Characterization of Electric Vehicle Fast Charging Forecourt Demand

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***Abstract*— Not all Electric Vehicle (EV) charging in future will take place at drivers' homes or on-street; at least some will take place at fast-charging 'forecourts' analogous to today's petrol stations. This paper presents a Monte Carlo (MC)-based method for the characterization of the likely demand profile of EV fast charging forecourts based on activity profiles of existing petrol stations, derived from smartphone users' anonymised positional data captured in the 'Popular Times' feature in Google Maps. Unlike most academic works on the subject to date which rely on vehicle users' responses to surveys, these data represent individuals' actual movement patterns rather than how they might recall or divulge them. Other inputs to the model are generated from probability distributions derived from EV statistics in the UK and existing academic work. A queuing model is developed to simulate busy periods at charging forecourts. The output from the model is a set of expected time series of electrical demand for an EV forecourt and statistical analysis of the variation in results. Finally, a method is presented for the probabilistic evaluation of the combined loading of an EV forecourt and existing demand; this could be used to assess the sufficiency of existing network capacity and the potential for innovative smart grid technologies to facilitate increasing penetration of EVs.**

***Index Terms* – Electric Vehicles, Fast Charging, Monte Carlo**

I. Introduction

A. Background

There are around 31 million cars registered on the road in Great Britain [1]. The UK Government has pledged to outlaw the sale of purely petrol or diesel-powered cars by 2040 [2]. Therefore, a number approaching that scale of vehicles could be electric (either pure battery-powered vehicles or plug-in hybrids) within the next two to three decades. Compared to the current GB stock of around 125,000 electric vehicles [3], this is a monumental increase. While it is often assumed in the large amount of academic work on the subject that Electric Vehicles (EVs) will be charged overnight at home slowly at rates of 3-7 kW, there are factors that bring this assumption into question:

1) Lack of off-street parking: in a UK Department for Transport survey of 1,100 'representative adults', only 57% had access to off-street parking. It is assumed that the remaining 43% would have nowhere to install an EV charge point [4].

2) Range anxiety: as the range of electric vehicles is, to date, typically shorter than their fossil-fuelled counterparts, there is demand for rapid on-route charging facilities to enable long journeys or subsequent journeys with not enough time between them for sufficient slow charging.

3) Changing car ownership: the UK Government's innovation agency Innovate UK believes that more than 90% of EVs are 'sold' under Personal Contract Plans [5]. Along with recent growth in car clubs [6], personal cars are increasingly effectively being rented; pushing the market to a mobility-as-a-service environment. This could have an influence on charging behaviour; if the EV is not owned outright, users may be more likely to opt for fast charging to enhance convenience at a potential detriment to battery longevity [7].

These factors are contributing to the ongoing growth in EV fast charging infrastructure [8]. It is envisaged by National Grid, the GB Transmission System Operator, that dedicated EV 'forecourts' with chargers rated in the hundreds of kilowatts that are able to fully recharge vehicles in a handful of minutes could be commonplace in the near future [9].

'Fit and forget' approaches to network reinforcement in the face of significant demand growth such as that presented by a rapid growth in EV fast charging infrastructure could lead to overinvestment in, and underutilization of, the network [10]. Instead, innovative smart grid technologies can be used to build active networks that exploit the inherent diversity and flexibility in electricity use; the aim being to spread energy use more evenly across the day, increasing network utilization and reducing the cost of energy delivered [11]. New planning tools based on probabilistic analysis of the temporal and spatial variation of demand are required in order for the potential benefits of these approaches to be evaluated.

B. Objective

The objective of this work was to develop a probabilistic method for the characterization of EV fast charging forecourts based on the activity of current UK petrol stations derived from smartphone users' anonymised positional data. Statistical comparison of the simulated EV forecourt demand to that of an existing distribution network is presented as an example of a method that could inform future network investment planning in high EV-uptake scenarios, including evaluation of smart grid technologies in enabling an economically efficient transition to an energy system that can support electrified transport.

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C. Literature Review

Huang and Infield [12], Beltramo et al. [13] and Lojowska et al. [14] each present models for study of the impact of EV charging on distribution networks based on probabilistic approaches. All three studies are based on the use of transport survey data, which introduces unreliability inherent in self-reported surveys. This work uses smartphone locational data, which represents users' actual movement patterns.

Etezadi-Amoli et al. [15] present a case study on the impact of rapid-charge EV stations on a US distribution network, assuming that the stations' peak demand occur coincidentally with the current network peak. This may be unduly pessimistic; a more thorough analysis would consider the temporal variation in EV charging demand in relation to the existing network peak.

Bae and Kwasinski [16] present a method for predicting the demand profile of a rapid EV charging station based on a multiple server, single queue Poisson-Arrival-Location Model (PALM) to simulate traffic flow. The paper presents an interesting model from the underlying assumption that EV fast-charging activity at any given time is primarily driven by traffic flow. In this paper, the authors suggest that the activity of such a forecourt is likely to be dependent on many other factors such as the time of day, the local employment patterns and proximity to other key infrastructure and points of interest.

In this paper, the fast-charging behaviour of EV users is assumed to be the same as the fuelling behaviour of combustion engine vehicle users, hence the usage patterns of EV forecourts are assumed to be the same as existing petrol stations.

D. Petrol Station Activity Data – Google Maps Popular Times

In their Popular Times feature (visible on the Google Maps website or smartphone application), Google collects and stores anonymised positional data from their smartphone users to allow other users to see when a certain venue is likely to be busy [17]. The data provides an average popularity for each day of the week, as a percentage value of the peak popularity. An example is shown in Fig. 1.

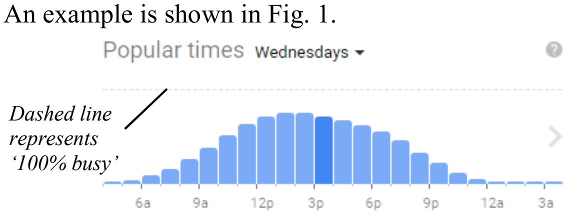

Figure 1. Example of Google Maps Popular Times curve for Wednesdays at a large, supermarket-based petrol station in Glasgow, Scotland [18]

Popular Times data was retrieved for a sample of 2,256 existing petrol stations in Great Britain in areas surrounding major cities (Scottish Central Belt, Glamorgan, Yorkshire, Greater London, Greater Manchester, West Midlands, Avon, Merseyside and Tyneside). Of the 2,256, 476 are supermarket-owned, 1,694 are independent/oil company-owned and 86 are at motorway service stations. For comparison, there were 8,476 petrol stations in the UK at the end of 2016 [19]: the sample used in this work makes up just over a quarter of the population.

E. Limitations to the Data

Firstly, the Google data is only captured from smartphone users who have the Google Maps application installed and have location history turned on (though this is the app's default setting). While this method is likely to capture a great many users (81% of UK adults – 37 million people – were smartphone users in 2016 [20] and Google Maps was installed on 57% of US smartphones in 2017 [21]), this could introduce a selection bias in the results if those who are less likely to be captured in the data are more likely to visit petrol stations at certain times.

Secondly, the petrol station popularity data is presented as an averaged percentage of the peak. This means that there is no indication of an absolute number of users; this paper assumes that the peak equates to all pumps being used in a petrol station. Also, no seasonal variation can be derived from the data.

Despite these limitations, it is suggested that using smartphone locational data for petrol station activity holds distinct advantages over survey-based data or traffic flow data.

II. Method

A. Overview

The MC-based method to characterise the demand profile of an EV forecourt is split into two parts:

i. A state sampling simulation to derive the number of vehicle arrivals per hour for an EV forecourt on a given day, based on the assumption that their activity will be the same as those of existing petrol stations.

ii. A time sequential simulation to characterise the power demand of the forecourt in allowing users to charge their EVs, given the arrival profile in (i), according to a set of parameters probabilistically assigned to each vehicle and a queueing model developed to simulate busy periods at the forecourt.

B. State Sampling Simulation

Using Google Maps Popular Times data (such as that in Fig. 1) for all petrol stations in the sample for a selected day of the week, a Cumulative Distribution Function (CDF) such as that shown in Fig. 2 was formed for each hour of the selected day.

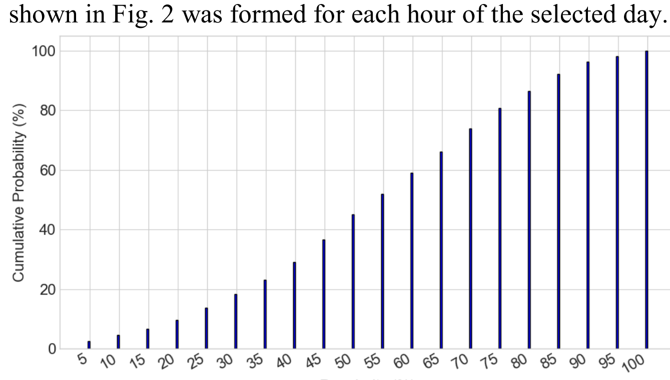

Figure 2. CDF for all sampled petrol stations' popularity for 16:00-17:00, from Saturday popularity data

For each MC trial, these CDFs were sampled from to derive a popularity profile (%) for the simulated EV forecourt (Fig. 3).

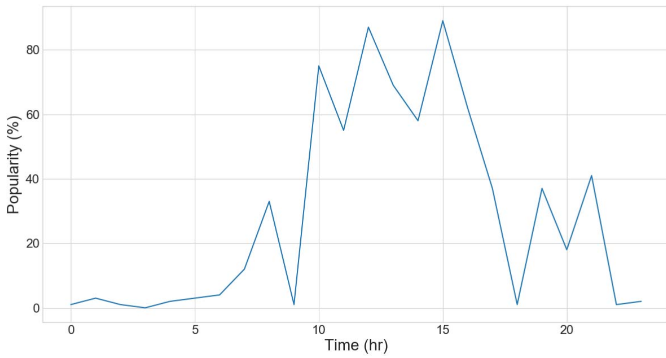

Figure 3. Popularity profile for one MC trial based on petrol station popularity data for Saturday

In 2013, the average number of pumps at a UK petrol station was 7.3 [19]. This was used to derive the hourly average forecourt occupancy by multiplying the popularity (%) by 7.3 and rounding to the nearest integer.

Little's theorem (1) [22] was used to derive the average arrival rate $\bar{\lambda}$ for a given hour of petrol station activity, given an average number of agents in the system N (i.e. the forecourt occupancy) and an average service time T (i.e. the total time spent at the petrol station).

$$N = \bar{\lambda} T \tag{1}$$

It was assumed that the petrol station activity could be represented by a multiple server, single queue problem with Poisson arrival process and deterministic service time (*M/D/s* in Kendall's notation used in Queue Theory [22]). T was assumed as 5 minutes, which can be supported by calculation: according to [23], the average throughput through a UK petrol station in 2017 was 6 million liters. Assuming an average delivery of 30 liters, this implies 200,000 vehicles per petrol station per year, or around 550 vehicles per day. Using (1) on the petrol station data with $T = 5$ results in a similar number of arrivals per day. The arrival rate λ for a given hour was then sampled from a Poisson distribution with mean $\bar{\lambda}$. The arrival rate profile for the same MC trial in Fig. 3 is shown in Fig. 4.

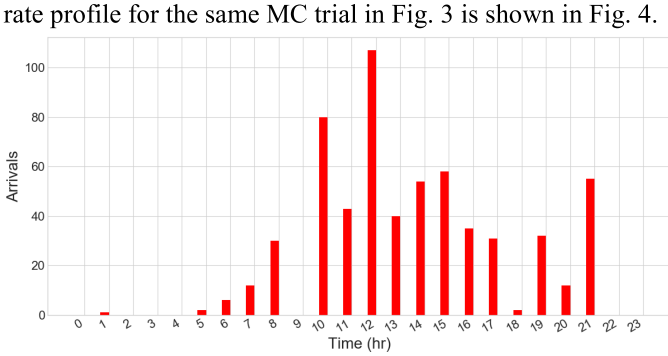

Figure 4. Arrivals per hour for one MC trial based on petrol station popularity data for Saturday

The arrival rate profile (Fig. 4) was input into the time sequential simulation in order to derive a demand profile characterization of an EV fast charging forecourt.

C. *Time Sequential Simulation*

The time sequential simulation models the minute-to-minute activity of the forecourt, which is then used to derive its demand profile. For each hour, an array of 'car' objects equal to the number of arrivals in that hour (given by the height of the bars in Fig. 4) is instantiated and each car is assigned parameters which, along with the fixed forecourt parameters, will dictate the duration of each vehicle's charge and hence the time series of demand at the forecourt. The forecourt and vehicle parameters are illustrated in Fig. 5 and discussed in subsections 1 and 2 below.

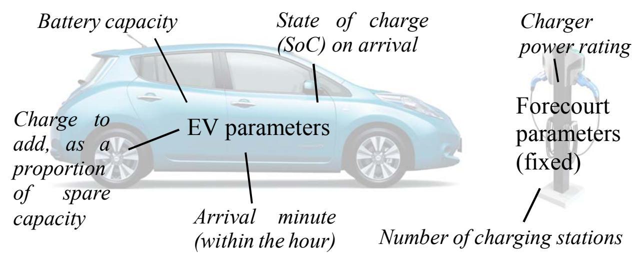

Figure 5. EV and forecourt parameters for time sequential simulation – images from [24] (left) and [25] (right)

1) *Forecourt Parameters*

a) *Number of charging stations*

The number of charging stations was selected as 8, based on the number of stations considered in the EV forecourt in [15].

b) *Power rating of chargers*

The power rating of fast EV charging infrastructure is a trade-off between convenience to the user, limitation of battery stress and cost versus the local demand for using them. If charging rates are too low, users would face perhaps an unacceptable amount of inconvenience as they wait for their vehicles to charge. If they are too high, users may be deterred from using them at their rated capacity out of concern for reductions in battery life; capital costs for their acquisition and connection will also increase with charger rating. In the literature, fast charging rates are in the range 100-350 kW [15], [16], [26]. The rating for this work was chosen to reflect a reasonable queue size (explained in more detail in subsection 2), which was set such that the average maximum daily queue time of an 8-charging station forecourt over 10,000 trials based on Saturday data (the busiest day for UK petrol stations) would not exceed 2 minutes, in accordance with what would be considered normal at a current UK petrol station. For the 'all EVs' case (Fig. 6), 100 kW gave an average maximum queue length of 2.0 minutes. For the 'BEVs only' case, 200 kW gave an average maximum queue length of 1.9 minutes. The average time spent charging for both cases was less than 5 minutes.

2) Vehicle Parameters

a) Battery capacity

A histogram showing the probability distribution of EV battery capacities (kWh) for UK sales in 2017 [3] is presented in Fig. 6, from which the simulated vehicle's battery size was randomly sampled. Two series are shown; one being for all EVs (including Battery Electric Vehicles (BEVs) and Plug-in Hybrid Electric Vehicles (PHEVs)) and one for BEVs only. It is perhaps reasonable to suppose that, as PHEVs have an internal combustion engine to rely on, BEV users (who normally have larger batteries to charge) would be more likely to charge at EV forecourts.

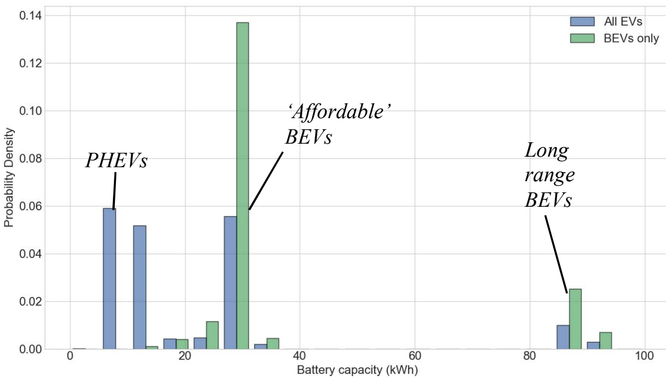

Figure 6. Histogram showing distribution of battery sizes for UK EV Sales, 2017 – data from [3]

If the 'BEVs only' option is selected then the energy requirement of vehicles increases due to their larger battery capacities. For a given charger capacity and number of charging stations, this has the effect of lengthening the queue as previously discussed. However, by increasing the charger power the queue can be kept to a similar length and the overall demand profile will tend towards a scaled version of that for the 'all EVs' case. Therefore, only results from the all EVs case are presented in this paper as an example of the method.

b) State of Charge (SoC) on arrival and added charge as a proportion of empty capacity

The SoC of a battery upon starting and finishing EV charging is often modelled by Gaussian distributions as exemplified by Qian et al [27]. However, Yi and Li [28] present χ^2 test results to argue that a Beta distribution offers a better goodness of fit to real charging behaviour than a Gaussian distribution does. According to Marra et al. [29], a Li-ion EV battery should ideally be cycled between 20% and 90% SoC; this was used to inform the setting of Beta distribution parameters α and β. SoC on arrival was treated as an independent variable with α = 2 and β = 5, shown by the blue line in Fig. 7. This gives a modal SoC on arrival of 20% and a mean of 29%. The post-charging SoC was derived by sampling a Beta distribution describing the added charge as a proportion of empty capacity, to ensure the EV cannot charge to above 100% or below its SoC on arrival. Parameters for the added charge Beta distribution were tuned by taking one million samples from the SoC on arrival distribution (blue line) and the added charge distribution (green line) for various α and β to produce a histogram of post-charging SoC. The probability of an EV leaving the forecourt with an SoC above 90% is less than 5%, which reflects the ideal charging behaviour in [29] but allows some users to violate it. The added charge Beta parameters were set as α = 3.2, β = 2.6.

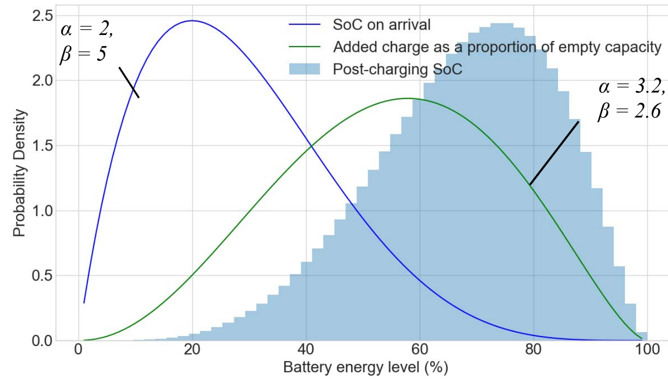

Figure 7. Beta distributions for SoC on arrival and added charge as a proportion of empty capacity

c) Arrival time

Within the hour, the vehicle's arrival minute was randomly assigned as a random integer between 0 and 59.

3) Queueing Model and Derivation of Demand Profile

For each vehicle known to be using the forecourt on the simulated day, the charge duration t_c can be calculated from (2), where P_c is the charger power (kW), C_a is the added charge as a proportion of the battery's empty capacity and B is the EV's battery capacity (kWh). Note that although all EVs' arrival times are fixed within the hour by the arrival profile derived in Fig. 4, their leave time can be within the next hour if their charge duration lasts to the next hour.

$$t_c = \frac{(1 - SoC)C_a B}{P_c} \tag{2}$$

The demand drawn by the forecourt at any given minute is equal to the number of cars connected multiplied by the charger power rating. To simulate busy periods at the forecourt, a queueing model was developed. Each time a car arrives it is assumed to begin charging immediately and leave when its charging time is finished, unless the number of vehicles connected is equal to the number of charging stations (i.e. the forecourt is full). In this case, the car must join a queue. The queue will continue to grow as more cars arrive and join the back of the queue. Cars will wait in the queue until the next vehicle leaves the forecourt, at which point the vehicle at the front of the queue connects to the free charger and their leave time is adjusted accordingly (their charge duration is assumed to be the same). It is assumed that vehicles join one queue for the forecourt and they take charging stations on a first come, first served basis. Once a vehicle joins the queue, it is committed to waiting to be charged and the queue length has no limit. At every minute, the number of cars connected multiplied by the charger power is equal to the electrical demand of the forecourt. Fig. 8 shows an example of the outputs for the same MC trial in Figs. 3 & 4; the demand profile (left) and the number of vehicles queueing (right) for an 8-station, 100 kW charger rating forecourt for the 'all EVs' case (see Fig. 6).

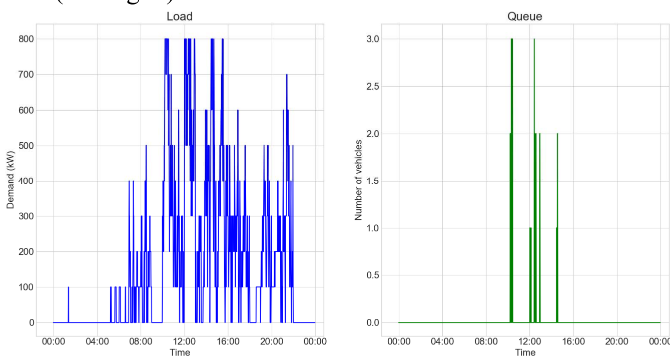

Figure 8. Expected load profile and queue length for one MC trial of an 8x100 kW EV charging forecourt, Saturday

III. Results

A. Monte Carlo Simulations of EV Forecourt Demand Profile

The EV forecourt simulation described in Section II was run for 10,000 trials. A probability distribution of the demand time series produced is shown by a 3D histogram in Fig. 9. For a given time of day, the probability that a simulated EV forecourt will draw a particular power demand is given by the bar height.

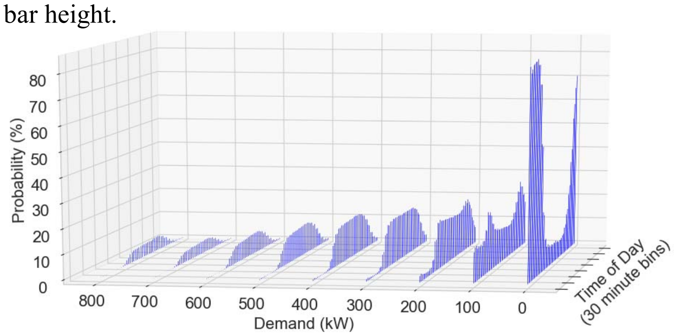

Figure 9. 3D histogram showing probability distribution of 10,000 trials of an 8 x 100 kW forecourt simulation based on Friday popularity data

Fig. 9 shows that there is significant variation of the forecourt's demand levels for most of the day. The discrete nature of the distribution is due to the constant-charging assumption used; as the distribution reflects forecourt occupancy, the total demand of the forecourt can only take one of nine levels between 0 and 800 kW. It is shown that probability reduces with increasing power, but there remains a ~5-10% likelihood of peak demand in the mid-afternoon.

B. Statistical Comparison with Existing Network Load

To assess the impact of an EV rapid charging forecourt on an existing electricity system, system planners would need to know the combined loading of the existing load and that presented by the EV charging station. Traditionally, the maximum demand would be equal to the present maximum network loading plus the maximum demand drawn by the EV forecourt. However, probabilistic methods can be used to better assess the impact of new load based on their temporal variation. For example, if the EV charging load and present network loading were to peak at different times, or if the combined loading breaches network limits for only a small proportion of the time, then network reinforcement could potentially be deferred in favour of employing a number of 'smart' grid technologies.

An EV charging forecourt at a rating of 800 kW would likely be connected to a primary distribution feeder (6-11 kV), either directly or via a dedicated secondary transformer. To compare the EV forecourt demand characterization with that of a network on which it would typically be connected, secondary (11/0.4 kV) substation loading data from SP Energy Networks' Flexible Networks project [30] were used to construct a CDF (Fig. 10) of the combined loading of 10,000 MC trials of an 8x100 kW EV forecourt based on Tuesday Popular Times data with all monitored winter weekdays in the period 2013-2015 for all secondary substations on an 11 kV feeder covering suburban areas and major roads in St Andrews, a town on Scotland's East Coast.

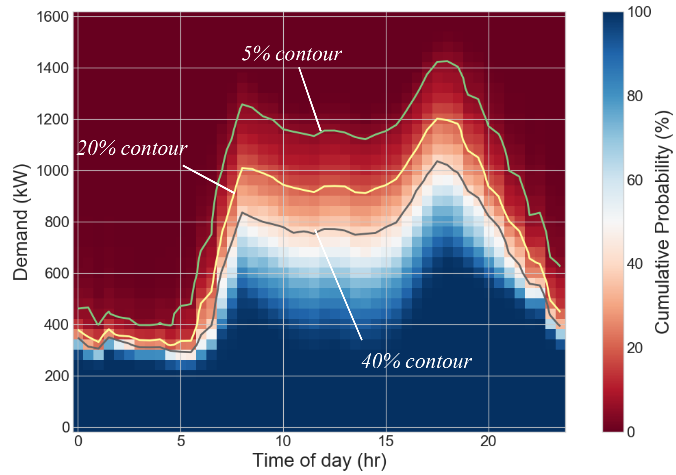

Figure 10. CDF of combined loading of 8x100 kW EV forecourt simulation (Tuesday) and St Andrews Feeder 24, winter weekdays 2013-2015

The method demonstrated in Fig. 10 provides an estimate of the likelihood that the feeder peak, following the integration of an EV forecourt, will exceed a certain value on a given day. For example, it is shown that there is a 5% probability that the peak on a given Tuesday will exceed approximately 175% of the original peak at around 17:30. The method also allows quantification of the amount of time the feeder loading will likely be above a determined value. This temporal aspect would be valuable in assessing the suitability of smart grid technologies, which often exploit the inherent diversity and temporal variation in electricity demand. For example, real-time ratings of assets could allow the system to exceed thermal ratings for a short time. Alternatively, a flexible connection could be given to the EV forecourt to enable its peak to be reduced in times of network peak and dynamic pricing could be used to encourage vehicle users to charge outside of times of network peak (e.g. in the morning) or at times of high local generation output. Furthermore, on-site battery storage could be employed at the EV forecourt to smooth out peaks in its demand.

IV. Conclusion and Further Work

This paper has presented a characterization of electrical demand profiles of EV fast charging forecourts, which are likely to be commonplace in high EV-uptake scenarios. The characterization is based on current petrol station usage data derived from smartphone locational data collected by Google's Popular Times feature.

The fundamental assumption on which this paper is based, that EV charging is likely to be done in the same way as fuelling of petrol and diesel-powered cars, can of course be called into question. However, in a future scenario where rapid charging is preferred as a main charging method to at-home charging due to the reasons described in Section I-A, the two activities are essentially analogous. A high EV-uptake future is likely to include a mix of rapid charging (such as presented in this paper), destination charging (while users are parked at amenities such as supermarkets and gyms), and at-home charging. The methods presented in this paper can be used to evaluate how the rapid charging portion contributes to the total EV charging load.

Following this assumption, there is likely to be significant variation in the demand of rapid EV charging forecourts. The method presented in Section III B could be used across an entire distribution network to model uptake of various modes of EV charging and how the temporal variations in their demand interact with one another. This could be used to assess the requirement for network reinforcement and evaluate the feasibility of 'smart' alternatives in preparing distribution networks for the widespread electrification of transport at minimum possible cost.

To improve the accuracy of the results, analysis of the petrol stations included in the data is recommended. It was suggested that vehicle fuelling activity is related to local employment patterns and proximity to key infrastructure; disaggregation on these factors and others would allow analysis on the basis of a number of more focused type-specific characterizations.

Aside from rapid-charging forecourts, a similar method using Google Maps Popular Times data could be used to characterize destination charging at locations such as gyms, supermarkets, cinemas and shopping centres. This analysis could then be combined with analysis of rapid and at-home charging to give a complete picture of the demand increase presented by the electrification of transport.

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