with new market players (e.g. charging infrastructure operators) as a way to efficiently manage existing distribution network infrastructure. In addition to alleviating the impacts on the distribution network and operating a less congested network, an EV charging demand that is spread through space and time could present more opportunities and flexibility for demand-side management schemes. Finally, the real world trial illustrated the stochastic nature of EV charging demand which could create planning uncertainties, for DNOs, associated with any potential plans to upgrade the electricity network.

Acknowledgments

The Switch EV project was co-funded by Innovate UK and the former regional development agency ONE North East. The Switch EV project partners are: Nissan, Future Transport Systems, ONE NE, Smiths EV, AVID EV, Simon Bailes Peugeot, Liberty EV and Newcastle University. EPSRC funded projects also supported the EV trials and subsequent analysis (namely SiDE Digital Hub (EP/G066019/1); Transforming Utilities' Conversion Points (no. EP/J005649/1); and iBuild (no. EP/K012398/1)). The Authors gratefully acknowledge the contributions and support of the Switch EV Partners and the EPSRC.

The Customer-Led Network Revolution (CLNR) project is funded by the Office of Gas and Electricity Markets (Ofgem) under the Low Carbon Network Fund. The collaborating CLNR project partners are: Northern Powergrid, British Gas plc, EA Technology Ltd, Durham University and Newcastle University. The Authors gratefully acknowledge the contributions and support of the CLNR partners.

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Energy Policy 108 (2017) 474–486

Contents lists available at ScienceDirect

Energy Policy

journal homepage: www.elsevier.com/locate/enpol

Analysing the usage and evidencing the importance of fast chargers for the adoption of battery electric vehicles

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ARTICLE INFO

Keywords:
Electric vehicle
Public charging infrastructure
Fast charging
Rapid charging
Driving range
Regression analysis

ABSTRACT

An appropriate charging infrastructure is one of the key aspects needed to support the mass adoption of battery electric vehicles (BEVs), and it is suggested that publically available fast chargers could play a key role in this infrastructure. As fast charging is a relatively new technology, very little research is conducted on the topic using real world datasets, and it is of utmost importance to measure actual usage of this technology and provide evidence on its importance to properly inform infrastructure planning. 90,000 fast charge events collected from the first large-scale roll-outs and evaluation projects of fast charging infrastructure in the UK and the US and 12,700 driving days collected from 35 BEVs in the UK were analysed. Using multiple regression analysis, we examined the relationship between daily driving distance and standard and fast charging and demonstrated that fast chargers are more influential. Fast chargers enabled using BEVs on journeys above their single-charge range that would have been impractical using standard chargers. Fast chargers could help overcome perceived and actual range barriers, making BEVs more attractive to future users. At current BEV market share, there is a vital need for policy support to accelerate the development of fast charge networks.

1. Introduction

The transport sector is responsible globally for approximately one quarter of the total energy-related greenhouse gas emissions, with over 70% of these emissions attributed to road transport. To reduce transport related emissions, sustainable mobility plans of many governments worldwide include the need for a substantial shift towards the use of ultra-low carbon emission vehicles such as battery electric vehicles (BEVs) (IEA, 2016; Sims, 2014). For instance, the Paris Declaration on Electro-Mobility and Climate Change calls for the global deployment of 100 million electric cars across all market segments by 2030 (IEA, 2016; UNFCCC, 2015). However, recent (2015) electric car stock figures have only reached 1.26 million[1] cars globally (IEA, 2016) indicating the need for a substantial market growth. The low market share of BEVs is explained by several barriers to adoption such as high purchasing cost compared to an equivalent liquid-fuel vehicle, limited driving range and the lack of an appropriate charging infrastructure. Policies are implemented in many countries to increase the attractiveness of EVs and potentially their adoption rates (Sierzchula et al., 2014; Silvia and Krause, 2016). These policy mechanisms include providing financial incentives such as purchase subsidies and non-financial incentives such as access to bus lanes, free or dedicated parking spots; raising awareness on EVs; and supporting the development of EV charging infrastructure (Coffman et al., 2017; Egbue and Long, 2012; IEA, 2013; Langbroek et al., 2016; Steinhilber et al., 2013).

Recent studies assessed the impact of policy mechanisms on EV adoption. One important finding is that policy interventions may yield different impacts across different groups of people (for example, early adopters versus mainstream consumers), indicating the need for a targeted intervention approach (Langbroek et al., 2016; Silvia and Krause, 2016). In addition, Langbroek et al. (2016) found that access to bus lanes and free parking are an efficient alternative to expensive subsidies; however, these kind of incentives must be in place temporarily to avoid crowding (e.g. many cars in the bus lane) that can make these policies less attractive and could also cause unwanted side effects (e.g. encourage driving instead of using public transport). Moreover, the authors emphasised the importance of informative interventions that could encourage more people to consider an EV, such as helping people differentiate between their perceived and actual travel patterns.

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[1] 740,000 Battery Electric Cars.

http://dx.doi.org/10.1016/j.enpol.2017.06.033
Received 22 December 2016; Received in revised form 28 April 2017; Accepted 14 June 2017
Available online 27 June 2017
0301-4215/

Similarly, Silvia and Krause (2016) recognised the importance of increasing awareness on EVs; moreover, they found that policy interventions perform considerably better when implemented synergistically rather than in isolation. An awareness-related policy strategy is described by Matthews et al. (2017); the authors analysed data collected by trained mystery shoppers and demonstrated the importance for policy makers to recognise the influential role market intermediaries such as car dealerships have in encouraging the adoption of BEVs. An example of an awareness campaign is the new national Go Ultra Low (GUL) campaign, a joint collaboration between the UK government and vehicle stakeholders. GUL aims to increase purchase consideration of EVs by helping potential users understand the benefits, cost savings and capabilities of available EV models on the market (Go Ultra Low, 2017). While many studies found that the presence of a public charging infrastructure is positively correlated with EV adoption rates, it is important to note that the direction of causality is not clear (Coffman et al., 2017; Mersky et al., 2016; Sierzchula et al., 2014). Coffman et al. (2017) reviewed recent studies assessing factors affecting EV adoption and found that public charging infrastructure is an important factor associated with EV uptake. Specifically, Sierzchula et al. (2014) examined the relationship between several socio-economic factors and 30 national EV market shares for 2012 and found that charging infrastructure was most strongly related to EV adoption. Looking at the country with the highest market share of EVs, Mersky et al. (2016) investigated the effects of several incentives on per capita EV sales in Norway and found that pricing incentives and increased access to charging stations may be the best policies to increase EV sales.

A public network of fast[2] chargers is argued to be a key component of an overall BEV charging infrastructure (Cruz-Zambrano et al., 2013; Jochem et al., 2016; Schroeder and Traber, 2012). Indeed, Nilsson and Nykvist (2016) investigated the near term interventions needed to enable a BEV breakthrough over the next 15 years in the EU and recognised that the availability of public fast charging is an important signal for consumers and it will support BEV growth. Unlike conventional slow charging stations that take hours to recharge a vehicle, current 50 kW fast charging stations can recharge a BEV from an empty battery to about 80% of full state of charge (SoC) in 20–30 min (DBT, 2013). Fast charging is a relatively new technology that barely existed for public use before 2013 (IEA, 2016) and it is of utmost importance to measure the usage of this technology, understand individuals' behaviour, and provide actual evidence on the significance of this infrastructure. This can appropriately inform the expansion and planning of the BEV charging infrastructure and inform subsequent studies on the topic.

Using assumptions instead of real world behaviour datasets, some studies assessed the business models for fast charging infrastructure to guide prospective investment. Profiling charging demand is critical in evaluating the profitability of BEV fast charging infrastructure business (Schroeder and Traber, 2012) and yet because of the lack of real-world data, assumptions had to be used when assessing the business case for this technology (Madina et al., 2016; Parasto Jabbari and Don MacKenzie, 2016; Pierre Ducharme and Catherine Kargas, 2016; Schroeder and Traber, 2012).

Similarly, some studies used assumptions instead of real BEV charging behaviour data to investigate the impact of fast charging on the electricity grid. In particular, these studies assumed that all BEV charging takes place on fast chargers and did not consider that BEVs can be easily charged at home for most car owners (Jakobsson et al., 2016). One study adapted the arrival time distribution of conventional vehicles at petrol filling stations to determine a typical arrival time distribution of BEVs at the fast chargers; this study found that fast chargers would affect the quality of power supply (e.g. voltage dip, flicker) and actions such as deploying energy storage solutions need to be taken in order to avoid these quality issues (Yunus et al., 2011). Another study found that fast charging has the potential to quickly overload local distribution equipment at peak times (Etezadi-Amoli et al., 2010) and even cause failure in lines and transformers unless the size and location of fast chargers are modified to avoid these impacts (Sadeghi-Barzani et al., 2014).

Using real world datasets, one study investigated the impact of the availability of fast charging on people's assessment of electromobility and found that the participants' attitudes towards BEVs improved when they used a fast charger. While the results indicated the importance of such an infrastructure in encouraging the uptake of BEVs, they were based on an experiment that exposed 62 participants who don't own a BEV to a fast charge event (Gebauer et al., 2016). Morrissey et al. (2016) analysed charging infrastructure data for the whole of Ireland including 11,000 fast charge events from 83 fast chargers. An interesting finding from the Irish study is that the mean energy consumption for fast chargers at car parks was 7.27 kWh per charge event which is similar to the mean recorded for standard public car park chargers at 6.93 kWh. While Morrissey et al. (2016) provided a preview of how BEV drivers are using fast chargers, their work did not investigate if fast chargers have an impact on driving behaviour.

This paper has two objectives. The first objective is to measure the real world usage of fast chargers by analysing over 90,000 fast charge events collected from the first large-scale roll-outs and evaluation projects of fast charging infrastructure to date in both the UK and the US. Similar trends from two distinct geographical locations were identified. This could indicate the widespread applicability of the results which may be transferable as lessons learnt to other geographic locations and assist in the rollout of future infrastructure. In addition, the findings based on real world datasets can inform theoretical assumptions used on fast charging and assist in more robust findings of subsequent studies on topics such as economic feasibility of fast charge infrastructure and impact on the electricity networks.

The second objective is to explore the impact of fast chargers on driving behaviour, specifically on driving distance, in order to evidence the importance of fast chargers. This was done by analysing 18,000 charge events from all types of charging infrastructure and 67,000 trips collected from data loggers installed in 35 BEVs that accessed and used fast chargers.

Following the introduction, Section 2 presents the datasets and methods used for the analysis, Section 3 presents the results of the analysis of the actual usage of fast chargers specifically time of use, duration and energy transferred during fast charge events. Using a multiple linear regression, Section 4 explores the influence of fast charging on daily driving distance. Finally, the discussion on the importance of fast chargers is presented in Section 5 and the conclusion and policy implications are presented in Section 6.

2. Data collection and methods

In this paper, we use three sources of data relating to fast charge infrastructure and BEVs. One dataset is collected from a network of fast chargers in the UK, a second dataset is collected from a number of BEVs in the UK that had access and used this network of fast chargers. Finally, a third dataset is collected from a network of fast chargers in the US. These datasets and the analysis methods are described below in more details.

2.1. Fast charge infrastructure data collection (UK and US)

2.1.1. UK fast charge infrastructure

Over 30,000 fast charge events were collected from 51 fast chargers (50 kW) over a period of 17 month between July 2014 and November 2015 in the UK. The fast chargers are part of the Rapid Charge Network

[2] Terminology varies by location; it is called "fast" charging in the US, "rapid" charging in the UK and Europe, and "quick" charging in Japan.

(RCN) project that was co-financed by the European Commission (INEA, 2015) with the aim to cover Trans-European Transport Network (TEN-T)[3] roads with charging infrastructure. As such, the location of the fast chargers were determined to ensure that these strategic European roads (full length of Priority Project (PP) Road Axes 13 and 26 through the UK and into Ireland) are covered with BEV charging infrastructure (Fig. 1). 76% of the RCN chargers were installed at motorway service stations with the remaining points installed at fuel filling stations, airports, seaports, Park and Rides, hotels and large retail stores to enable a fully connected route covering over 1000 km. The fast chargers were accessible to anyone with a BEV and an access card. Data collected from each charging transaction contained information on the start time of a charge event, duration and energy transferred during the transaction. Due to privacy issues, the dataset did not contain details on the network users. More details on the RCN project can be found in the project final report (Neaimeh et al., 2015).

2.1.2. US fast charge infrastructure

Over 62,000 fast charge events were collected from 106 fast chargers (50 kW) over a period of 18 months between April 1, 2012 and September 30, 2013 in the US. The fast chargers were deployed as part of The EV Project which was funded by the United States Department of Energy through the American Recovery and Reinvestment Act and private sector partners. The fast chargers were located in and around the major metropolitan areas shown in Fig. 2. Half of the chargers were in locations that could serve highway travel. A charger was deemed capable of serving highway travel if it was less than a one-mile drive from a highway. Since these chargers were also located in metropolitan areas, it is expected that they are used for a mixture of local travel and highway travel, but the exact proportion of each is unknown. Anyone with a BEV capable of fast charging could use the chargers. Similarly to the UK dataset, each charging transaction collected from the US fast charge network contained information on the start time of a charge event, duration and energy transferred. Again, the dataset did not contain details on the users who used the fast chargers. More information on The EV Project, the largest plug-in electric vehicle infrastructure demonstration in the world, can be found in this project report (Idaho National Lab, 2015).

2.2. Battery electric vehicles data collection (UK)

For in-depth monitoring of driving and charging behaviour beyond what can be measured using the data from a fast charge network, high resolution data were collected from a selected number of BEVs in the UK. A 200GBP voucher was offered to attract BEV drivers to participate in the data collection and over 120 BEV drivers expressed interest in participating. The 35 selected BEVs were privately owned and their users were able to access the RCN fast chargers (i.e. live or work within a BEV driving range of the network) and expressed that they will be using the electric car as their primary vehicle. The participants owned their vehicles for at least 3 months before data collection began to ensure their familiarity with their BEV.

Age and income of the drivers participating in the BEV data collection trial were compared to the UK population demographics, and as expected the profile of these drivers is similar to the profile of BEV early adopters. First, the age groups of the sample were compared to the age groups of the UK population holding a valid driving license (Department for Transport, 2016a; Office for National Statistics, 2016). There were no participants younger than 21 years old (2% nationally), 10% were between 21 and 29 years old (15% nationally), 37% were between 30 and 39 years old (17% nationally); 33% were between 40 and 49 years old (21% nationally); 10% were between 50 and 59 years old (17% nationally); 7% were between 60 and 69 years old (15% nationally) and 3% were 70 or above (13% nationally). Second, the income of the participants was compared to the average annual gross income of all households grouped by quintiles (Office for National Statistics, 2017). No participants belonged to the bottom quintile where the national average gross income is 14,765 GBP. 6.5% of the participants belonged to the second quintile (national average gross income is 23,509GBP). 10% belonged to the third quintile (national average gross income is 33,820 GBP), 23% belonged to the 4th quintile (national average gross income is 48,008 GBP) and 61% of the participants belonged to the top income quintile group where the national average gross income is 87,625 GBP. Moreover, over 90% of the participants were Male. Previous studies identified some of the characteristics of individuals who would mostly fit early adopters and found that early adopters tend to be men, with high income level and aged between 25 and 59 years old (Campbell et al., 2012; Kawgan-Kagan, 2015; Tran et al., 2013) which is similar to what we found about the RCN trial participants.

The cars of the participants comprised of 29 Nissan LEAFs (24kWh battery, 200 km driving range) and 6 Renault ZOEs (22kWh battery, 240 km driving range). The advertised driving range of these vehicles were obtained from laboratory testing and over-estimate real world driving ranges. A realised driving range of a BEV is influenced by factors such as speed and use of auxiliary power and it is estimated that the realised range of a 24kWh LEAF won't exceed 150 km (Neaimeh et al., 2013; Needell et al., 2016). The cars were fitted with data logging devices (logger, GPRS and GPS antenna) to monitor driving and charging behaviour of their users. These loggers provided up to second by second data allowing the project to monitor how the vehicles were driven, where and when they were charged and how much energy was consumed. The data collected included the timestamp, GPS coordinates, state of charge, speed of the vehicle, battery current, battery voltage and ambient temperature. As an example, the GPS coordinates collected during a trip were used to calculate the distance travelled. The GPS coordinates during a charge event were used to determine the location of this charge event (i.e. home, work, public, public-fast). In more details, the charge events' GPS information from the data loggers was correlated with the addresses of any private location that the users might charge at (e.g. home, work)[4]; and with the addresses of all the public chargers in the UK using the information available in the national charge point registry (OLEV, 2012). The data loggers collected over 18,000 charge events (from all charging infrastructure) and 770,000 km driven in over 67,000 trips over a period of 18 month between February 2015 and July 2016. In total, this resulted to around 12,700 driving days (a day when the vehicle was driven) with 12% of these days included one or more fast charge event. The users contributed a similar number of driving days each, with an average of 3% driving days per participant and a standard deviation of 0.67%.

More information on the driving and charging patterns of the users is presented. On average, the users drove on 83% of the days during the trial (i.e. almost 6 days per week) and the standard deviation was 11%. Fig. 3 shows the daily distances recorded in the trial for each of the 35 users grouped in boxplots. The boxplots compactly display the distribution of daily distances. The bottom edge of the box is the 25th percentile of the data (value below which 25% of the observations are found). The top edge of the box is the 75th percentile of the data. The horizontal bold line inside the box is the median (50th percentile of the data) and it ranges between 20 km and 113 km for these 35 drivers. It is noticed that there is a variation in daily distances recorded and most of the events are under 150 km (realised range of the BEVs in this

[3] The Trans-European Transport Networks (TEN-T) are a planned set of road, rail, air and water transport networks in the European Union.

[4] Participants in the trial provided the postcodes of the private locations where they might charge (e.g. home, work, parents or friends' house). "Other" indicate when these users charged at a different private location than previously disclosed.

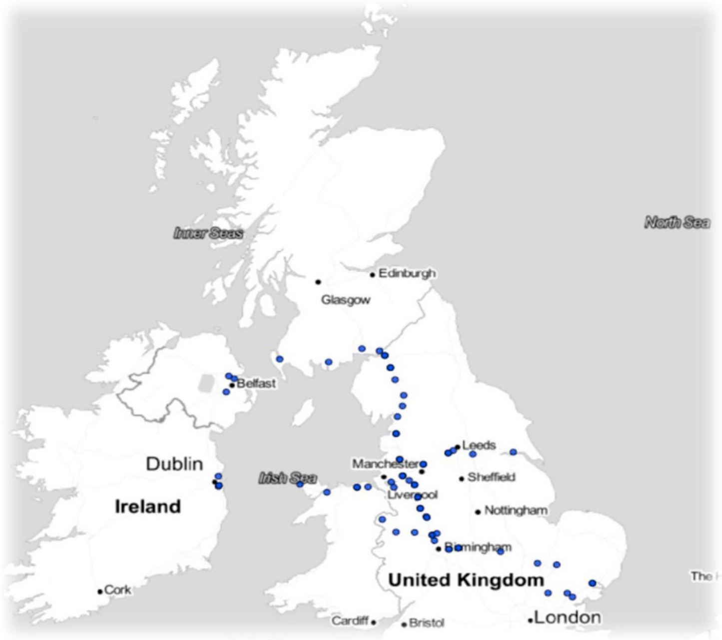

Fig. 1. Location of RCN fast chargers covering two European strategic roads (Priority Axis number 13 and 26 roads).

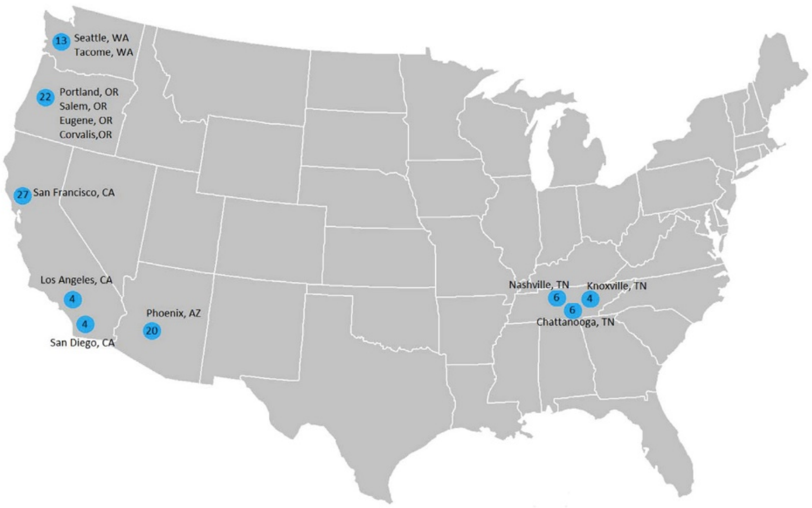

Fig. 2. Locations and numbers of fast chargers installed by The EV Project.

trial). The few daily events over 150 km are spread among the users. Fig. 4 shows the distribution of daily distances grouped for all users, with a median of 50 km and a mean of 61 km per day. The average daily distance captured from this group of drivers was higher than the UK National Travel Survey (NTS) average daily distance of 43.47 km (Department for Transport, 2015a). The distribution of daily distances and the percentage of days the cars were driven during the study period indicated that the participants used the BEV as their primary car, confirming what they stated in the user selection survey. 5% of the days captured in the data set included long journeys of more than 150 km and the highest recorded daily distance was 610 km. When comparing with the UK NTS average daily distance, a remarkable similarity is found with 5% of daily distance using conventional vehicles in the UK is above 150 km (Department for Transport, 2015a). As noted in the previous paragraph, daily driving over 150 km is above the actual single-charge driving range of the vehicles being tested and would require recharging during that day. It is worth noting that the participants indicated that they had access to a second vehicle (conventional liquid-fuel car) in their household, but, as shown here, they did not avoid the BEV in favour of the conventional car to go on the long journeys that were above the single-charge range of the BEV.

For more information on charging behaviour, Fig. 5 shows the

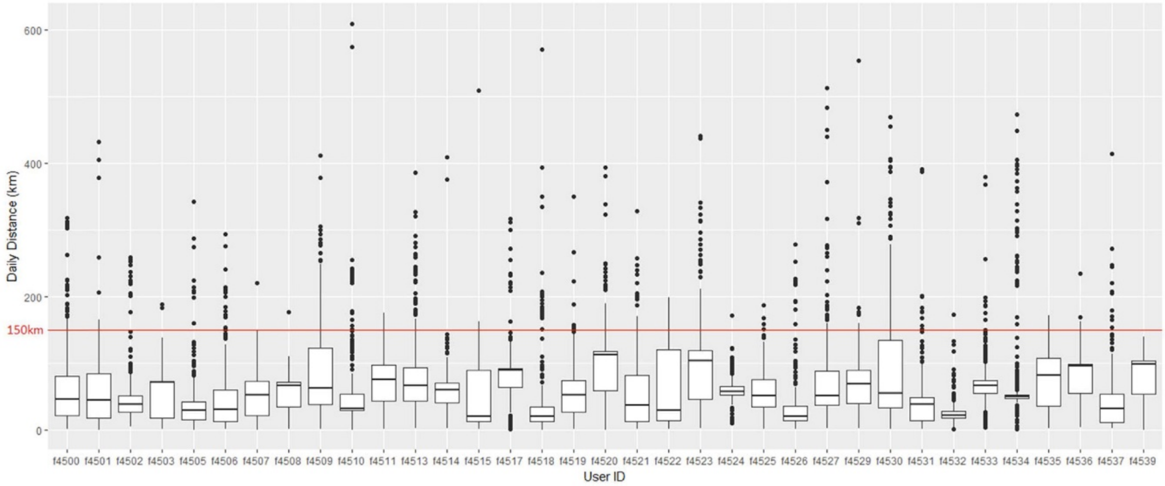

Fig. 3. Distribution of daily distance for each of the 35 BEV participants on the trial.

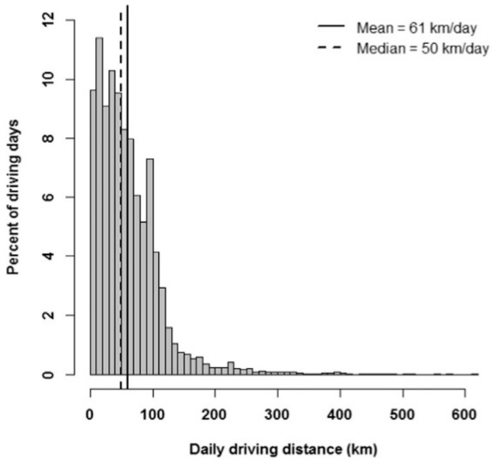

Fig. 4. Distribution of daily driving distance on the RCN data logger trial.

proportion of energy transferred on fast chargers for the whole trial for each of the 35 users. The x-axis shows the median daily driving distance for each user (same information shown by the boxplots' bold lines in Fig. 3). It can be noticed that most of these 35 participants used the fast chargers that they had access to, with one participant (f4527) relied on fast chargers for 78% of their BEV's total charge energy demand. Five participants used fast charging for less than 1.5% of their total charge energy requirements including one user (f4535) who did not use fast charging at all.

Fig. 6 shows the breakdown of the total charge energy by location for the 35 participants with over 72% of the charging energy transferred at home and 12% transferred on fast chargers. These users predominately relied on home charging which is aligned with previous studies on BEV charging behaviour (Morrissey et al., 2016; Pearre et al., 2011) and indicate that the charging behaviour of this group of users is not dissimilar to what previous studies have found.

2.3. Analysis methods

The first objective of this paper is to analyse fast chargers' usage in the UK and the US. Descriptive analysis and plots were used to visualise results on the time of use of fast chargers, duration and

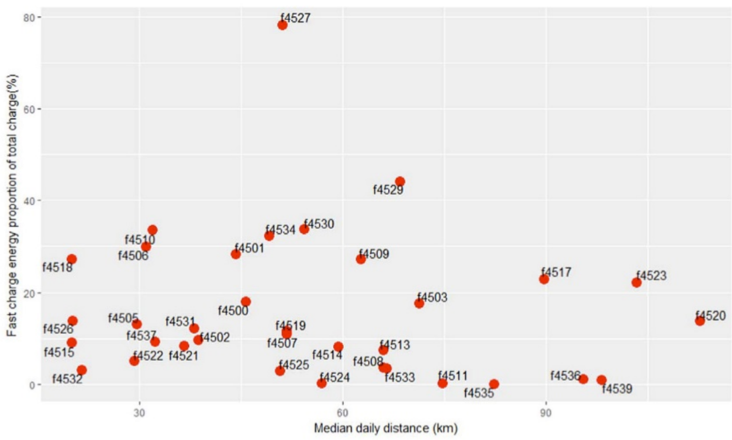

Fig. 5. Median daily distance and proportion of fast charge energy for the 35 BEV users.

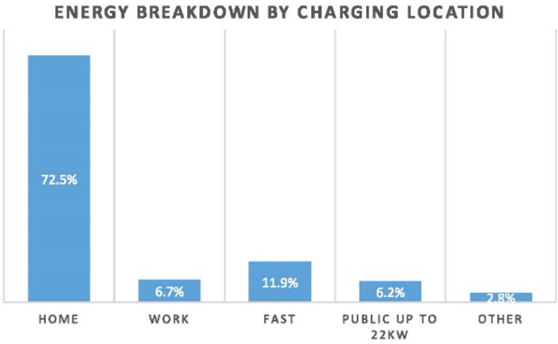

Fig. 6. Energy breakdown by location of 18,000 charge events on the UK BEV trial.

energy transferred per fast charge event. The second objective of this paper is to analyse the driving distance of a group of BEV users who had access and used fast chargers. In addition to some descriptive analysis, multiple linear regression was conducted for a more detailed study on the driving behaviour of these BEV drivers. For the regression, the outcome variable was daily distance and the predictors were daily standard charge and fast charge energy. Multiple regression is used in two distinct applications: prediction and explanation (Courville and Thompson, 2001; Faraway, 2016). For this work, the more interesting use of multiple regression is for the explanation of the contribution of each predictor (standard charge energy, fast charge energy) to daily distance. This allows the identification of which predictor is relatively more important than the other- which what is typically meant by the relative importance of predictors in multiple regression (Johnson and Lebreton, 2004).

Many metrics exist to assess the individual predictor's importance in a model. A most typical approach of assessing importance is to examine the magnitude of the standardized regression coefficients associated with each predictor, where predictors with larger coefficients are viewed as more important than those with smaller weights. However, other methods for establishing predictor importance are more accurate (Braun and Oswald, 2011; Calbick and Gunton, 2014) and for this work, Lindeman, Merenda and Gold (lmg) method in the Relaimpo package in R is used to assess predictor's importance (Groemping, 2006). For this method, the relative importance of a predictor is defined as the proportionate contribution each predictor in a linear multiple regression model makes to the model coefficient of multiple determination, R^2, considering both the unique contribution of each predictor by itself and its incremental contribution when combined with the other predictors (Groemping, 2006; Johnson and Lebreton, 2004). All the relative R^2 sum to the model R^2.

Since the collection of new (or fresh) data from the BEV users beyond the trial period was not possible, resampling was used instead to investigate the model's performance. Resampling methods can produce reasonable predictions of how well the model will perform on future data (Kuhn and Johnson, 2013). Resampling consists of using a subset of the data to fit a model and using the remaining data to estimate the efficacy of the model. This process is repeated many times and the results are aggregated and summarised (Kuhn and Johnson, 2013). The resampling method used in this work is called "repeated 10-fold cross-validation" where the dataset is randomly partitioned into 10 sets of roughly equal size. A model is fit using all the dataset except for the first set (called the first fold). The data points in this first set (i.e. daily distance) are predicted by this model and used to estimate performance measures (e.g. R^2). The first set is returned to the dataset and the process repeats with the second set held out and so on until the tenth set. The 10 resampled estimates of performance are summarised usually with the mean and standard error (Kuhn and Johnson, 2013).

There were 23 data points out of 12,700 between 400 and 600 km; in order to ensure that this small number relative to the remainder of the data did not have a disproportionately high influence on the regression analysis, robust regression was explored. Ordinary least squares (OLS) regression can be sensitive to unusual data (e.g. outliers and high leverage points). Robust regression is an alternative to OLS regression when the data contain potentially influential observations. The robust regression is done by iterated re-weighted least squares (IRLS) and the idea is to down-weight or ignore unusual data (Fox and Weisberg, 2010). These data points were deemed valid and were not data entry errors, nor were they from a different population than most of our data.[5] Therefore, we had no compelling reason to exclude them from the analysis. In this work, the robust regression implements M-estimation with Huber weighting where observations with small residuals get a weight of 1 and the larger the residual, the smaller the weight (Faraway, 2016; Fox and Weisberg, 2010).

3. Measuring the usage of fast chargers

3.1. Energy transferred during fast charge events

The distribution of AC charging energy from the RCN chargers is shown in Fig. 7 (top). The AC kWh numbers correspond to how much energy was drawn from the grid (AC). The amount of energy delivered to the vehicles' batteries was not collected, but it could be estimated to be around 90% of the AC energy from the grid, due to charger inefficiency (Idaho National Lab, 2016). In the UK, the average and median energy transferred per charge event were 9.2 AC kWh and 7.9 AC kWh respectively. The average and median energy used per charge event from EV Project fast chargers were 9.2 and 9.3 AC kWh respectively. The distribution of AC charging energy from EV Project chargers is shown in Fig. 7 (bottom). The results from the US and the UK show similar trends and corroborate the findings from the Irish fast charge network roll-out that found that the average fast charge energy consumption is 8.32kWh (Morrissey et al., 2016). These results show that typical energy transfer on fast chargers is approximately half of the vehicle battery capacity.[6] It is worth noting that the amount of energy transferred is dependent on duration of charging and initial battery state of charge, due to the fact that at higher state of charge, charging power will decrease (Idaho National Lab, 2016).

The distribution of actual energy usage on fast chargers is significant for subsequent studies investigating the impact of fast charging on the electricity grid and studies developing a business case for such an infrastructure and would need to be aware of the ranges of energy used per charging transaction. As an example, the queue model developed by Parasto Jabbari and MacKenzie (2016) to investigate operators' cost and access reliability of fast chargers could result in more accurate findings if the authors used real data instead of having to assume that each vehicle's energy usage is 20 kWh per charge event. Similarly, assuming a full charge of the vehicle on fast chargers (Etezadi-Amoli et al., 2010; Sadeghi-Barzani et al., 2014; Yunus et al., 2011) instead of using measured data can result in overestimating the impacts on the electricity grid.

3.2. Duration and time of use of fast charge events

In terms of transaction duration, the median recorded for fast charge events in the RCN was 24 min and the mean was just over 27 min as shown in Fig. 8 (top). Transaction times in 32% of the recorded transactions were above 30 min. Charge events on EV Project fast chargers tend to be of similar duration, but slightly shorter than in

[5] Details of the 610km driving day with 7 fast charge events are shown in the RCN final report.

[6] Around 10% of available battery capacity is dedicated to reserve limits in both cars (LEAF and ZOE), dropping the available battery capacity to around 21kWh for the LEAF and 20 kWh for the ZOE.

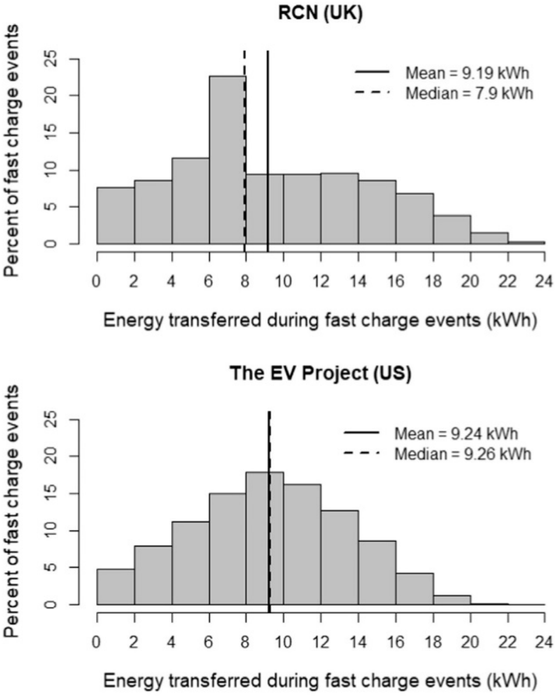

Fig. 7. AC energy transfer during charges on the RCN project (top) and The EV Project fast chargers (bottom).

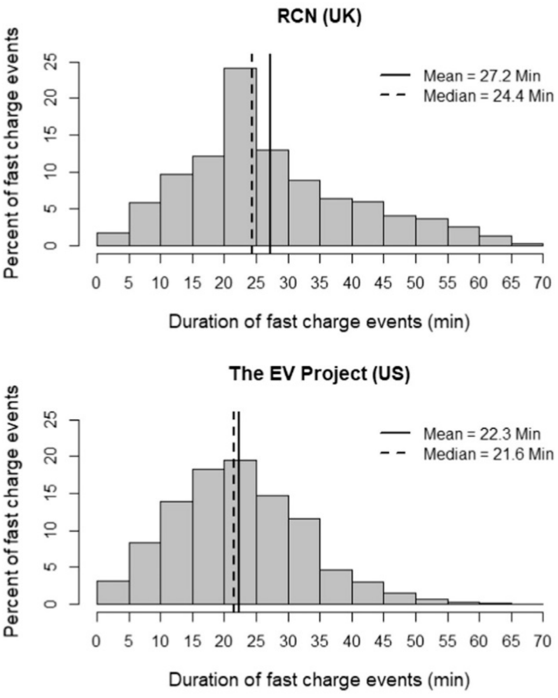

Fig. 8. Distribution of charge duration from fast chargers in The RCN project (top) and The EV Project (bottom).

the RCN. The EV Project fast charges shown in Fig. 8 (bottom) have median and mean duration of 21 and 22 min, respectively, and 21% of charges are longer than 30 min. After 30 min of charging on a fast charger, the vehicle battery will often be close to fully charged and charging will occur at a much slower rate to completely charge the battery. Long charges can severely impact charger availability and it is suggested that limiting the duration of a charge event could provide fairer access to the charger and reduce waiting times. Another alternative would be to introduce a rate structure for the charge event payment where it becomes more expensive after 30 min. In general, there is a need to decrease the uncertainties associated with the availability of fast charge infrastructure to allow journeys to be completed confidently and without significant increase in journey times.

While both datasets show a similar trend, there are some differences that can be noticed between the UK and the US. Much of these differences can likely be attributed to the difference in vehicles capable of using fast chargers, notably the Mitsubishi Outlander PHEV. The Outlander PHEV, a plug-in hybrid, is one of the most popular plug-in vehicles available in Europe, and it is not sold in the United States at the time of this writing. A full charge for the Outlander is 9.8 kWh, which is approximately half the capacity of most BEVs in the United States. The Outlander can be fast charged for an 80% charge (up to 7.8kWh) in approximately 25 min (Mitsubishi UK, 2017). Fast charging of this vehicle likely contributes to a large number of events from the RCN with energy between 6 and 8kWh (over 20% of the UK dataset) and the associated 20–25 min charging duration. Many of the RCN participants had recommended discouraging unnecessary usage of the fast chargers by plug-in hybrids with small batteries and internal combustion engines due to the fact that BEV users might need them more urgently.

Finally, fast chargers in the RCN and The EV Project have similar usage profiles. As expected, the majority of fast charge events took place during the day. Over 50% of charges began between 11:00 and 18:00, and very little use occurred between midnight and 6 A.M. (Fig. 9). The vertical lines on the graphs delimit 50% of the data. Similarly to the importance of information on energy transferred, knowing when the chargers are being used is relevant for grid impact studies and significant for studies trying to develop a business case, as revenue generation opportunities will vary throughout the day.

4. Investigating the impact of fast chargers on driving distance

The analysis in this section is based on a group of 35 BEV drivers who had access and used fast chargers. Over 12,700 driving days associated with these 35 drivers were analysed with 12% of these days included one or more fast charge event and in total 11.9% of the total charging energy was transferred on fast chargers (Fig. 6). At first, the analysis involves graphical representation of the data to identify general trends, then statistical models are fitted to the data for a more robust analysis.

4.1. Graphical exploration of driving distance and fast charging

The relationship between daily distance and the number of daily fast charge events is shown in Fig. 10. The graph displays the mean daily distance at different numbers of fast charge events performed in a day, and the confidence intervals of those means based on bootstrapping. It can be seen that there were days when drivers used fast charging infrastructure multiple times and it can be appreciated that the relationship between fast charging and increased daily distance is obvious. Similarly, the positive relationship between driving distance and number of fast charge events can be strongly identified when aggregating the data by weekly events. The data were separated in three groups, each represented by a boxplot (Fig. 11) with the median weekly

Fig. 9. Distribution of fast charge start times from The RCN project (top) and The EV Project (bottom).

driving distance increasing with an increase in the number of fast charge events. The number of observations for each group is indicated on the graph.

4.2. *Evidencing the role of fast chargers in enabling driving distances above the single-charge range of BEVs*

The graphical exploration of the data in Section 4.1 indicated a relationship between fast charging and increased driving distance. A robust analysis of this relationship is carried out using multiple regression where daily distance is predicted from standard charge energy and fast charge energy. The regression results, described in the following sections, showed that both predictors have a statistically significant and positive effect on daily distance at over 95% confidence level (see Table 2) and fast charging was determined to be more influential than slow charging.

4.2.1. *OLS and robust linear regression results*

A few observations with either high leverage or large residuals were identified as possibly problematic to the model. The mean daily distance for these observations was 430 km. Robust regression was carried out to deal with these potentially influential observations that could be problematic when using a simple ordinary least squares regression. Fig. 12 shows that the predicted values from the linear model and the predicted values from the robust linear model fall on a straight line indicating the similarities between the models, also evident in Table 1. The R^2 statistic is not given in the context of a robust regression (Faraway, 2016). The results of the robust regression were similar to the OLS regression (Fig. 12, Table 1) and as such, the analysis in this work will be based on the OLS linear model.

4.2.2. *Overall fit of the model, cross validation and model parameters*

To assess how well the multiple regression model fits the data, we look at the values of the coefficient of multiple determination-R^2 and

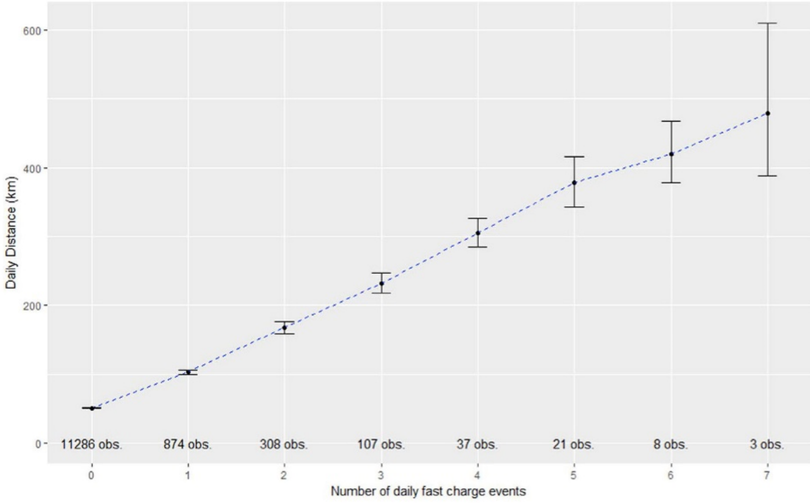

Fig. 10. Relationship between daily distance travelled and fast charge events.

the F-ratio of the model outcome (Field et al., 2012). R^2 is a measure of how much of the variability in the outcome is accounted for by the predictors. For this model, the adjusted $R^2 = 0.64$ and as such 64% of variation in daily distance can be explained by daily standard and fast charge energy. This also means that 36% of the variation in daily distance cannot be explained by daily charging energy alone. Second, we look at the value of the F-ratio that indicate how much variability the model can explain relative to how much it can't explain. A good model should have a large F-ratio value and the statistical significance of this value should be assessed. For this dataset F is 11,180, which is significant at p-value < 0.001. Therefore, it can be concluded that the regression model results in significantly better prediction of daily distance than if we used the mean value of daily distance. In other words, the 64% of variance that can be explained is a significant amount. In short, this regression model overall predicts daily distance significantly well.

In the absence of a fresh dataset from the BEV drivers, resampling was used to examine the model's performance. The mean of the 10 resampled estimates of performance (R^2) is 0.635 which is almost the same as the R^2 of the model used in this work. The standard error is 0.014.

After looking at the overall fit of the model and realising that it significantly improves the ability to predict daily distance, the next part is to look at the b-values in the model outcome. Table 2 shows the estimates, standard error, *t*-value and *p*-value of these b-values. If a predictor is having a significant impact on the ability to predict the outcome, then its associated regression coefficient value (b-value)

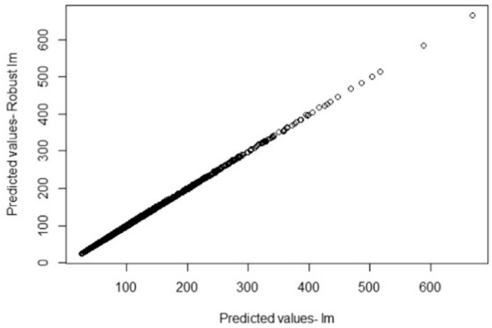

Fig. 12. Predicted values of the OLS regression and predicted values of the robust regression.

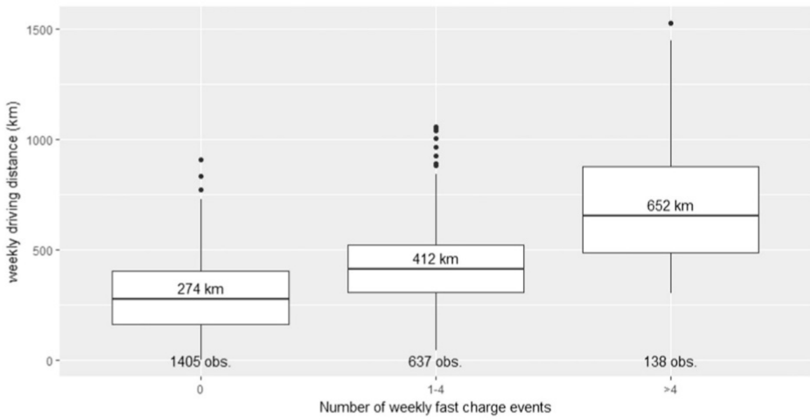

Fig. 11. Weekly driving distance and weekly number of fast charge events.

Table 1
Comparison between linear and robust linear models.

Beta values	OLS Linear Model	Robust Linear Model using Huber Weights
Constant (b0)	26.28	24.64
b1	2.67	2.78
b2	5.58	5.54

Table 2
OLS multiple regression report.

	Adjusted R^2 0.64	b	SE b	t-value	*P*
Constant (b0)		26.28	0.43	61.24	< 0.001
Standard Charge Energy (b1)		2.67	0.034	78.42	< 0.001
Fast Charge Energy (b2)		5.58	0.044	127.86	< 0.001

should be different than zero and large relative to its standard error (SE b). A *t*-test is used to determine whether the b-value is different from zero, where *t*-value=*b*-value/SE b. If the *t*-test is significant (if the value under the *P* column is less than 0.05) then the predictor is making a significant contribution to the model. The regression coefficients of this model are significantly different from 0 and we can conclude that standard charge energy and fast charge energy make a significant contribution ($P < 0.001$) to predicting daily distance.

In the context of linear regression, the variance inflation factor (VIF) can be used to diagnose multicollinearity. The VIF indicates if there is a strong correlation between the predictors. If there is multicollinearity then the coefficient values are untrustworthy and makes it difficult to assess the individual importance of a predictor (Field et al., 2012). The square root VIF values of the predictors is 1.000027 (< 2) indicating that there is no multicollinearity between standard and fast charge energy.

Finally, we used graphical analyses (histogram and scatter plot) to ensure that the data met expectations of linearity, homoscedasticity and normality.

4.2.3. *Relative importance of fast and standard charge energy*

It is interesting to look at the individual contribution of the predictors (standard charge, fast charge) in the model and identify which predictor makes a greater contribution to daily distance. The results of the analysis indicated that fast charge energy most influence daily distance, explaining about 46% of the observed variation, while standard charge energy explains 18% of the variation. The sum of the proportionate contribution of each predictor is equal to the total R^2 of the model (64%). Thus, fast charge energy is about 2.5 times as important as standard charge energy in predicting daily distance for BEV users who have access and use fast chargers.

Furthermore, the model R^2 and the proportionate contribution of each predictor to R^2 was investigated in an incremental approach. The contribution of each predictor was measured at incremental daily distance values of 50 km, starting with daily distance up to 50 km per day and going to up to 600 km per day. The results are shown in Fig. 13. The values of proportionate R^2 at daily distance (up to) 600 km correspond to the values for the whole dataset.

It can be noticed that standard charge energy is more important than fast charge energy up to daily distance=240 km. After 240 km, fast charge energy becomes more important. The findings from this multiple regression model, looking at the relative importance of predictors, demonstrate the importance of fast chargers in enabling driving distances beyond the single-charge range of a BEV. In other words, fast chargers become more important the farther we drive; their availability extended the BEV driving range and enabled driving distances that would have been otherwise impractical using standard (slow) chargers with associated long recharging times.

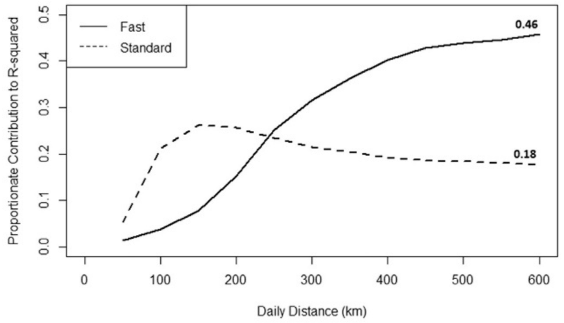

Fig. 13. Proportionate contribution to R^2 for fast and standard charge energy predictors.

5. Discussion

In this work, the regression model's R^2 is 0.64 which means that almost 2/3 of the variation in daily distance is explained by daily standard and fast charging. In addition, fast chargers are more influential than slow chargers (higher contribution to R^2) and they start to become more important for journeys that are above 240 km per day. Yet, journeys above 240 km per day are rare, 1.5% were recorded on the RCN trial and 2% were recorded in the UK NTS dataset (Department for Transport, 2015a). It is clear then that the majority of daily driving can be met with current BEV models and standard slow chargers at private locations (i.e. home or work). This is aligned with previous studies that confirmed the suitability of existing BEV models to meet almost all of the users' daily travelling needs (Greaves et al., 2014; Needell et al., 2016; Pearre et al., 2011), even if relying only on slow night-time charging, suggesting that the BEV range is primarily a psychological barrier (Franke et al., 2012; Needell et al., 2016).

While this raises the question on whether a fast charge infrastructure is required, especially that it is expensive to install, it is important that policy makers don't interpret actual daily distance requirements as evidence against supporting the roll-out of a fast charge infrastructure.

Without fast chargers, the transition from liquid-fuel vehicles to BEVs will be affected. First, it may be possible to overcome perceived range barriers with fast chargers. Fast chargers could provide assurance and comfort to reduce range anxiety and the perceived unsuitability of BEVs beyond short city driving. Second, fast chargers can add range quickly into a BEV to make the occasional long journeys possible. Consequently, a network of fast chargers might help overcome both these perceived and actual range barriers, making BEVs more attractive to potential buyers and helping to increase their adoption rates. We expand on both these points in the following paragraphs.

Driver range anxiety is the fear of depleting the battery and therefore lack sufficient range to complete a trip. Range anxiety can lead to underutilizing the available range and limit the number of miles travelled in a BEV, even when the BEV is capable of adequately completing the required journey (Egbue and Long, 2012; Jensen et al., 2014; Neubauer and Wood, 2014). This reduces the utility of BEVs that are then considered only suitable for short city driving and unsuitable for long journeys (Greaves et al., 2014). However, this paper provided evidence that drivers are using their BEVs to go on long journeys that are above the single-charge range of the vehicle and fast chargers were used to enable these long journeys. This indicates the importance of fast charge infrastructure because their availability, and usage, allowed drivers to use a limited-range car on long journeys thought only possible using conventional liquid-fuel vehicles. These results are not intended to demonstrate that fast chargers promote or encourage long journeys; but instead that fast chargers enable long journeys that would have been impractical, if not impossible, using conventional slow chargers with associated long recharging times. The fast chargers helped reassure drivers about the possible driving range; and could help overcome range anxiety, and as a consequence make BEVs more attractive to potential buyers. Albeit the daily driving distances presented in this paper are based on a sample of 35 drivers that might not necessarily experience range anxiety, our participants have demonstrated that long journeys above the single-charge range of a BEV are possible with the availability of fast chargers. It is argued that some factors affecting the adoption of BEVs include public visibility and raising awareness of this technology (Coffman et al., 2017; Silvia and Krause, 2016). These findings can be communicated to potential buyers as a way to enhance the perception towards BEVs and their suitability to meet drivers' needs; for example through car dealerships as suggested by Matthews et al. (2017) and as part of the UK GUL campaign.

Second, when a car purchase is made, the customer wants to be able to make all their journeys, not just the majority of their journeys (Kempton, 2016). Even with BEVs with increased battery capacities (e.g. Chevrolet Bolt), a remaining small number of driving days won't be met without recharging (Needell et al., 2016). In addition, not every household has access to an additional vehicle that will allow the occasional long journeys; in England, only one third of the households have access to two or more cars (Department for Transport, 2016a). A network of fast chargers could enable the occasional long journeys with limited time spent charging (for example, during a typical rest stop).

Consequently, developing the BEV market to reduce emissions from road transport could be predicated on the availability of a fast charge network. Road transport accounts for 21% of the country's CO2 emissions and most of these emissions come from cars and light vans (Department for Transport, 2016b). The total distance travelled by cars and light vans in 2015 was 475 billion kilometres. It is worth noting that the Strategic Road Network, where the RCN chargers are installed, carried 144 billion kilometres in 2015, almost one-third of all motorised traffic in England (Department for Transport, 2017). Road traffic is expected to rise in the coming years, predominately because of the projected growth in the population levels, and this growth is expected to be particularly strong on the Strategic Road Network, between 29–60% from 2010 to 2040 (Department for Transport, 2015b). During the period of study, The 51 RCN chargers delivered around 300 MWh of energy that approximately equates to 1.65 million electric kilometres driven.[7] The RCN network operator is a renewable energy electricity company that generates and supplies near-zero carbon emission electricity (Ecotricity, 2015). As such, the RCN network has saved 230 t of CO_2 when compared against the emissions which could have been produced by new registered cars (140 g CO_2/km) (Department for Transport, 2015c). Expanding the fast charge infrastructure on road networks that carry a significant share of motorised traffic can support the electrification of kilometres driven on these roads and contribute to meeting decarbonisation goals.

Governments and car manufacturers have financed the majority of the current pilot deployments of fast chargers (Ducharme and Kargas, 2016). Nonetheless, finding a profitable business case for future investment in fast charging is becoming imperative as government or automakers financial support of fast charging is unlikely to continue forever. Yet, at current BEV market share, fast charge networks might not be profitable in the near-term (Madina et al., 2016; Schroeder and Traber, 2012) to encourage private investment. This is a particular political challenge as withdrawing the financial support for the fast charge infrastructure too early, before the market and rates of BEV adoption have matured to a point where this support is no longer needed, could severely inhibit the growth in BEV numbers. As an example of this challenge, the UK government financed early deployments of fast chargers; however, current policy support for this type of infrastructure is not currently clear. The UK National Infrastructure Commission is a newly established agency that will identify and help build the UK's future infrastructure needs (National Infrastructure Commission, 2016). The commission identifies the need to electrify transport; however, the importance of fast chargers hasn't been highlighted yet as a key component necessary in the overall BEV infrastructure. In addition, the 2016 UK Autumn Statement- an economic statement made by the government every year identifying spending- mentions £120 million to support electric vehicles' charging infrastructure (HM Treasury, 2016) but doesn't specifically mention fast chargers.

There are some limitations to this study. The daily driving results are based on a sample of 35 BEV drivers. The problem with small samples is that they are unable to capture the behaviour of the whole population of potential BEV owners. For example, this sample is based on private users and doesn't include fleet drivers. Similarly to previous studies on BEVs, the participants of this work also fit the profile of BEV early adopters. Moreover, inferences about the causal relationship between fast chargers and long driving distances cannot be drawn and this must be considered when interpreting the results.

6. Conclusions and policy implications

Data from the first large-scale roll-outs and evaluation projects of fast charging infrastructure and BEVs have been analysed to measure actual usage of fast chargers and demonstrate their importance in the overall BEV charging infrastructure. The findings from this work can inform subsequent studies on the topic and help shape the planning and deployment of future charging networks.

The data from the fast charge networks showed that a typical energy transfer from fast chargers is approximately half of the vehicle battery capacity (Section 3.1). The majority of fast charging took place during the day with over 50% of the events began between 11:00 and 18:00 (Section 3.2). The analysis of energy data in the UK suggested a substantial usage of the fast charge infrastructure by plug-in-hybrids. These cars have a smaller battery to provide electric operation and a combustion engine to extend their vehicle range. This means that plug-in hybrid drivers don't need to rely on charging infrastructure to complete their journeys. As such, it may be necessary to ensure that battery electric cars have a priority over plug-in-hybrids in using the fast charge infrastructure that can be essential for BEVs to complete their journeys. This finding is especially relevant for the fast charge network operators in the US considering the planned introduction of the plug-in Outlander, though it is not clear yet if the US model will be capable of fast charging (Mitsubishi U.S., 2017).

In terms of transaction duration, 32% of the events in the UK and 21% of the events in the US were above 30 min (Section 3.2). The charging rate slows down when the battery is close to full resulting in long charge events that impact the charger availability. Policies that would encourage the development and the enforcement of Information and communications technology (ICT) solutions for charging management can help reduce waiting time and queuing at the charging stations. Some of the proposed solutions include a charger reservation system (Zhang et al., 2015) or a platform that sends text messages to inform drivers that they had reached the maximum allowable time allocation on the fast charger (SmartCEM, 2015).

Actual trip and charging event data of BEV owners over a period of 18 months were used to carry out an explorative multiple regression. The analysis examined the relationship between daily distance and standard and fast charging and showed that both predictors have a statistically significant and positive effect on daily distance. The relative importance of the predictors in the regression model was calculated and fast charging was determined to be more influential than standard charging.

In terms of policy support and planning for an overall charging infrastructure, it is important for relevant stakeholder to recognise that publically accessible fast chargers are an important feature of the

[7] Using an average EV energy consumption of 182.2Wh/km as derived from the data loggers on the trial. $300*10^6$Wh/182.2Wh/km=1.65million km (Neaimeh et al., 2015).

overall charging infrastructure. Developing the BEVs market to reduce emissions from road transport could be predicated on the availability of a fast charge network that could help overcome perceived and actual range barriers to the adoption of BEVs.

The fast charge infrastructure provision is expensive and its utilisation levels are going to be low in the coming few years (Jochem et al., 2016) which is not appealing to private investors. Policy makers will have to make a judgement on the costs of supporting the early development of this infrastructure and the associated adoption rates and emissions' benefits. Evidence from this work can be used to justify decisions to dedicate some funding to specifically support fast chargers, at least initially, while it is still not attractive for investors.

In 2015, 65% of the 28,000 fast chargers installed worldwide were located in China and Japan while these two countries accounted for 40% of the global BEV stock (IEA, 2016). Fast chargers can encourage more and more customers to opt for a battery electric vehicle and there is a vital need to accelerate the development of fast charge networks.

U.S. Department of Energy disclaimer

Acknowledgments

Newcastle University's authors gratefully acknowledge the contributions and support of the RCN project Partners and the support of the UK's Engineering and Physical Sciences Research Council (EPSRC) through the LC Transform (EP/N010612/1) and iBuild (EP/K012398/1) research grant awards.

Idaho National Lab's work on this study was funded, in part, by the Vehicle Technologies Office, Office of Energy Efficiency and Renewable Energy, U.S. Department of Energy.

The authors gratefully acknowledge the detailed and thoughtful comments of the reviewers and colleagues.

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