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Analysing the usage and evidencing the importance of fast chargers for the adoption of battery electric vehicles.

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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 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 can help overcome perceived and actual range barriers and make 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.

Key words: Electric Vehicles; EV charging infrastructure; Fast charging; Rapid charging; Quick charging; User behaviour.

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. 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

[1] 740,000 Battery Electric Vehicles

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 50kW fast charging stations can recharge a BEV from an empty battery to about 80% of full state of charge (SoC) in 20 to 30 minutes (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

[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.

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 (50kW) 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 (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 (Figure 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 1,000km. 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

[3]The Trans-European Transport Networks (TEN-T) are a planned set of road, rail, air and water transport networks in the European Union.

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).

Figure 1. Location of RCN fast chargers covering two European strategic roads (Priority Axis number 13 and 26 roads).

2.1.2. US fast charge infrastructure

Over 62,000 fast charge events were collected from 106 fast chargers (50kW) 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 Figure 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).

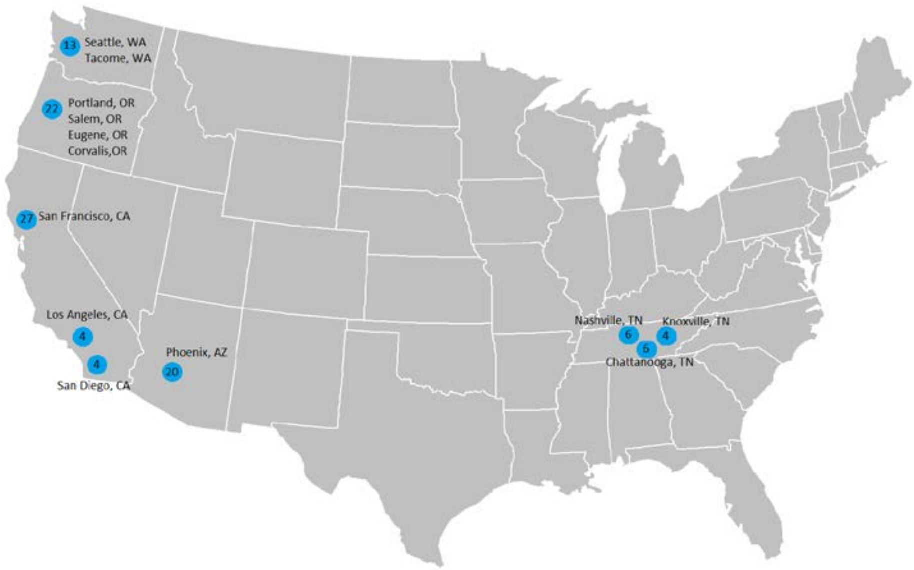


Figure 2.Locations and numbers of fast chargers installed by The EV Project

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 21-29 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). 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, 200km driving range) and 6 Renault ZOEs (22kWh battery, 240km 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 150km (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 kilometres 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%.

[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.

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%. Figure 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 20km and 113km for these 35 drivers. It is noticed that there is a variation in daily distances recorded and most of the events are under 150km (realised range of the BEVs in this trial). The few daily events over 150 km are spread among the users.

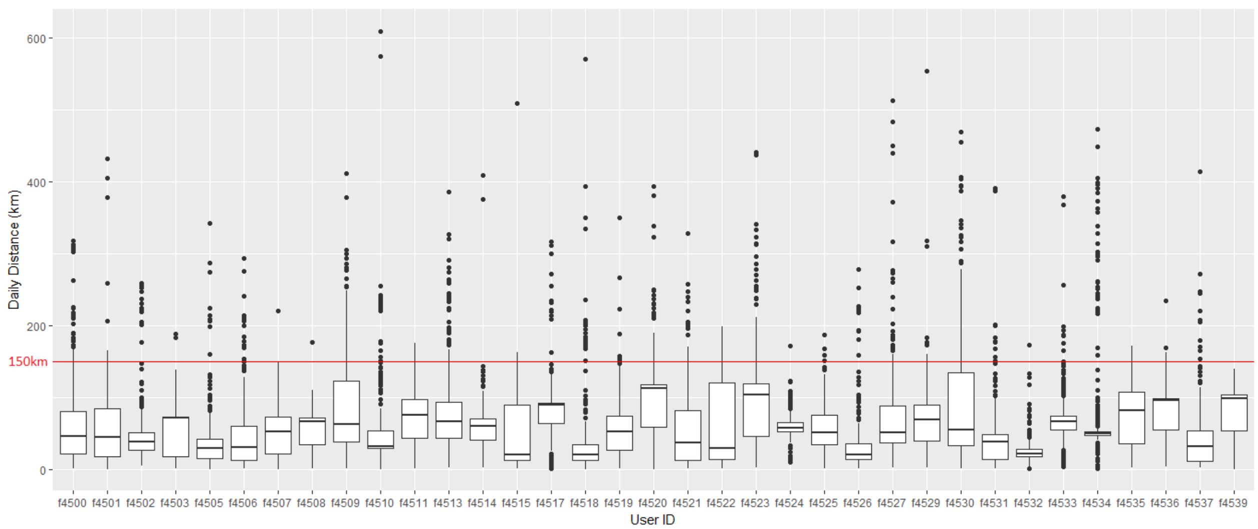


Figure 3: Distribution of daily distance for each of the 35 BEV participants on the trial.

Figure 4 shows the distribution of daily distances grouped for all users, with a median of 50km and a mean of 61km 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 43.47km (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 150km and the highest recorded daily distance was 610km. 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 150km (Department for Transport, 2015a). As noted in the previous paragraph, daily driving over 150Km 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.

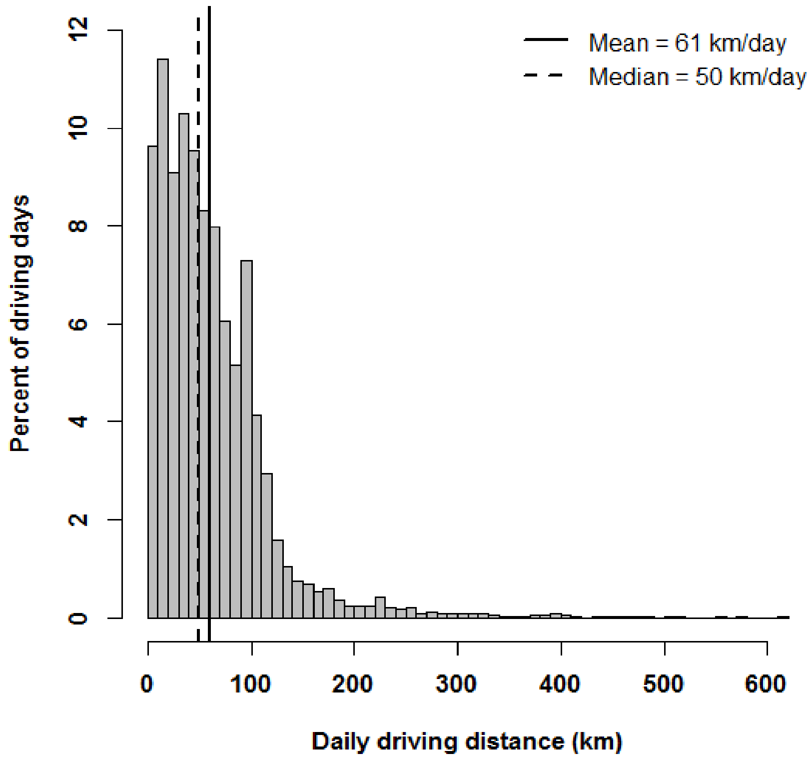


Figure 4.Distribution of daily driving distance on the RCN data logger trial.

For more information on charging behaviour, Figure 5 shows the 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 Figure 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.

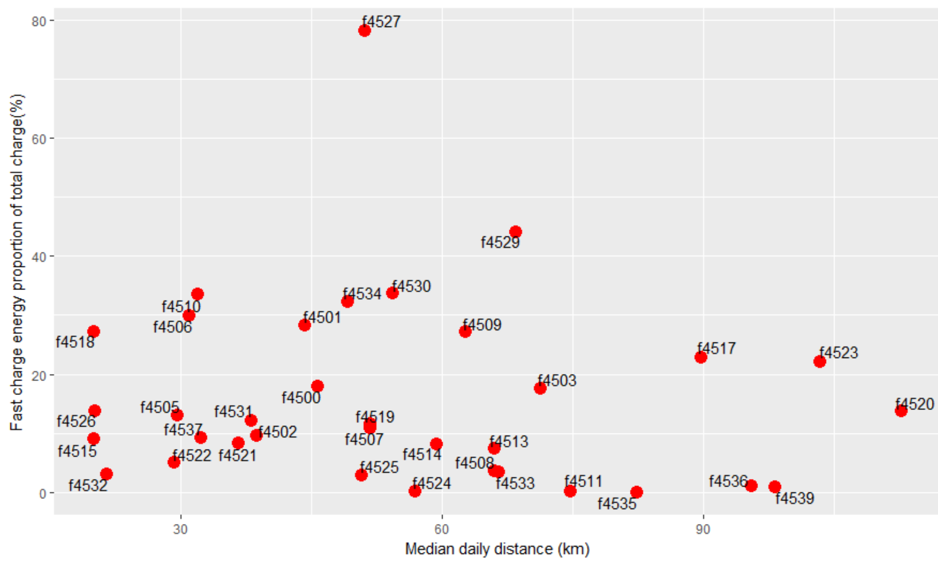


Figure 5. Median daily distance and proportion of fast charge energy for the 35 BEV users

Figure 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.

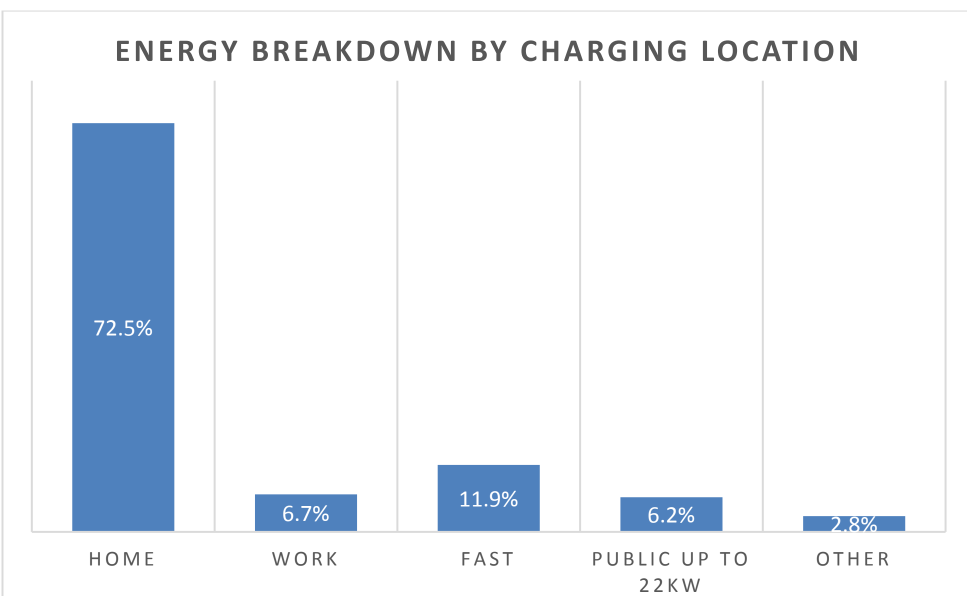


Figure 6.Energy breakdown by location of 18,000 charge events on the UK BEV trial.

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 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 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 (Fox and Weisberg, 2010).These data points were deemed valid and weren't 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).

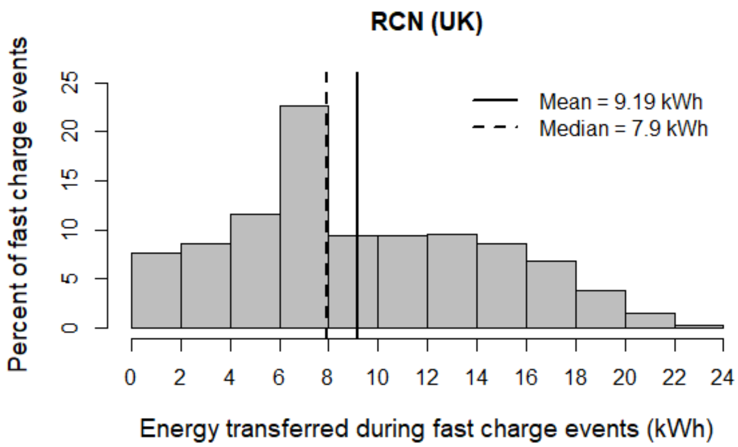
3. Measuring the Usage of Fast Chargers

3.1. Energy transferred during fast charge events

The distribution of AC charging energy from the RCN chargers is shown in Figure 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 Figure 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

[5] Details of the 610km driving day with 7 fast charge events are shown in the RCN final report

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).



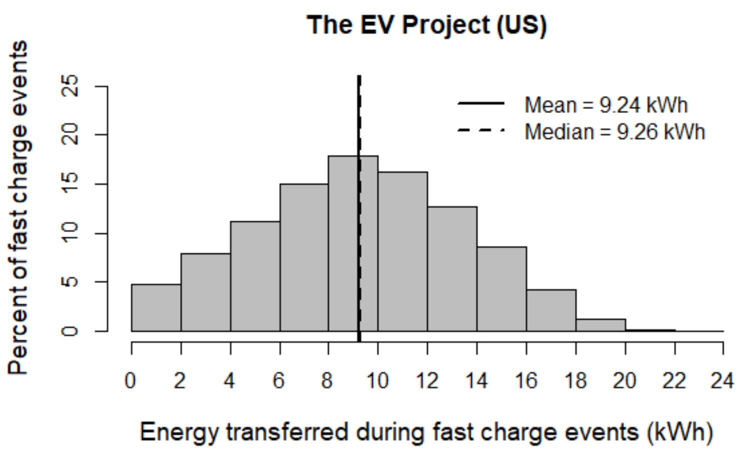


Figure 7.AC energy transfer during charges on the RCN project (top) and The EV Project fast chargers (bottom)

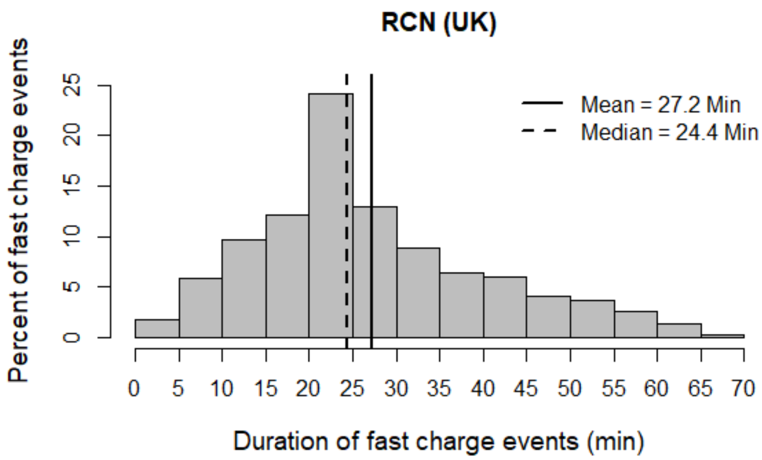
The distribution of actual energy usage on fast chargers is significant for subsequent studies investigating the impact of fast charging on the electricity grid and studies developing a business case for such an infrastructure and would need to be aware of the ranges of energy used per charging transaction. As an example, the queue model developed by Parasto Jabbari and Don 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 20kWh per charge event.

[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

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 minutes and the mean was just over 27 minutes as shown in Figure 8 (top). Transaction times in 32% of the recorded transactions were above 30 minutes. Charge events on EV Project fast chargers tend to be of similar duration, but slightly shorter than in the RCN. The EV Project fast charges shown in Figure 8 (bottom) have median and mean duration of 21 and 22 minutes, respectively, and 21% of charges are longer than 30 minutes. After 30 minutes 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 minutes. 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.



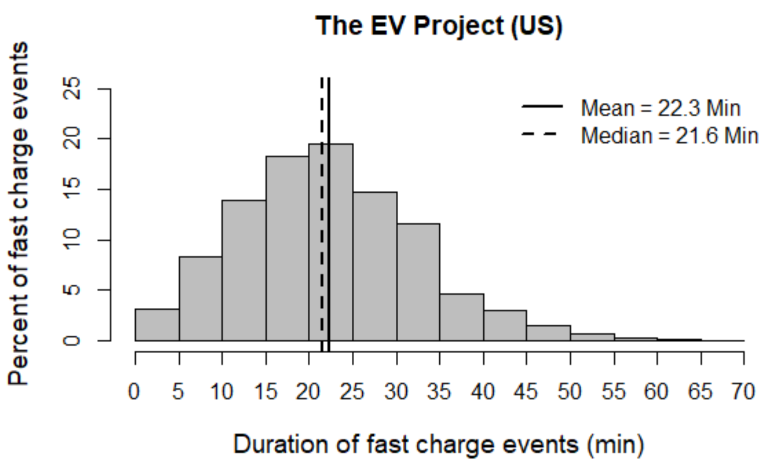


Figure 8.Distribution of charge duration from fast chargers in The RCN project (top) and The EV Project (bottom).

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 9.8kWh, 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 to 25 minutes 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 AM (Figure 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.

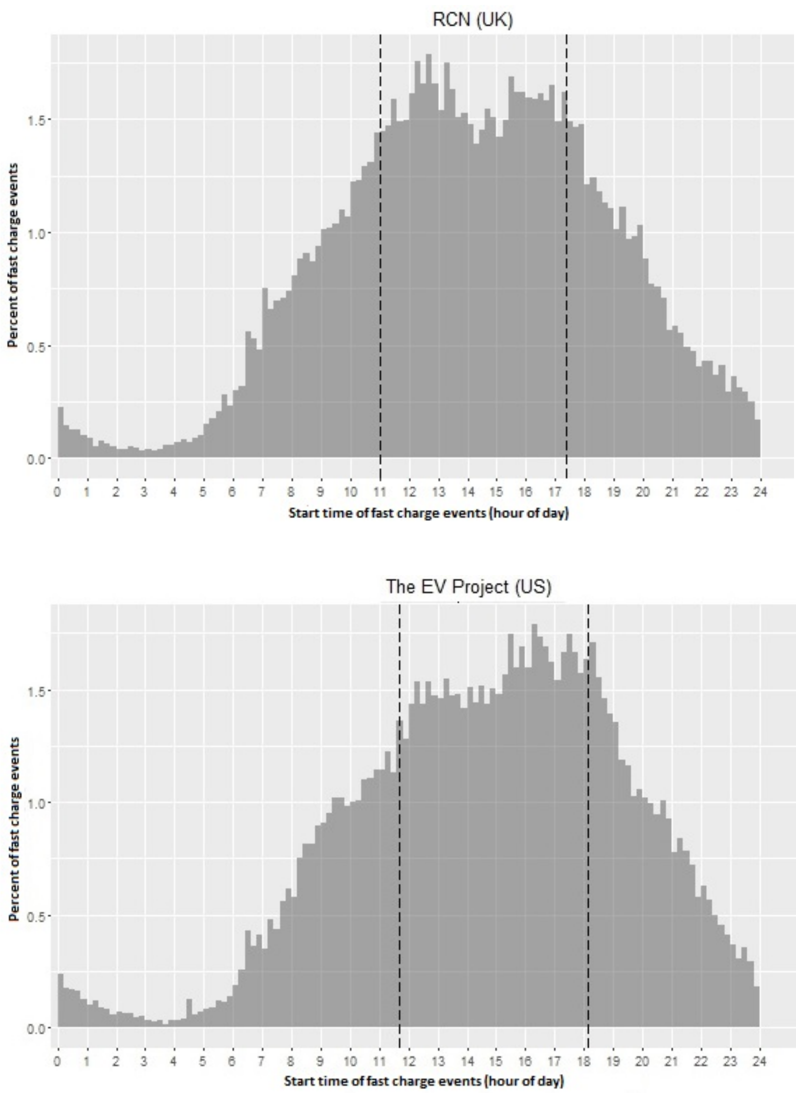


Figure 9.Distribution of fast charge start times from The RCN project (top) and The EV Project (bottom).

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 (Figure 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 Figure 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.

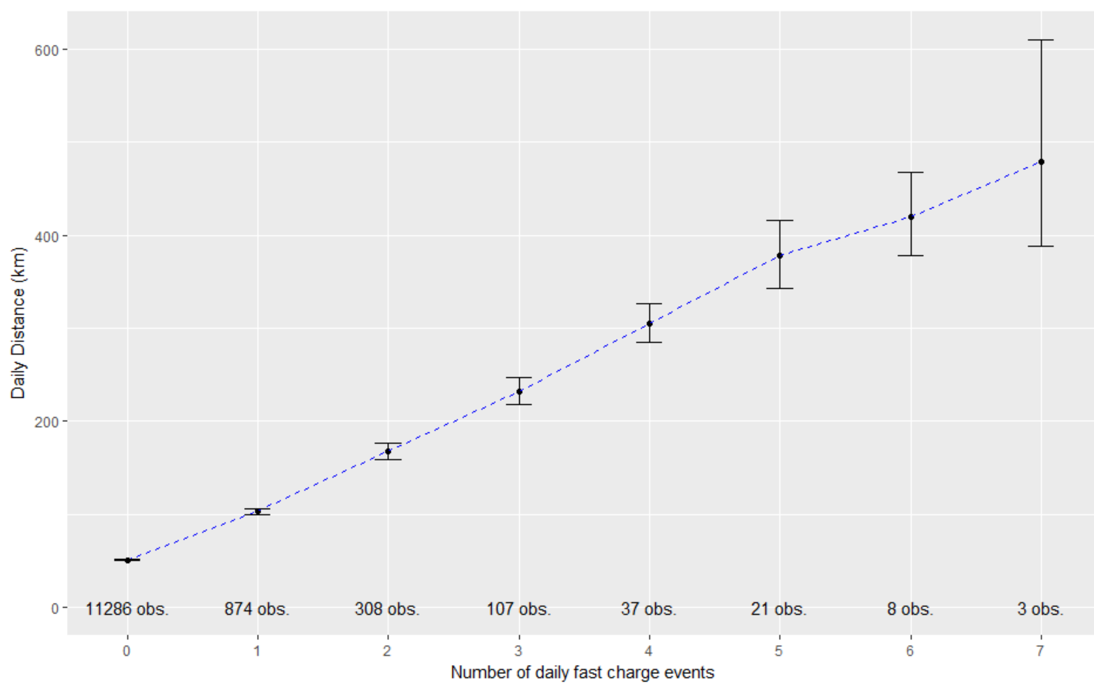


Figure 10: Relationship between daily distance travelled and fast charge events

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 11) 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.

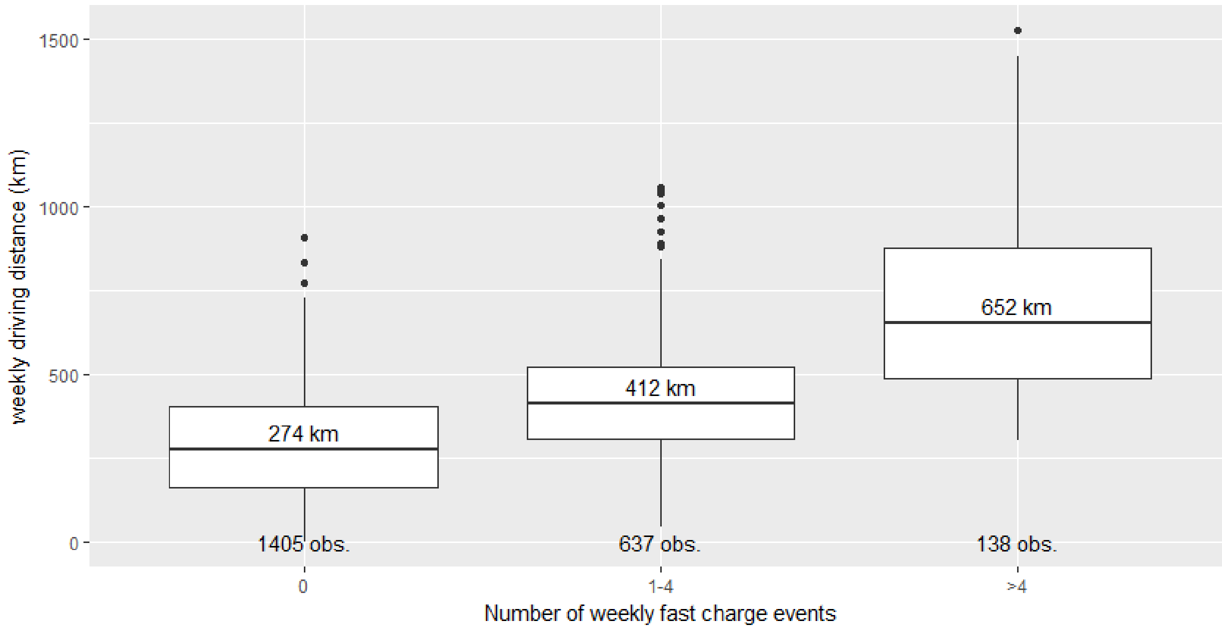


Figure 11: Weekly driving distance and weekly number of fast charge events

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 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 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).

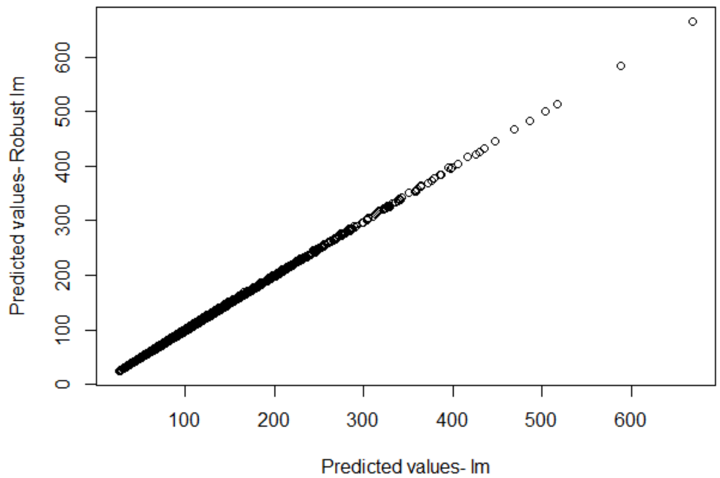


Figure 12: Predicted values of the OLS regression and predicted values of the robust regression

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

Table 1.Comparison between linear and robust linear models

The results of the robust regression were similar to the OLS regression (Figure 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 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<.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) 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				
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)		5.57	0.044	127.86	<0.001

Table 2. 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(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 50km, starting with daily distance up to 50km per day and going to up to 600km per day. The results are shown in Figure 13. The values of proportionate R^2 at daily distance (up to) 600km correspond to the values for the whole dataset.

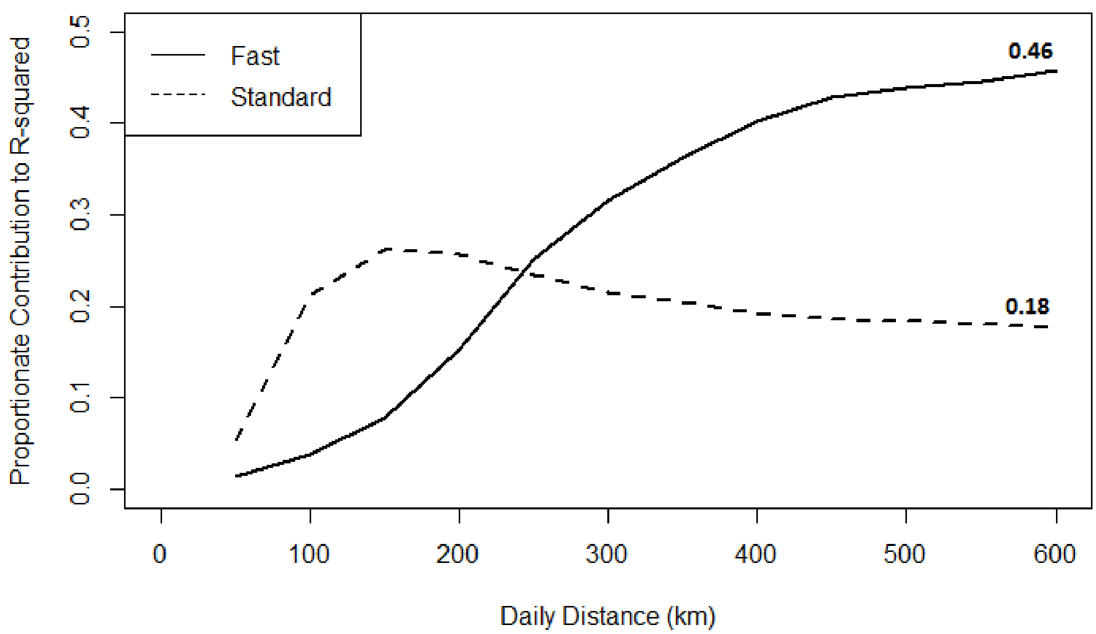


Figure 13.Proportionate contribution to R^2 for fast and standard charge energy predictors.

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. 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.

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 240km per day. Yet, journeys above 240km 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% to 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 tonnes of CO_2 when compared against the emissions which could have been produced by new registered cars (140 gCO_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 (Pierre Ducharme and Catherine 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

7 Using an average EV energy consumption of 182.2 Wh/km as derived from the data loggers on the trial. $300*10^6$Wh/182.2Wh/km=1.65million km(Neaimeh et al., 2015).

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 US, 2017).

In terms of transaction duration, 32% of the events in the UK and 21% of the events in the US were above 30 minutes (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 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.

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