Capturing Diversity in Electric Vehicle Charging Behaviour for Network Capacity Estimation

Constance Crozier[a,b,*], Thomas Morstyn[c], Malcolm McCulloch[a]

[a] *Department of Engineering Science, University of Oxford, OX1 3PJ, UK*
[b] *Department of Civil, Environmental, and Architectural Engineering, University of Colorado, Boulder, CO 80301, US*
[c] *School of Engineering, University of Edinburgh, EH9 3FB, UK*

Abstract

This paper proposes a stochastic data-driven model for uncontrolled charging that accurately captures diversity in individual consumer behaviour. This is important because understanding the diversity between consumers is necessary to accurately estimate the number of electric vehicles' charging a distribution network could support without reinforcements. The model combines readily available travel survey data with high resolution data from an electric vehicle trial, using clustering and conditional probabilities. We demonstrate through a case study of UK residential charging that existing approaches may overestimate the increase in peak distribution network demand by 50%, which has implications for assessing the cost of network investments required. We also show that the peak charging demand varies regionally from 0.2–1.4 kW per household, demonstrating the importance of using locally representative vehicle usage data.

Keywords: Clustering, Demand forecasting, Electric vehicle charging, Stochastic modelling

1. Introduction

This paper demonstrates the importance of accurately modelling diversity in electric vehicle (EV) charging behaviour in order to determine the number of EVs that a distribution network can support, using a novel model based on conditional probabilities and clustering.

EVs represent a rapidly increasing share of the vehicle fleet; for example, in the UK it is projected that there could be 36 million EVs on UK roads

*Corresponding author.

by 2040 [National Grid (2018)]. This will contribute significantly to the CO_2 emissions reduction [Bishop et al. (2012)], which will be required to meet the Paris Climate agreement [UNFCCC (2015)]. However, charging of EVs will present challenges for the power system, as peak demand [Wu et al. (2011)], system losses [Leou et al. (2014)], and voltage violations [Dubey and Santoso (2015)] are all expected to rise as a result of the additional load. If these issues are not appropriately mitigated, then the adoption of EVs may be impeded. Various options have been proposed for managing the additional load, including: time of use prices, localised smart charging, and intelligent upgrades to the distribution network [Sohnen et al. (2015)]. To understand the extent to which new strategies or upgrades will be required, it is important to accurately model the charging behaviours of EV owners.

Power systems are designed to operate under variable loading, with a high degree of confidence [Fulli (2016)]. Therefore, when planning for the future, it is insufficient to estimate the average load due to EV charging, an upper bound needs to be predicted. In the case of EV charging, there are two sources of variability: the vehicle use, and the charging behaviour. The first describes variations in travel behaviour, both between individual users and a single user over different days. The second describes variations in the circumstances under which a user will charge their vehicle. These must both be modelled in order to fully capture the variability in charging. Underestimating the variability of individual actors has the effect of overestimating the aggregated action. So in the case of EV charging, underestimating the variability of individual vehicle owner's charging will result in an overestimate of the peak charging demand. This could result in expensive network reinforcements being carried out unnecessarily.

A variety of methods for modelling the variability of EV charging have been proposed, and they can be broadly divided into three groups: bottom-up charging models applied to varied vehicle use, stochastic bottom-up charging models applied to a fixed set of vehicle usage, and top down stochastic charging models.

The first group encompasses the majority of the early research in this area. In these models, a set of deterministic rules are defined for charging. The most common of these are that charging begins after completion of the final journey of the day (e.g. Pashajavid and Golkar (2012)). However, other assumptions include: anytime the vehicle is home (e.g. Wu et al. (2011)), arrives at the destination (e.g. Arias and Bae (2016)), or as soon as a charger is available (e.g. Olivella-Rosell et al. (2015)). However, some define more complicated rules based on location [Hu et al. (2019)], distance to the nearest charger [Kontou et al. (2019)], availability of chargers [Dong et al. (2014)], or whether the vehicle has enough charge to make it to the next destination [Xing et al. (2019)]. In Zhang et al. (2020) the decision to charge is formulated as an optimisation problem, which balances maximising state of charge with minimising cost.

In all these models, variation in predicted charging is then due only to varied vehicle use, which is captured by sampling either raw vehicle data (e.g. Hu et al. (2019)), or probability distribution functions (PDFs) for energy use and arrival times (e.g. Leou et al. (2014) or Hilton et al. (2018)). Providing the data source is large and representative, these models will capture variability in vehicle use. However, these models do not include variability introduced by users' charging decisions – all variability will be due to the distribution of arrival times, and therefore these models are likely to overestimate the peak demand.

The second group of models take a given vehicle use and produce a stochastic estimate of charging. Creating these models generally requires data in which both the use and charging of EVs are recorded. Fuzzy logic models are used in Shahidinejad et al. (2012) and Omran and Filizadeh (2014), where certain combinations of input parameters result in a low, medium, or high probability of charging. In Shahidinejad et al. (2012), the vehicles' state-of-charge (SOC) and length of parking time are assumed to have an impact on the users' decision to charge, while Omran and Filizadeh (2014) also incorporates the distance from home. Considering only three probability states limits the accuracy of these models. However, more states introduce additional parameters. If highly detailed vehicle use information is available (including the locations of all origin and destination pairs) then more complicated models are available.

In Daina et al. (2017), a utility function is defined which describes the value of charging to a consumer (charging decisions are then taken so as to maximise each consumer's utility function). The function includes both deterministic parameters (e.g. cost and available energy) and stochastic parameters with probability distributions that must be determined. Alternative utility function models are available which include, for example, variables for road conditions [Yi et al. (2020)], dwell time [Wen et al. (2016)], and demographics [Chakraborty et al. (2019)]. In Daina et al. (2017), Chakraborty et al. (2019), and Wen et al. (2016) the models are parameterised using stated preference survey data, while in Yi et al. (2020) define their own parameters using a variety of studies.

Models falling into this second group could, in theory, be used to capture both variability in use and charging, by using Monte Carlo simulations with varied vehicle usage data. However, in order to do this there must be a vast set of appropriate vehicle usage data available and the model needs to have a low computational complexity (as thousands of runs of simulation are necessary). Without using Monte Carlo simulations to vary vehicle usage, these models will only capture variability in charging decisions, implicitly assuming that all vehicles exhibit the usage of those producing the charging data. This means that when individual predictions are aggregated the diversity between users is likely to be underestimated, resulting in an overestimate for the peak aggregated charging demand.

The third group directly models charging, rather than the relationship between vehicle use and charging. In other words, these are top-down models for EV charging. Sometimes standard probabilistic models are used: Gaussian Mixture Models in Godde et al. (2015) and Quirós-Tortós et al. (2018a), and a non-homogenous Markov Process in Rolink and Rehtanz (2013). In Marmaras et al. (2017) an agent based model is proposed, where driving and charging activities are randomly assigned to agents depending on their SOC and location, allowing simultaneous modelling of traffic and charging. Random point processes are used in Alizadeh et al. (2014) and Liang et al. (2014) to describe EV arrivals, and queueing theory is used to model EV charging. However, this approach is better suited to public charging, where the availability of chargers is a limiting factor. These models likely capture the variability from their constituent datasets, but also any sources of bias present in the data. This makes it difficult to assess the number of EVs that a specific network could support, because there is unlikely to be charging data available that is representative of vehicles on that network. Another downside of these models is that, since their parameters normally do not have a physical interpretation, they are hard to generalise to a different set of vehicle usage.

In data-driven modelling there is a trade-off between the expressivity and the adaptability of models. Expressivity describes the detail with which a process is modelled; highly expressive models typically describe complex dynamics use a large number of parameters. Adaptability describes how easily the model can be adjusted to describe a slightly different process to that present in the training data; adaptable models typically use a smaller number of parameters that are easy to interpret, such that changes to their value can be reasonably estimated. In the field of transportation modelling there exist higher fidelity stochastic models which model consumer behaviour in detail, e.g. in Brandstätter et al. (2017) a stochastic model for vehicle use is developed using estimates of individual journeys origin and destination pairs, and in An and Lo (2015) demand is stochastically modelled by generating trips from a gravity distribution. However, while these models have high expressivity, they require a large number of case specific parameters which are hard to obtain. On the other hand, in the field of power systems modelling there are methods for modelling EV charging that are very adaptable as they require little information to parameterise, e.g. in Sundstrom and Binding (2012) discrete probability distributions are defined for arrival and departure times of all vehicles, and in He et al. (2012) arrival times and state-of-charge are sampled from uniform distributions. However, these do not provide enough expressivity to accurately model the diversity between consumers.

The models discussed here predominantly use one of two data sources. Those incorporating only variability through vehicle use mainly use travel surveys (.e.g Wu et al. (2011), Pashajavid and Golkar (2012)). Travel surveys are typically collected by governments or local authorities, and document the travel of randomly selected households or consumers. These datasets are usually large, and contain regional information – allowing geographic variation to be considered. However, they primarily describe conventional vehicles, so no charging behaviour is recorded, and the accuracy of the data is limited by human error. The second two groups require charging data, and therefore typically use data from small scale EV trials (e.g. Quirós-Tortós et al. (2018a), Alizadeh et al. (2014)). These trials are conducted in order to investigate consumer charging, and typically involve recording the use and charging of a small group of EVs. As these trials are opt-in, the participants are likely to be a biased set of drivers. In Haustein and Jensen (2018), it is suggested that early EV adopters are likely to have high incomes and more than one vehicle, which would result in a narrower range of vehicle use, and in Dixon and Bell (2020) it is demonstrated that vehicle usage is dependant on population demographics. Therefore, extrapolating data from these trials to represent the charging patterns of a larger fleet of vehicles is unlikely to produce accurate results. Additionally, these trials are small and in sparse geographic locations, so the regional variation in EV charging can not be investigated. Therefore, using either of these data sources in isolation is likely to overestimate the peak demand of a group of vehicles charging, and therefore underestimate the number of vehicles that could be supported using the existing infrastructure.

In this paper, we develop a stochastic model for EV charging which combines the benefits of both data sources, by modelling the charging from an EV trial but usage from travel survey vehicles. This allows the diversity of consumer behaviour to be captured, while limiting the amount of data required fro parameterisation. The stochastic model is based on conditional probabilities, and uses clustering to reduce the dimensionality of the vehicle use data. Using data from the United Kingdom (UK) as a case study, we demonstrate the difference that incorporating both sources of variability makes to predictions of peak demand.

The contributions of this paper can be broken down into methodological contributions, and results based contributions. From a modelling perspective, the proposed method incorporates variability into both charging behaviour and vehicle use, without requiring EV specific data (e.g. historic charging data) to make predictions. In contrast, existing models either only incorporate variability into one of these aspects, or they require detailed EV specific parameters as inputs. Additionally, the proposed method uses clustering to reduce the vehicle use data to a single dimension. This significantly reduces the amount of data required to train the model, allowing the model to be built using existing datasets at low cost. From a results perspective, the case study in this paper quantifies the difference that including both forms of variability makes to the estimated aggregate charging demand of a group of vehicles. Simulations are also run using a variety of regional vehicle datasets, quantifying the impact of vehicle use on the estimated charging demand. These results are important for transport electrification policy, as the estimated charging demand of a group of vehicles will dictate whether infrastructure upgrades will be necessary to support EV charging.

Although the model accuracy and results in this paper are specific to the UK, the model formulation is presented using generic parameters, allowing the model to replicated for other areas providing sufficient data are available. The results here also only consider domestic charging, however the formulation would also hold for public charging, or an industrial fleet of vehicles.

The remainder of this paper is structured as follows. In Section 2, the data used in this analysis are described, Section 3 describes the methodology for both the clustering and the modelling. In Section 4, the proposed model is parameterised for UK domestic charging and its accuracy is quantified. Results and a comparison with existing methods are presented in Section 5 and Section 6 concludes the paper.

2. Required Vehicle Data

The proposed model combines two sources of data. In this section the data requirements are explained and the specific datasets used for the main case study in this paper are described.

2.1. Conventional Usage Data

A large set of vehicle usage data, recording the time and distance of trips, is used as a model input. This paper will predominately focus on travel survey data, however other representative datasets that record trips could be used. Travel surveys are carried out routinely by many countries and local authorities, in order to understand the travel behaviour of their citizens. Households are randomly selected and asked to record all of their trips undertaken during a trial period. Providing the dataset is rigorously sampled and representative, the behaviour captured should be representative of the population as a whole.

The main case study in this paper will use the UK National Travel Survey (NTS) [Lepanjuuri et al. (2016)], which has been carried out annually since 2002. Participants record all of their journeys for a week and the trial periods are staggered throughout the year. The full data set includes the time, distance, purpose, and mode of transport of nearly 2 million journeys – from which more than 100,000 vehicles' usage can be extracted.

2.2. EV Trial Charging Data

Early scale EV trials have started to record the way consumers are actually charging. These trials provide valuable information about charging behaviour, but are small and typically opt-in – meaning that a sample bias is likely. The proposed model requires both trip and charging information for a fleet of vehicles. For trip data, distances, and start and end times of journeys are recorded using either an on-board monitor or using a GPS device. For charging data, the time and state-of-charge (SOC) of the vehicle at both the start and end of the charge are required. In addition to including actual charging behaviour, this data is likely to be more precise than travel survey data, as it is electronically recorded. It should be noted that if the model is to capture the behaviour of consumers on a tariff pricing structure, the trial participants need to be on this tariff.

The main case study in this paper uses data from My Electric Avenue (MEA) [Electric Nation (2016)], a UK trial which finished in 2016. During an 18 month trial period, 213 Nissan Leafs were loaned out to households, with the condition that all of their vehicle use and charging would be recorded and available for research purposes. For a more complete analysis of the data from this trial, see Quirós-Tortós et al. (2018b).

3. Methodology

This section describes the methodology of the proposed stochastic charging model. First, clustering is used to reduce the dimensionality of vehicle usage as a model parameter. Then, a conditional probability model is formulated which describes the probability of charging as a function of SOC, time, weekday, and vehicle usage.

3.1. Clustering

Vehicle usage data, such as that recorded in travel surveys, is high dimensional – as the timings and distance of a potentially large number of journeys are recorded for each vehicle. Clustering allows data to be grouped, thereby reducing the dimension to a single parameter – the cluster to which the vehicle belongs. In Crozier et al. (2018a) the authors proposed clustering travel survey data to identify different types of vehicle owner. Since the objectives are different, the clustering in this paper differs from this previous work in several respects. Here, each vehicle-day is considered as a separate point, while the previous analysis considered each vehicle as a single point. This means that types of driving day are investigated, rather than types of vehicle ownership. Additionally, in the previous analysis, feature vectors were not normalised and a different distance metric was used. Clustering of vehicle trajectories is a more mature research topic (e.g. Atev et al. (2010)), however the aim of these works is to identify common origin-destination pairs. Here, we consider the different problem of identifying days of vehicle use that are temporally similar - and therefore likely to exhibit similar charging behaviour.

Clustering groups data points (each described by a feature vector) that are similar according to some distance metric. Here, each vehicle-day is considered as a separate data point, meaning that a single vehicle from the dataset can belong to different clusters on consecutive days. This is consistent with the way that vehicles are actually used (e.g. a vehicle could be used to commute on one day, but not the next). The common practice of separating weekday and weekend behaviour is also adopted [Agarwal (2004)].

Vehicles' normalised velocity profiles are used as the feature vector. For each time interval, the average velocity is found by dividing the distance travelled during that period by the length of the period. The model formulation holds for any time resolution, but a balance must be found between the training data requirement and the model fidelity. Half-hourly resolution is suggested, in which case there are 48 features, each representing the average velocity of the vehicle in that half hour. For each data point (or each vehicle-day) the features are then normalised, such that they sum to 1. Normalising sacrifices the total distance travelled information, however vehicles travelling further are likely to be used for longer, so this information is still captured indirectly. Normalising is a common choice in profile clustering, as it tends to result in a more even distribution of points between clusters.

Here we use K-means clustering, an algorithm that chooses clusters so as to minimise the inter-cluster variance. Each cluster c' is defined by a centroid $\mathbf{y}^{(c')}$ that represents its average point and is given by:

$$\mathbf{y}^{(c')} = \frac{1}{N_{c'}} \sum_{i}^{N_{c'}} \mathbf{x}_i^{(c')}, \tag{1}$$

where $\mathbf{x}_i^{(c')}$ is the feature vector of the ith point belonging to cluster c', and $N_{c'}$ are the total number of points in that cluster. Each point is assigned to the cluster whose centroid is closest to it, as measured by Euclidean distance. The algorithm finds the cluster centroids that minimise the inter-cluster variance (the spread of points within a cluster). This is a common clustering method, largely due to its computationally simplicity. More complex methods are available for time series clustering (e.g. Paparrizos and Gravano (2016)), however the size of typical travel survey datasets makes computational cost paramount.

One of the downsides of the K-means algorithm is that the number of clusters, K, needs to be defined. Various metrics have been proposed to do this, and here the elbow method is followed (e.g. Bholowalia and Kumar (2014)). This method dictates that K is found by examining the variation of *sum of squares* with number of clusters. Sum of squares is defined as:

$$SoS = \sum_{i}^{N} \left\| \mathbf{x}_i^{(c)} - \mathbf{y}^{(c)} \right\|^2 , \tag{2}$$

where N is the total number of data points across all of the clusters. This is a measure of inter-cluster variance, and will necessarily decrease as K is increased. K is then chosen at the *elbow* (or the corner point) of this curve, where the reduction in variance achieved by an additional cluster is no longer significant. In this case, there is an implicit extra cluster containing vehicles that are not used in that day; these all have zero feature vectors and are removed before the clustering process.

3.2. Modelling Charging

The most prevalent assumption in the literature is that EV charging begins immediately after the completion of the vehicle's final journey of the day Huang and Infield (2010); Darabi and Ferdowsi (2011); Yan et al. (2017); Barghi-Nia

Table 1: The random variables included in the model

Variable	States	Description
c	$\mathbb{Z} \in [0, 1]$	Describes whether a charge begins
j	$\mathbb{Z} \in [0, 1]$	Describes whether a journey has just ended
d	$\mathbb{Z} \in [0, 1]$	Describes if it is a weekend or weekday
k	$\mathbb{Z} \in [1, \dots K]$	The usage cluster the vehicle belongs to on that day
t	$\mathbb{Z} \in [1, \dots N_T]$	Time of day
s	$\mathbb{Z} \in [1, \dots N_S]$	State of charge

and Sirios (2015); Pashajavid and Golkar (2012); Klayklueng et al. (2015); Ahmadian et al. (2015). However, in practice charges begin at any time between the arrival of the vehicle at home and its next departure. Therefore, two distinct types of charging are modelled here: those taking place directly after the end of a journey and those starting at unconnected times. Hereafter these are referred to as *after journey* and *independent* charges. In order to incorporate both types of charging a variable j is introduced to determine whether a journey has just been completed.

In the proposed model, the variables considered to influence charging decision are: the vehicle's SOC, the time, and the usage cluster that the vehicle belongs to. SOC is discretised into N_S states and time is discretised into N_T time periods. The variables and their possible states are described formally in Table 1, where $\mathbb{Z}$ represents the set of integers. Now instead of considering only the probability that a charge will occur, the *joint probability distribution* of all variables must be considered. Every possible scenario is described by a combination of these variables, meaning that:

$$\sum_{c,j,d,k,t,s} P(c, j, d, k, t, s) = 1, \tag{3}$$

where P is the probability distribution function. The prediction problem becomes calculating the *posterior* probability that a charge begins, given the known values for the other variables. For after journey charges, this is written as:

$$P(c = \text{True} \mid j = \text{True}, d, t, k, s), \tag{4}$$

where $\mid x$ implies that the value of x is known. This expression is a function of the four variables (d, t, k, s) and so the probability distribution is defined over $2 \times N_T \times K \times N_S$ possible scenarios. This discrete distribution can be populated using the observed charging events from the trial data. For each (d, t, k, s), (4) is approximated as the percentage of instances of those variables which resulted in a charge. Note that, as we are only considering cases where $j = \text{True}$, only times when a journey has just ended are considered.

Similar analysis can be performed for independent charges, such that a discrete estimate is made of

$$P(c = \text{True} \mid j = \text{False}, d, t, k, s), \tag{5}$$

These distributions can then be applied to the travel survey data, as (d, t, k) are known and s can be estimated by assuming a battery capacity and a relationship between energy consumption and distance. The simplest method is to use a linear relationship, such that a constant coefficient maps the distance to an energy consumption. If additional information were available, the relationship of consumption on driving style and vehicle parameters could be incorporated by altering the parameter according to the information. This allows a Monte Carlo simulation to be set up, which is described by the flow chart in Figure 1. For each vehicle, the cluster, k, type of day, d, state of charge, s, and time, t, are initialised, then for incremental values of time, t:

- Determine whether a journey has just ended, j, and reduce the state of

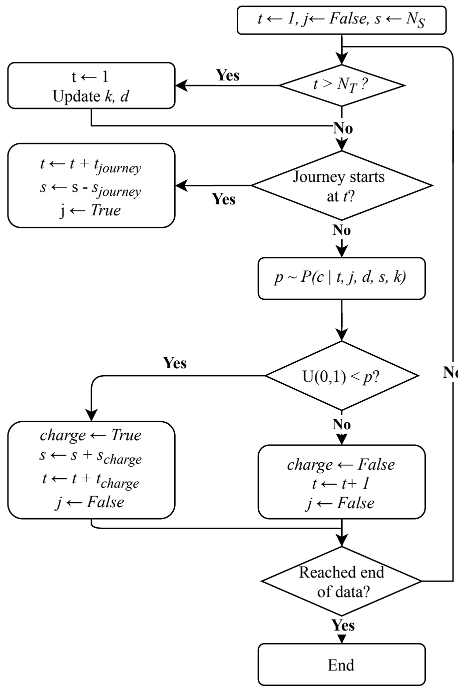


Figure 1: A flow chart describing the simulation process for one vehicle.

charge, s, by the required amount if $j = \text{True}$

- Sample the probability of charging $P(c = \text{True} \mid j, d, t, k, s)$,.
- Sample the uniform distribution $U(0,1)$ and if it is less than the sampled P, begin charging.
- Charging ends either when the battery is full, or the vehicle is next used – whichever occurs first. Update the time, t, and state of charge, s, as necessary.

Stepping through the data once will result in a single estimate of charging. Stochasticity is captured by repeating the simulation, resulting in a distribution of predicted charging. Variation in both charging and vehicle use can be incorporated by running further Monte Carlo simulations where the input vehicles are randomly sampled from the travel survey.

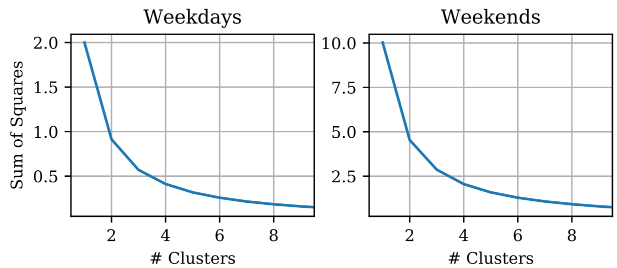


Figure 2: The variation of sum of squares with number of clusters for both the weekday and weekend datasets.

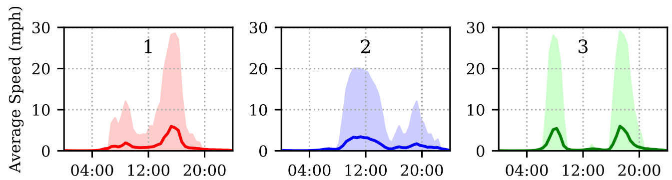
4. Model Validation

In this section, the proposed model is parameterised using the NTS and data from the EV trial 'My Electric Avenue' (MEA), both from the UK. The accuracy with which the model predicts the charging of the MEA data is then quantified using vehicles that were excluded from the training data.

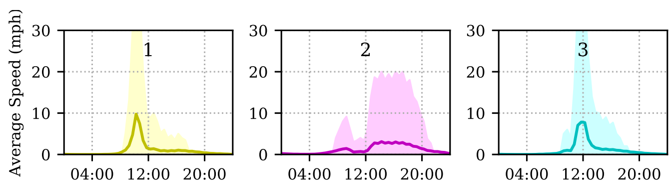
4.1. Clustering Results

Clustering was performed on the NTS data in accordance with the procedure described in Section 3.1. Figure 2 shows the variation of sum of squares with the number of clusters for both weekend and weekday vehicle usage. An *elbow* can be observed at $K = 3$ so this number of clusters was chosen for both weekday and weekend datasets. Note that the variance in the weekend dataset was significantly higher than in the weekday data, meaning we can expect these days to be harder to model accurately.

The average velocity profile of the vehicles from each cluster is shown in Figure 3. The mean values are shown with solid lines, and the shaded areas cover 90% of the data. Unlike the feature vectors, these profiles are not normalised, so overlap between the profiles is to be expected. For weekdays, cluster 3 follows a typical commuting pattern, 1 is dominated by evening use, and 2 by morning use. For weekends, clusters 1 and 3 suggest a single short journey at different times,



(a) Weekday clusters



(b) Weekend clusters

Figure 3: The average speed profile of the vehicles in each cluster. The lines show the mean values, and the shaded areas cover the 90% confidence interval. There is no significance to the ordering of the clusters.

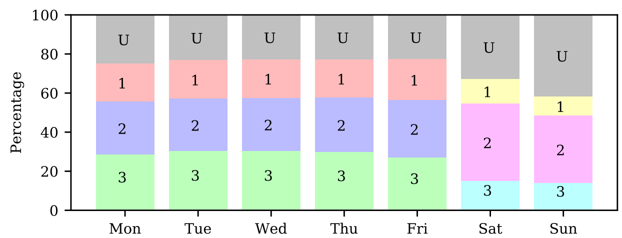


Figure 4: The percentage of each cluster occurring on each weekday. The colours correspond to those in Figure 3 except grey which indicates unuse.

while 2 shows more distributed use throughout the day. Figure 4 shows the weekly composition of clusters, where the colours correspond to those in Figure 3. Vehicle use is fairly consistent across the weekdays, although commuting is slightly less common on Mondays and Fridays. Overall vehicle usage is lower at the weekends and lowest on Sunday.

MEA provides the best available evidence for EV user residential charging behaviour in the UK. However, the vehicle use exhibited represents a biased set of drivers – 67.3% of participants were male, and 41% were within the 40-49 age bracket. Quantifying this bias enables prediction of the likely error from

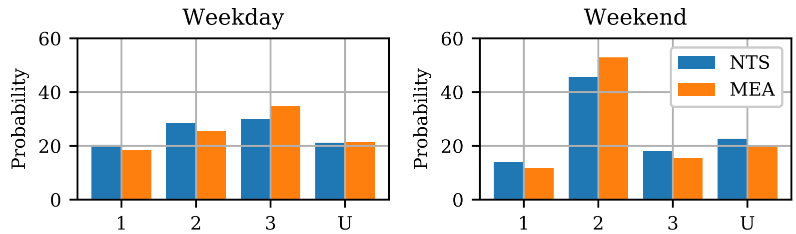


Figure 5: A comparison of the cluster composition of the NTS and MEA data.

Table 2: The average distance travelled by each cluster (miles).

	NTS Cluster			**MEA Cluster**		
	1	**2**	**3**	**1**	**2**	**3**
Weekday	25.42	25.41	27.17	28.83	29.33	29.70
Weekend	23.87	28.10	25.15	22.49	26.47	24.61

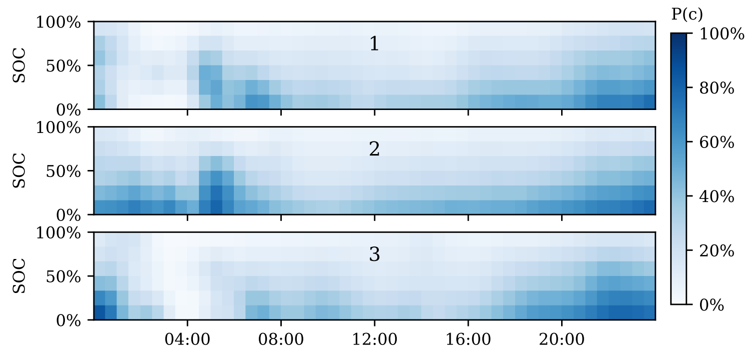
extrapolating this trial data to represent a large fleet of vehicles. This is achieved by creating equivalent feature vectors from the MEA data and classifying points according to the clusters defined from the NTS data. By comparing the cluster composition of the datasets, modes of vehicle use that are over represented in the trial data can be identified. Figure 5 shows the distribution of clusters for both datasets and Table 2 shows the average daily distance travelled by vehicles in each cluster. The cluster composition is broadly similar, although there is a slight bias in the MEA data towards weekday commuters. However, distance travelled varies more significantly – all weekday MEA clusters travel further than the NTS clusters and all weekend clusters travel shorter distances. Overall the average MEA driver travels 12% further than the average NTS driver on a weekday. Therefore, using the MEA data to directly forecast future charging is likely to overestimate demand.

4.2. Model Parameterisation

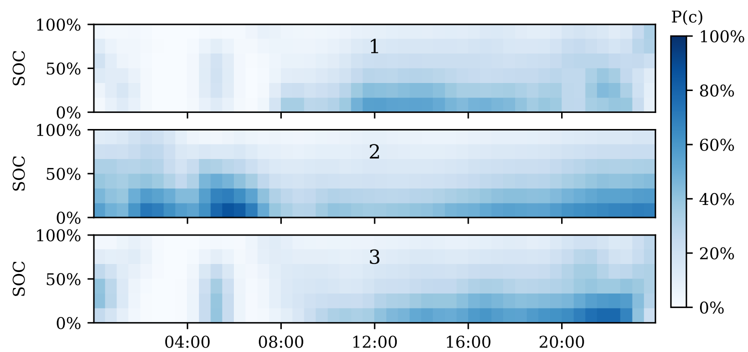
Examination of the MEA data showed that only 70% of charges took place within 10 minutes of completing a journey. Although this is a majority, a significant proportion of charging will not be captured if only after journey charging is considered. This supports the proposed approach of modelling after journey and random charges separately. Taking into account the size and resolution of the MEA data, it was decided to use $N_T = 48$ (half-hourly time resolution) and $N_S = 6$ (SOC to the nearest 4 kWh, given that the trial vehicles all had a 24 kWh capacity). Half-hourly time resolution aligns with the peak load rating of distribution networks [Croucher (2011)], while six SOC units was found to best balance the model's expressivity with coverage of the probability distribution space. It should be noted that the parameterised model can be applied to vehicles of any capacity, providing the SOC can be rounded to the nearest $\frac{1}{6}$. However, the behaviour of drivers with much larger capacity vehicles may be different to the 24 kWh vehicle drivers present in the trial, so results may be less accurate where the vehicle capacity varies significantly from the trial. Figure 6 illustrates (5), the probability of an after journey charge beginning, using heatmaps. A separate set of axes is used for each possible k and d combination, with t on the horizontal axis and s on the vertical.

The fact that the distributions vary significantly with k supports its incorporation as a parameter; if EVs' charging were independent of usage cluster, the three heat maps would be identical. The peaks occur at low values of SOC (as expected), in both the evening and early morning. Note that this does not mean that all vehicles are likely to charge in the early hours, but that those completing journeys at this time are.

For independent charging it was found that the vehicle usage had a negligible effect on whether or not a charge was started. In fact, often these events occurred on days where there was no vehicle use – and as a result no value of k. Therefore it was assumed that $P(c_i)$ was independent of k, such that the



(a) Weekday



(b) Weekend

Figure 6: The % probability that a charge will follow the completion of a journey, as a function of both time and SOC, for each vehicle use cluster.

posterior distribution to be estimated becomes:

$$P(c_i = \text{True} \mid t, d, s), \tag{6}$$

Figure 7 illustrates this distribution. In this case there is not significant difference between weekend and weekdays, suggesting that d could also be excluded from (6). However, as minor differences are observed in the early evening (which is the time of greatest interest) the variable was kept in this analysis. The distribution peak occurs shortly after midnight, which may be the result of Economy 7 (the UK's dual tariff scheme, which means some consumers have seven hours of cheaper electricity overnight).

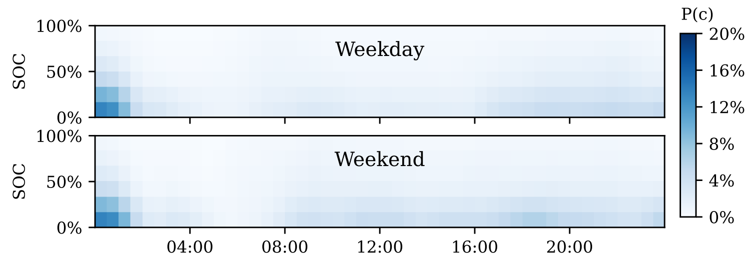


Figure 7: The % probability that a charge will start independent of a journey, as a function of both time and SOC, for each vehicle use cluster.

4.3. Accuracy

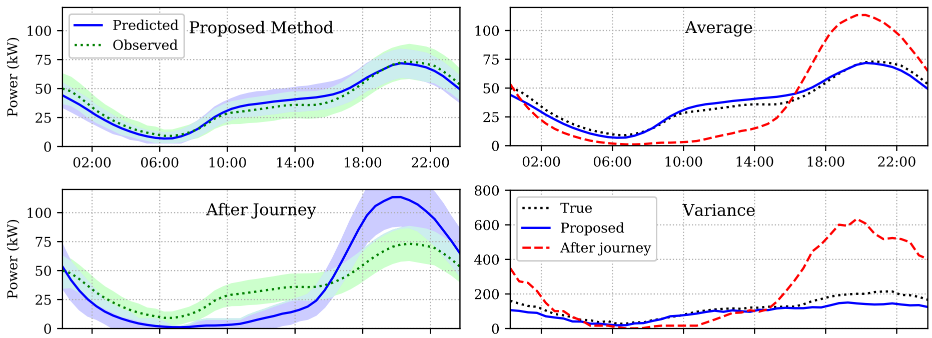
The accuracy of the model proposed in Section 3.2 can be quantified by predicting the charging of the MEA vehicles from their usage data. It is important to use different data to train the model and test its accuracy; otherwise the model may be overfit – meaning it fits the training data with very high accuracy, but performs badly on unseen data. Given the limited amount of data collected in MEA, significantly reducing the size of the training data is likely to degrade the performance of the model. Therefore here we use leave-one-out cross validation, where the algorithm is applied once for each vehicle, with the remainder of the vehicles used as training data. This approach maintains the lack of contamination between testing and training data, while maximising the available testing data. However, it has been shown that this approach can lead to models with higher variance, particularly when training data points are highly correlated [Bengio and Grandvalet (2004)]. Therefore, where larger datasets are available for training, the more traditional k-fold cross validation may be a better choice.

The proposed application of this model is in stochastically modelling the charging of a fleet of vehicles based on their usage. This type of modelling is paramount in planning future requirements for transmission and distribution networks. Therefore, here we consider the accuracy with which the proposed method models the charging demand of a group of the vehicles from the trial. The accuracy of the proposed method is compared to the standard assumption that charging begins after the completion of a vehicle's final journey. Although there are more complex models available, standard charging assumptions are the only directly comparable models as they can be applied directly to vehicle usage data without additional parameterisation.

In order to test the proposed method 50 vehicle-days were randomly selected from the MEA dataset and their charging individually forecast then aggregated. This process was repeated using a Monte Carlo simulation with 2000 runs, in order to generate a distribution of charging power for each time interval. Figure 8a shows the predicted profile, compared to the actual charging observed in the trial, and that obtained used after journey charging. It can be seen that the proposed method follows a similar shape to the observed data, while the after journey charging significantly over-estimates demand in the early evening. This means that, even if the prediction of individual vehicles charging is not highly accurate, the model accurately captures the statistical behaviour of fleet charging.

This can be seen more clearly in 8b which shows the mean and variance of each method super-imposed to the observed mean and variance. Apart from a minor bias towards mid-day charging, the proposed method closely follows the observed charging, while the after journey method over-estimates the peak demand by more than 50%. The variance is also modelled accurately, which is important because networks need to be designed to an upper bound rather than the average loading.

Overall, accuracy demonstrated here suggests that the proposed method can be used to accurately model the charging of a fleet of vehicles stochastically.



(a) Predicted charging power (b) Mean and variance comparison

Figure 8: The charging demand predicted from a group of 50 vehicles from the MEA dataset. The solid line shows the mean prediction and the shaded area covers one standard deviation either side.

5. UK Domestic Charging Case Study

In this section a domestic charging case study is used to demonstrate the difference with using the proposed approach over traditional methods. Here we consider the aggregated charging of 50 households' vehicles. This is representative of charging in a low voltage (LV) distribution network, where 100% of vehicles are electric. Simulations of this kind are important, because we need to understand how diversity between vehicles is likely to manifest at low levels of aggregation. If all the vehicles on a residential network charged simultaneously then the network's limits would likely be violated. However there are existing appliances (e.g. kettles or showers) which would cause overload if all households used them simultaneously; in reality natural diversity between users renders this situation extremely unlikely. As EV adoption increases, accurately modelling the diversity of EV charging will be crucial in predicting the peak demand.

Initially vehicle data was taken from NTS households in North Lincolnshire (a county in the North East of England). Households were selected at random, regardless of the number of vehicles the household owned (which could be zero). This means that the number of EVs charging on the network depends on the

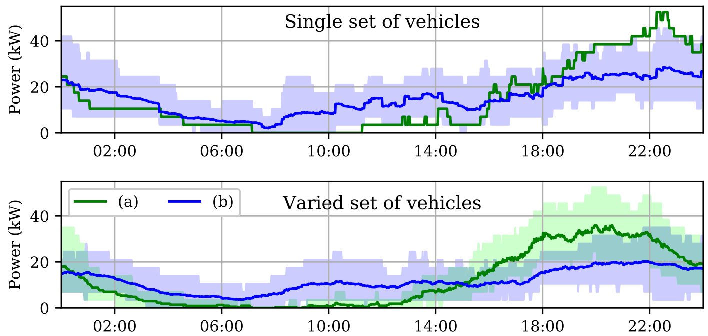


Figure 9: Aggregated charging of 50 households' vehicles under both: (a) the assumption that charging always begins after a vehicle's final journey, and (b) the proposed model. The top plot shows the result for one set of vehicles, and the bottom takes into account variation is vehicles as well as charging. The shaded area covers the 90% confidence interval of simulation results.

vehicle ownership of the selected households. Based off the analysis in Crozier et al. (2018b) conversion factors of 0.26 and 0.35 kWh /mile were used for vehicles from rural and urban areas respectively and 24 kWh batteries were assumed. These numbers are based on the Nissan Leaf, which was the vehicle model used in the MEA trial. Therefore these values were chosen in order to maximise the relevance of the charging data. It was assumed that chargers were rated at 3.5 kW and had an efficiency of 90%.

A week long simulation was run (the maximum length available from the NTS data) but the Wednesday results were isolated for analysis. This day was chosen to investigate typical weekday behaviour, while minimising the edge effects of the simulation. Monte Carlo simulations were constructed to estimate the average and variance of the predicted charging profile. Two simulations were carried out, one considering only variation in charging, and one considering both variation in vehicle use and charging. In the first, a single set of 50 households was chosen from the data, and in the second, the 50 households were allowed to varied between runs of the Monte Carlo simulation.

The simulation results are shown in Figure 9, using both the proposed model

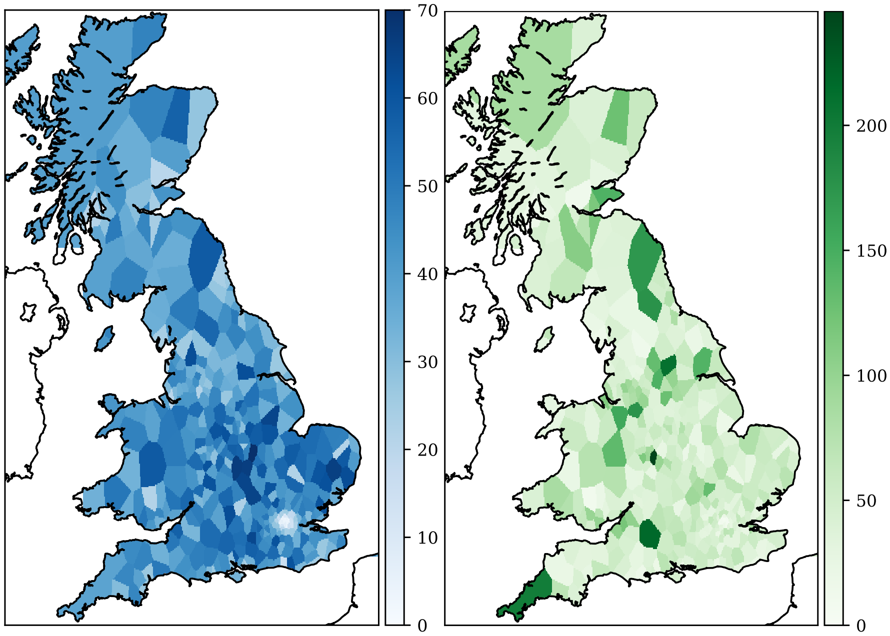
Table 3: The peak power and energy demand of 50 vehicles' charging using various methods.

	MEA	NTS with after journey	NTS with proposed
Peak Power	73.5 kW	52.5 kW	35.7 kW
Energy Demand	805 kWh	453 kWh	453 kWh

and the assumption that vehicles charge after their final journey. The latter was chosen for comparison because of its prevalence in the literature, providing insight into how the proposed methodology would alter existing results. Additionally, it was one of the only directly comparable models – as it could be applied to usage data without requiring any additional parameters. In the single set simulation, there is no variation using this assumption as it is deterministic. When the set of vehicles is varied, stochasticity is introduced via the vehicle use. In both simulations, the peak demand predicted by the new model is lower than that predicted by assuming charging begins after the final journey. This is significant because it suggests that existing predictions of the impact of EV charging on distribution networks are overestimates.

This is further demonstrated in Table 3, which shows the average charging energy and peak demand of 50 households' vehicles, using three methods: (1) sampling from the MEA data, (2) sampling from the NTS and assuming charging occurs after finals journey, (3) sampling from the NTS and applying the proposed model. Using the MEA data directly results in significant overestimates for both energy consumption and power demand. The predicted energy consumption is the same for both the NTS cases, but the proposed model introduces diversity to the charging behaviour, resulting in a reduction in peak demand.

Due to the abundance of travel survey data available, it is possible to compare the likely impact of EV charging in different areas, assuming that electrification does not cause a significant change in driving patterns. This section



(a) per 50 household network (kW)

(b) per local authority (MW)

Figure 10: The peak charging demand varied across GB

uses the NTS data combined with the charging data from MEA to estimate the regional variation in the impact of EV charging on LV distribution networks. Figure 10a shows the expected peak demand of 50 households' EV charging on a residential network for each local authority in Great Britain, assuming a penetration of 100% EVs. It can be seen that the value varies significantly, due to varied travel distance and vehicle availability. The increase in peak demand of a 50 household network varies from 10–70 kW, giving an expected increase of approximately 0.2–1.4 kW per household.

It is notable that the increase is very low in both central and outer London. In central London vehicle ownership is low, and therefore the average number of vehicles owned by 50 random households is likely to be small. In outer London vehicle ownership is high, but the average distance driven is small, meaning that the energy demand of the 50 households' vehicles will be relatively small. The highest increases in demand are seen in rural southern parts of the UK, where both vehicle ownership and driven distance are high.

Figure 10b shows the peak charging demand per local authority, i.e. the previous result scaled by the number of households in that area. This demonstrates the geographic distribution of additional peak load on the national power system. Of particular note is Cornwall on the most southwest point of GB; the peak demand per 50 household network is average, while it has the highest total additional demand. This demonstrates the importance of considering the impact on both local and national networks.

These results could be extended to consider the impact that charging will have on the transmission network. In order to perform this analysis the loads should be aggregated according to the locations of the grid supply points. Given the need for additional network and population data, this analysis is left as further work.

6. Conclusion

In this paper a stochastic model for EV charging was presented that is trained using real charging data, but can be adapted to any vehicle usage data (including from conventional vehicles). The model is based on conditional probability distributions and incorporates random variables for vehicle usage, SOC, time, and type of day. K-means clustering was used to reduce the dimensionality of vehicle usage to a single parameter, reducing the complexity of the probability distribution – and hence the required amount of training data. Clusters are identified from the larger survey dataset, but the EV trial data is used to formulate the discrete probability distributions.

A domestic charging case study was constructed using the UK National Travel Survey and the EV trial 'My Electric Avenue'. Assuming charging began immediately after completion of the final journey (the traditional assumption) overestimated demand in the early evening by 50%, whereas the proposed model showed no significant bias at any time of day. It was also shown that the trial EVs travelled further on average than those documented in the travel survey, demonstrating the importance of being able to generalise charging models to vehicle usage not present in the trial. This simulation was repeated for each local authority in Great Britain to demonstrate the large geographic variation in future EV charging demand.

This case study demonstrated the importance of accurately capturing diversity between consumers' charging demands. Diversity plays a large role in the stability of small networks, which rely on cancellation between consumers to keep peak demand below the network limits. Traditional methods overestimate the aggregated charging demand of EVs, and this could lead to networks being un-necessarily upgraded at high cost. This result demonstrates the importance of accurately modelling vehicle usage in making intelligent upgrade decisions.

It was also demonstrated that there is a large variation in predicted demand across the UK; the peak demand of 50 vehicles varied from 10 to 70 kW. This shows the importance of using local travel information to estimate network capacity; using one set of parameters to model vehicle use across a whole country would under-estimate demand in some areas, and over-estimate in others. If possible, distribution network operators should gather data describing the vehicle use of customers on the specific network they are considering upgrading.

The results in this paper focus on domestic charging is the UK, however the methodology could be applied to scenarios providing the following two types of data are available. First, the vehicle usage and charging data from a trial, which will be used for clustering and populating the conditional probability distributions. If the study being carried out focuses on domestic charging for countries with a broadly similar work and life culture to the UK (e.g. in Europe or US), then the data utilised in this paper could be used – as differences in trip distance and timings will be offset by the second dataset. However, for industrial fleet charging or domestic charging in countries will vastly different working patterns, a separate trial will be required. Second, a set of highly representative vehicle usage data, which will dictate the timings and volume of charging modelled. This data can be captured using surveys, so is very cheap to collect, but needs to be diverse and representative of the population being modelled.

Although this model shows improved results compared to existing methods, there are a couple of limitations to this approach. First, that charging is assumed to be only a function of SOC, time, whether a journey has just ended, and the vehicle usage cluster. These reduced set of parameters were required in order to parameterise the model with the available data, however it means the model does not capture the dependance on other variables e.g. the weather. Second, that a large amount of charging data is still required to operate the modelSecond, that a large amount of charging data is still required to operate the model; the success of the model is dependant on the availability a small but detailed charging dataset which also records the driving behaviour of the vehicles. While such datasets exist, this means the method may not be suited for estimating charging behaviour in settings that have not been experimentally studied.

Acknowledgment

The authors would like to that Jaguar Land Rover and EPSRC [EP/S000887/1] for their support.

References

Agarwal, A., 2004. A comparison of weekend and weekday travel behavior characteristics in urban areas. Ph.D. thesis. University of South Florida.

Scholar Commons.

Ahmadian, A., Sedghi, M., Aliakbar-Golkar, M., 2015. Stochastic modeling of Plug-in Electric Vehicles load demand in residential grids considering non-linear battery charge characteristic, in: 20th Electrical Power Distribution Conference, EPDC 2015. doi:10.1109/EPDC.2015.7330467.

Alizadeh, M., Scaglione, A., Davies, J., Kurani, K.S., 2014. A scalable stochastic model for the electricity demand of electric and plug-in hybrid vehicles. IEEE Transactions on Smart Grid 5.

An, K., Lo, H.K., 2015. Robust transit network design with stochastic demand considering development density. Transportation Research Part B: Methodological 81, 737 – 754. URL: http://www.sciencedirect.com/science/article/pii/S0191261515001216, doi:https://doi.org/10.1016/j.trb.2015.05.019. iSTTT 21 for the year 2015.

Arias, M.B., Bae, S., 2016. Electric vehicle charging demand forecasting model based on big data technologies. Applied Energy 183, 327 – 339. URL: http://www.sciencedirect.com/science/article/pii/S0306261916311667, doi:https://doi.org/10.1016/j.apenergy.2016.08.080.

Atev, S., Miller, G., Papanikolopoulos, N.P., 2010. Clustering of vehicle trajectories. IEEE Transactions on Intelligent Transportation Systems 11, 647–657.

Barghi-Nia, S., Sirios, F., 2015. Development of Stochastic Models for Assessing the Impact of Electric Vehicles in Distribution Grids, in: IEEE Power & Energy Society General Meeting.

Bengio, Y., Grandvalet, Y., 2004. No unbiased estimator of the variance of k-fold cross-validation. Journal of machine learning research 5, 1089–1105.

Bholowalia, P., Kumar, A., 2014. Ebk-means: A clustering technique based on elbow method and k-means in wsn. International Journal of Computer Applications .

Bishop, J.D., Axon, C.J., McCulloch, M.D., 2012. A robust, data-driven methodology for real-world driving cycle development. Transportation Research Part D: Transport and Environment 17, 389 – 397. URL: http://www.sciencedirect.com/science/article/pii/S136192091200034X, doi:https://doi.org/10.1016/j.trd.2012.03.003.

Brandstätter, G., Kahr, M., Leitner, M., 2017. Determining optimal locations for charging stations of electric car-sharing systems under stochastic demand. Transportation Research Part B: Methodological 104, 17 – 35. URL: http://www.sciencedirect.com/science/article/pii/S0191261516308359, doi:https://doi.org/10.1016/j.trb.2017.06.009.

Chakraborty, D., Bunch, D.S., Lee, J.H., Tal, G., 2019. Demand drivers for charging infrastructure-charging behavior of plug-in electric vehicle commuters. Transportation Research Part D: Transport and Environment 76, 255 – 272. URL: http://www.sciencedirect.com/science/article/pii/S1361920919301919, doi:https://doi.org/10.1016/j.trd.2019.09.015.

Croucher, D., 2011. Design and Planning: Framework for underground networks in UK Power Networks. Technical Report. UK Power Networks.

Crozier, C., Apostolopoulou, D., McCulloch, M., 2018a. Clustering of Usage Profiles for Electric Vehicle Behaviour Analysis, in: 2018 IEEE PES Innovative Smart Grid Technologies Conference Europe (ISGT-Europe), pp. 1–6.

Crozier, C., Apostolopoulou, D., McCulloch, M., 2018b. Numerical analysis of national travel data to assess the impact of uk fleet electrification, in: Power Systems Computation Conference.

Daina, N., Sivakumar, A., Polak, J.W., 2017. Electric vehicle charging choices: Modelling and implications for smart charging services. Transportation Research Part C: Emerging Technologies 81, 36 – 56. URL: http://www.sciencedirect.com/science/article/pii/S0968090X17301365, doi:https://doi.org/10.1016/j.trc.2017.05.006.

Darabi, Z., Ferdowsi, M., 2011. Aggregated impact of plug-in hybrid electric vehicles on electricity demand profile. IEEE Transactions on Sustainable Energy 2, 501–508.

Dixon, J., Bell, K., 2020. Electric vehicles: Battery capacity, charger power, access to charging and the impacts on distribution networks. eTransportation 4, 100059. URL: http://www.sciencedirect.com/science/article/pii/S2590116820300163, doi:https://doi.org/10.1016/j.etran.2020.100059.

Dong, J., Liu, C., Lin, Z., 2014. Charging infrastructure planning for promoting battery electric vehicles: An activity-based approach using multiday travel data. Transportation Research Part C: Emerging Technologies 38, 44 – 55. URL: http://www.sciencedirect.com/science/article/pii/S0968090X13002283, doi:https://doi.org/10.1016/j.trc.2013.11.001.

Dubey, A., Santoso, S., 2015. Electric Vehicle Charging on Residential Distribution Systems: Impacts and Mitigations.

Electric Nation, 2016. My electric avenue. http://myelectricavenue.info/.

Fulli, G., 2016. Electricity Security: Models and Methods for Supporting the Policy Decision Making in the European Union. Ph.D. thesis. Politecnico Di Torino.

Godde, M., Findeisen, T., Sowa, T., Nguyen, P.H., 2015. Modelling the charging probability of electric vehicles as a Gaussian mixture model for a convolution based power flow analysis, in: 2015 IEEE Eindhoven PowerTech, PowerTech 2015.

Haustein, S., Jensen, A.F., 2018. Factors of electric vehicle adoption: A comparison of conventional and electric car users based on an extended theory of planned behavior. International Journal of Sustainable Transportation , 1–13.

He, Y., Venkatesh, B., Guan, L., 2012. Optimal Scheduling for Charging and Discharging of Electric Vehicles. IEEE Transactions on Smart Grid 3, 1095–1105. doi:10.1109/TSG.2011.2173507.

Hilton, G., Kiaee, M., Bryden, T., Dimitrov, B., Cruden, A., Mortimer, A., 2018. A Stochastic Method for Prediction of the Power Demand at High Rate EV Chargers. IEEE Transactions on Transportation Electrification 4, 744–756.

Hu, L., Dong, J., Lin, Z., 2019. Modeling charging behavior of battery electric vehicle drivers: A cumulative prospect theory based approach. Transportation Research Part C: Emerging Technologies 102, 474 – 489. URL: http://www.sciencedirect.com/science/article/pii/S0968090X18312087, doi:https://doi.org/10.1016/j.trc.2019.03.027.

Huang, S., Infield, D., 2010. The impact of domestic Plug-in Hybrid Electric Vehicles on power distribution system loads. POWERCON doi:10.1109/POWERCON.2010.5666513.

Klayklueng, T., Dechanupaprittha, S., Kongthong, P., 2015. Analysis of unbalance Plug-in Electric Vehicle home charging in PEA distribution network by stochastic load model, in: Proceedings - 2015 International Symposium on Smart Electric Distribution Systems and Technologies, EDST 2015. doi:10.1109/SEDST.2015.7315241.

Kontou, E., Liu, C., Xie, F., Wu, X., Lin, Z., 2019. Understanding the linkage between electric vehicle charging network coverage and charging opportunity using gps travel data. Transportation Research Part C: Emerging Technologies 98, 1 – 13. URL: http://www.sciencedirect.com/science/article/pii/S0968090X18305539, doi:https://doi.org/10.1016/j.trc.2018.11.008.

Leou, R.C., Su, C.L., Lu, C.N., 2014. Stochastic analyses of electric vehicle charging impacts on distribution network. IEEE Transactions on Power Systems 29, 1055–1063.

Lepanjuuri, K., Cornick, P., Byron, C., Templeton, I., Hurn, J., 2016. National Travel Survey: 2015 Report. Technical Report. Department for Transport.

Liang, H., Sharma, I., Zhuang, W., Bhattacharya, K., 2014. Plug-in electric vehicle charging demand estimation based on queueing network analysis, in: IEEE Power and Energy Society General Meeting. doi:10.1109/PESGM.2014.6939530.

Marmaras, C., Xydas, E., Cipcigan, L., 2017. Simulation of electric vehicle driver behaviour in road transport and electric power networks. Transportation Research Part C: Emerging Technologies 80, 239 – 256. URL: http://www.sciencedirect.com/science/article/pii/S0968090X17301341, doi:https://doi.org/10.1016/j.trc.2017.05.004.

National Grid, 2018. Future Energy Scenarios.

Olivella-Rosell, P., Villafafila-Robles, R., Sumper, A., Bergas-Jane, J., 2015. Probabilistic agent-based model of electric vehicle charging demand to analyse the impact on distribution networks. Energies 8, 4160–4187.

Omran, N.G., Filizadeh, S., 2014. Location-based forecasting of vehicular charging load on the distribution system. IEEE Transactions on Smart Grid 5, 632–641.

Paparrizos, J., Gravano, L., 2016. k-shape: Efficient and accurate clustering of time series. Special Interest Group on Management of Data Rec. , 69–76.

Pashajavid, E., Golkar, M.A., 2012. Charging of plug-in electric vehicles: Stochastic modelling of load demand within domestic grids, in: ICEE 2012 - 20th Iranian Conference on Electrical Engineering. doi:10.1109/IranianCEE.2012.6292415.

Quirós-Tortós, J., Navarro-Espinosa, A., Ochoa, L.F., Butler, T., 2018a. Statistical Representation of EV Charging: Real Data Analysis and Applications, in: 20th Power Systems Computation Conference, pp. 1–7.

Quirós-Tortós, J., Ochoa, L., Butler, T., 2018b. How Electric Vehicles and the Grid Work Together: Lessons Learned from One of the Largest Electric Vehicle Trials in the World. IEEE Access , 64–76.

Rolink, J., Rehtanz, C., 2013. Large- Scale Modeling of Grid-Connected Electric Vehicles. IEEE Trans. Power Deliv. 28, 894–902.

Shahidinejad, S., Filizadeh, S., Bibeau, E., 2012. Profile of charging load on the grid due to plug-in vehicles. IEEE Transactions on Smart Grid 3, 135–141.

Sohnen, J., Fan, Y., Ogden, J., Yang, C., 2015. A network-based dispatch model for evaluating the spatial and temporal effects of plug-in electric vehicle charging on ghg emissions. Transportation Research Part D: Transport and Environment 38, 80 – 93. URL: http://www.sciencedirect.com/science/article/pii/S1361920915000462, doi:https://doi.org/10.1016/j.trd.2015.04.014.

Sundstrom, O., Binding, C., 2012. Flexible charging optimization for electric vehicles considering distribution grid constraints. IEEE Transactions on Smart Grid 3, 26–37.

UNFCCC, 2015. Paris agreement. U.n.t.c. XXVII 7.d.

Wen, Y., MacKenzie, D., Keith, D.R., 2016. Modeling the charging choices of battery electric vehicle drivers by using stated preference data. Transportation Research Record 2572, 47–55. doi:10.3141/2572-06.

Wu, D., Aliprantis, D.C., Gkritza, K., 2011. Electric energy and power consumption by light-duty plug-in electric vehicles. IEEE Transactions on Power Systems 26, 738–746.

Xing, Q., Chen, Z., Zhang, Z., Huang, X., Leng, Z., Sun, K., Chen, Y., Wang, H., 2019. Charging demand forecasting model for electric vehicles based on online ride-hailing trip data. IEEE Access 7, 137390–137409.

Yan, Q., Qian, C., Zhang, B., Kezunovic, M., 2017. Statistical analysis and modeling of plug-in electric vehicle charging demand in distribution systems, in: 2017 19th International Conference on Intelligent System Application to Power Systems, ISAP 2017.

Yi, T., Zhang, C., Lin, T., Liu, J., 2020. Research on the spatial-temporal distribution of electric vehicle charging load demand: A case study in china. Journal of Cleaner Production 242, 118457. URL: http://www.sciencedirect.com/science/article/pii/S095965261933327X, doi:https://doi.org/10.1016/j.jclepro.2019.118457.

Zhang, A., Kang, J.E., Kwon, C., 2020. Multi-day scenario analysis for battery electric vehicle feasibility assessment and charging infrastructure planning. Transportation Research Part C: Emerging Technologies 111, 439 – 457. URL: http://www.sciencedirect.com/science/article/pii/S0968090X18312117, doi:https://doi.org/10.1016/j.trc.2019.12.021.