Electric Vehicle Destination Charging Demand Characterizations at Popular Amenities

James Dixon, Ian Elders, Keith Bell
Dept. of Electronic and Electrical Engineering
University of Strathclyde, Glasgow, United Kingdom
{james.dixon, i.elders, keith.bell}@strath.ac.uk

***Abstract*— A key enabler for Electric Vehicles (EVs) is destination charging – allowing users to charge their vehicles while parked at amenities such as supermarkets, gyms, cinemas and shopping centres – leaving their vehicles for periods ranging from 10 minutes to 3 hours. This paper presents a Monte Carlo (MC)-based method for the characterization of likely demand profiles of EV destination charging at these locations based on smartphone users' anonymised positional data captured in the Google Maps Popular Times feature. Unlike the majority of academic works on the subject, which tend to rely on users' responses to surveys, these data represent individuals' actual movements rather than how they might recall or divulge them. Through a smart charging approach proposed in this paper, likely electrical demand profiles for EV destination charging at different amenities are presented. The method is demonstrated by way of two case studies. Firstly, it is applied to a large GB shopping centre to show how the approach can be used to derive suitable specifications for large charging infrastructure to maximise revenue or EV service provision. Secondly, it is applied to a GB supermarket in a residential area to show how the approach can be used to examine network impact for a distribution-connected destination charging facility.**

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

I. Introduction

A. Motivation

The UK Government has pledged to outlaw the sale of purely petrol or diesel-powered cars by 2040 [1]. Given the current market dominance of battery Electric Vehicles (EVs) over other alternative forms of private vehicle propulsion such as hydrogen fuel cell-powered vehicles [2], it is reasonable to expect that within the next two to three decades, a significant proportion of Britain's 31 million cars [3] could be replaced with plug-in EVs; likely a combination of pure battery EVs (BEVs) and plug-in hybrid EVs (PHEVs).

While it is often assumed in the academic literature that EVs will be charged slowly overnight at home, typically at rates of 3-7 kW, a significant proportion of EV charging could exist as 'destination' charging while parked during their users' visits to workplaces or amenities such as supermarkets, shopping centres, gyms, cinemas and motorway service stations – where cars are left for durations ranging from ten minutes to three hours. A move from a solely domestic charging-based EV uptake to one focused on the widespread availability of public charging could serve to enhance the convenience of EV usership, enable EV access to those without off-street parking (which, according to a Department for Transport survey [4], applies to 43% of households in the UK) and has the potential to reduce system cost: according to [5], 32% of local electricity networks across GB will require intervention when 40% - 70% of customers have at-home EV charging. By encouraging users to charge away from home at their place of work or other places where they leave their car, the installation of charging infrastructure can be directed towards areas of greater spare capacity or with more potential for 'smarter' network operation which could allow a higher penetration of EV charging. It can be supposed that as EV uptake continues to increase, the market for destination charging will expand as the owners of the listed amenities would likely be eager to offer destination charging either to establish new revenue streams or to encourage more visitors.

There is, to date, little analysis of the likely temporal variation in EV destination charging, and therefore little direction for network operators' investments in securing a system that is fit for the electrification of transport at minimum cost to the customer. 'Fit and forget' approaches to network reinforcement in the face of EV growth could lead to overinvestment in, and underutilization of, the network [6]. Instead 'smart grid' technologies can be used to exploit the inherent diversity and flexibility in electricity use; the aim being to spread energy use more evenly over time, thereby increasing network utilization and reducing the system cost [7]. 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 for this work was to develop characterizations of EV destination charging from a Monte Carlo (MC) method based on the activity of amenities at which it is likely to exist. This is derived from data in the Google Maps 'Popular Times' feature and likely statistical variations of EV parameters based on UK EV statistics and existing academic work. Based on the work carried out, this paper presents the following studies:

1. Characterization of EV charging in the car parks of gyms, based on Popular Times data from a sample of 2,221 gyms in and around major GB cities.
2. Characterization of EV charging at Braehead, a large (6,500 car parking spaces) shopping centre in Scotland, based on its Popular Times data and a case study detailing the required specification of

necessary charging infrastructure for a given level of EV charging service provision.

3. Analysis of network impact of EV charging at a branch of a large UK supermarket chain in a residentially-dominated area of Glasgow, if the EV charging infrastructure were to be connected to the High Voltage (HV) (11 kV) network by way of a dedicated transformer.

II. Synthesis of Arrivals Profile of Vehicles using Google Maps Popular Times Data

A. Google Maps Popular Times Data

The Popular Times feature [8] within the Google Maps website and smartphone application allows users to see when a certain business is likely to be crowded, based on anonymised positional data collected from smartphone users with the Google Maps application installed and location history enabled over the last several weeks. The display shows an average popularity for each hour of each day of the week, as a percentage value of the peak popularity. An example is shown in Fig. 1.

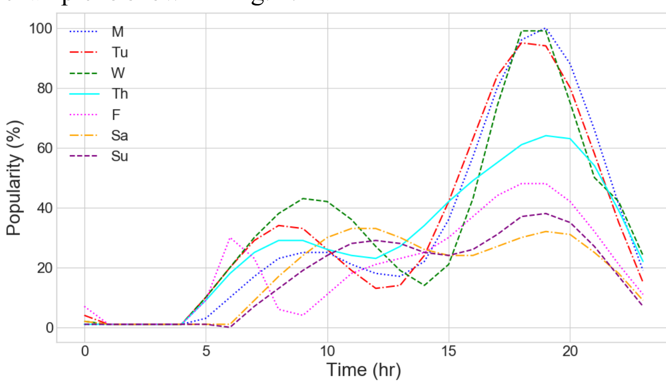

Fig. 1. Example of Google Maps Popular Times data for a particular large gym in the West of Scotland retrieved on 20th August 2018

B. Limitations to Using the Data

Firstly, the data is captured from visitors to these amenities only if they are smartphone users with the Google Maps application installed and have not actively disabled location services. While this method is likely to capture a great many users (37 million people – 81% of UK adults – were smartphone users in 2016 [9] and Google Maps was installed on 57% of US smartphones in 2017 [10]), 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 these amenities at certain times.

Secondly, the popularity data is presented as an averaged percentage of the peak and there is no indication of the absolute number of visitors. This paper assumes that amenities are well-suited to their local markets and, although it is expected that not all users of these amenities will travel there by car, '100% busy' in the Google data is taken to correspond to a 100% full EV charging car park. If using this method to examine amenities in a particular location, such as in Section V, more detailed work to ascertain the peak popularity should be carried out.

Thirdly, as the data is compiled and presented for seven days of the week, no seasonal variation can be derived.

Despite these limitations, it is suggested that using smartphone locational data for activity holds distinct advantages over using survey-based data. Firstly, the data encapsulates individuals' actual movement patterns rather than what they recall or divulge. Secondly, the burdensome nature of surveys results in a relatively low sample size: while 15,840 individuals were polled in the 2016 UK National Travel Survey [11], the approach used in this paper has the potential to cover tens of millions of UK vehicle users.

C. Synthesis of Arrivals Profile of Vehicles

In order to translate the occupancy of the amenity, as in Fig. 1, to an arrival rate of vehicles for input to the smart charging algorithm (Section III-D), the peak popularity was assumed equal to the capacity of the EV charging car park. For each hour, the arrival rate λ (number of vehicles arriving per hour) was sampled from a Poisson distribution (1), where T is the mean parking time and N is the car park occupancy (e.g. in Fig. 1).

$$P(\lambda) = e^{-\frac{N}{T}} \frac{\left(\frac{N}{T}\right)^{\lambda}}{\lambda!} \tag{1}$$

T was fixed depending on the amenity in question. For MC analysis based on gyms presented in Section IV, the mean parking duration was assumed as 60. This was established by examining Google Maps entries for businesses of that type to derive typical stay times. For the case study based on Braehead shopping centre presented in Section V, the mean parking duration was taken as 134 minutes from [12].

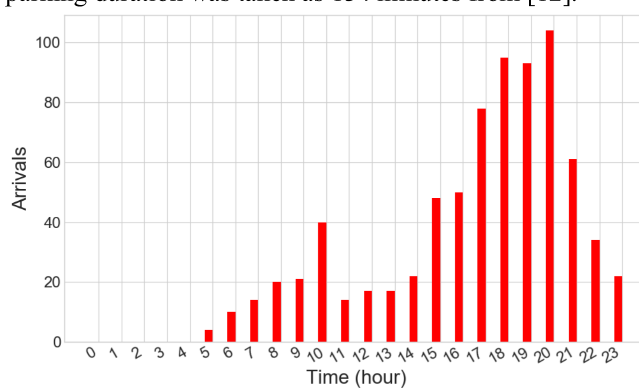

Fig. 2. Example arrivals profile based on Monday data for a particular large gym in the West of Scotland with 100 EV charging spaces

III. Smart Charging of Electric Vehicles

A. Smart Charging Philosophy

'Smart' (i.e. controlled) EV charging can be used to minimise stress to the network [13], match times of high charging demand to times of low energy cost [14] or high renewable output [15], [16], or maximise service provision to the EV user [17].

Proposals for smart charging presented in [13]–[17] all rely on bidirectional flow to and from the vehicle – 'Vehicle 2 Grid' (V2G) – and some extent of consumer engagement over and above parking and plugging in, ranging from the EV user entering their intended stay time [15] to having the EV user enter four separate 'preference parameters' upon parking [17]. Although the approaches in these studies can lead to optimised charging schemes in an ideal world, in providing user engagement the system is inherently vulnerable to unpredictable non-ideal behaviour likely to compromise the economic benefits of smart charging [18]. For example, users could 'game' the system by entering a false intended stay time in [15] to prioritise the charging of their EV over others. The option to allow V2G operation would have to be consented by the vehicle owner, as it has been shown that doing so has a detrimental effect on battery longevity: according to [19], a 'base case' EV following the median trip distances from the UK National Travel Survey could face a 57-fold increase in daily battery degradation rate from providing ancillary services and a 115-fold increase from providing bulk energy services by operating in V2G mode.

For these reasons, this paper proposes a simpler charging algorithm with unidirectional operation that seeks to provide optimal service provision to all users with no consumer engagement over plugging the car in to the charger, given the available grid capacity. This is presented in Section III-D.

B. Destination Charging Car Park Topology

The work presented in this paper is based on the concept of a multi-terminal DC charging network with one central AC/DC converter and a separate DC/DC converter at each car parking space. The concept is well established; presented in more detail in [16], [20] and replicated in Fig. 3.

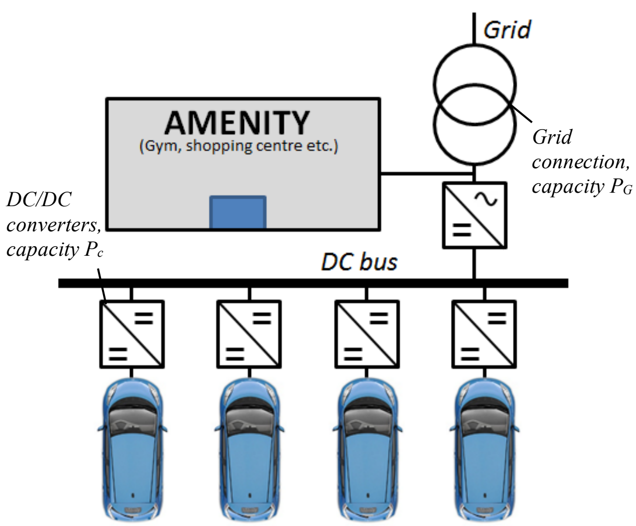

Fig. 3. Proposed topology for EV destination charging car park

C. Simulation of EV Parameters

Following the arrivals profile synthesised from the method described in Section II-C, an array of EVs equal in size to the height of the bars in Fig. 2 is instantiated for each hour of the day. Each EV is assigned parameters which dictate how it is treated by the smart charging algorithm. These are discussed in subsections i)-iv) below.

1) Arrival Time (within the hour)

Within the hour from which the EV instance was instantiated (Fig. 2), the EV's arrival minute was randomly assigned an integer between 0 and 59.

2) Battery Capacity

The EV is assigned a battery capacity randomly sampled from the distribution of EV battery capacities (kWh) for UK sales in 2017 [21] (Fig. 4). Two series are shown; one for all EVs (including PHEVs and BEVs) and one for BEVs only. The model can be run with either setting; however, all results presented in this paper are for the 'all EVs' option.

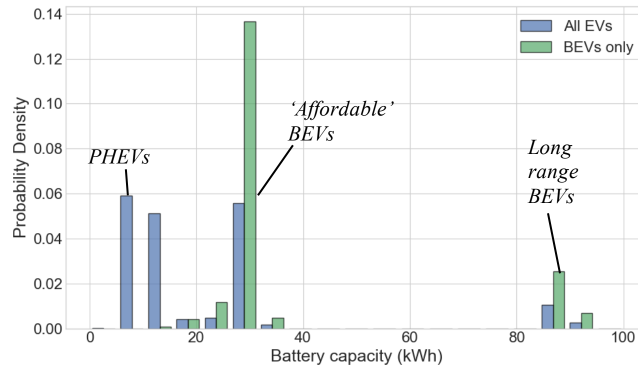

Fig. 4. Histogram showing distribution of battery sizes for UK EV Sales, 2017 – data from [21]

3) State of Charge (SoC) on Arrival

The EV is assigned a SoC on arrival by randomly sampling from a Beta distribution (α=3.7, β=5) (Fig. 5). These parameters were chosen to reflect the assumption that the distribution of SoC of arriving cars would be centred near 50%, as the primary reason for users' visits to the chargers is to visit the amenity, rather than charge their EVs. The skew to the left (mode = 40%) reflects the assumption that those with very high SoC may be less likely to visit the charging car park or plug in.

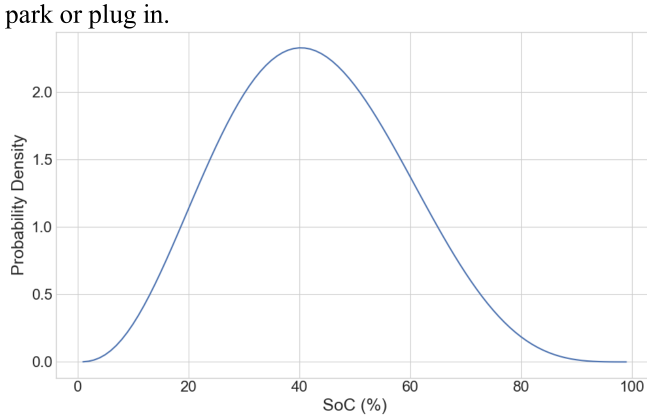

Fig. 5. Beta distribution (α=3.7, β=5) used for modelling SoC on arrival

4) Parking Duration

The length of time the EV spends in the car park was modelled by a Poisson distribution, a method taken from [22] which uses the distribution to model patient length of stay in hospital beds. The distribution used for this work is the same as that in (1), with the mean value set depending on the type of amenity being analysed (Section II-C).

D. Proposed Smart Charging Algorithm

From the set of vehicles each with parameters discussed in Section III-C, the smart charging algorithm can be applied. For the j^{th} minute of the day, ($j \in \mathbb{R}, 0 \le j < 1440$), and the i^{th} car in the car park, out of a total of n cars, ($i \in \mathbb{R}, 0 \le i <$

n), the Total Energy Requirement (TER) of the car park at the beginning of the j^{th} minute is found from (2).

$$TER_j = \sum_{i}^{n} (1 - SoC_{ij}) \cdot C_i \qquad (2)$$

Where SoC_{ij} is the i^{th} car's SoC at the start of the j^{th} minute and C_i is the i^{th} car's battery capacity.

The Potential Charge Rate (PCR) of the i^{th} car at the start of the j^{th} minute, i.e. the maximum charge rate it could draw if unconstrained, is (3):

$$PCR_{ij} = \frac{(1 - SoC_{ij}) \cdot C_i}{TER_j} \cdot P_G \qquad (3)$$

Where P_G is the total available grid capacity. The power drawn by each EV in each minute is then subject to a series of constraints. Firstly, the maximum power the EV battery can accept is limited by the charge profile P_B, taken from [17] (Fig. 6). Below an SoC of 90%, the charger will operate in constant current mode and the power is not limited. Above 90%, the power drawn will linearly decrease to zero at 100%.

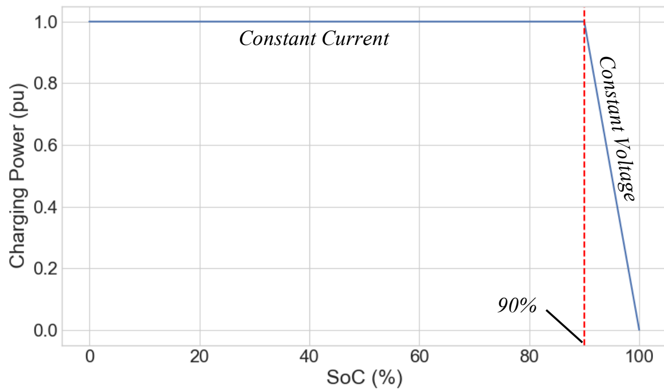

Fig. 6. Charging profile used for P_E

The power draw is also limited by the rating of the converter, P_C, and the maximum power the EV can draw, P_{EV}. This is assigned as either 50 kW, if the car's battery capacity is less than 60 kWh, or 120 kW if the car's batter capacity is over 60 kWh. This was done to reflect typical values in EVs currently on the market [23], [24].

The Charge Rate (CR) of the i^{th} car in the j^{th} minute is then given by (4).

$$CR_{ij} = \begin{cases} PCR_{ij}, PCR_{ij} < \min\,(P_{B\,ij}, P_C, P_{EV\,ij}) \\ \min\,(P_{B\,ij}, P_C, P_{EV\,ij}), \mathit{otherwise} \end{cases} \qquad (4)$$

E. *Queueing Model*

If a car arrives such that n is greater than the number of charging spaces, the car joins a queue. The queue continues to grow in length as more cars arrive, until any cars within the charging spaces leave. When that happens, a car is picked at random from the queue to join the charging space to reflect real queueing processes in car parks. The time at which that car begins charging is adjusted accordingly, and it is assumed that its parking duration and all other parameters remain the same.

IV. Characterization of EV Charging at Gyms

A. *Monte Carlo Simulation of Amenity Activity*

The Google Maps Popular Times data (Fig. 1) was fetched for a sample of 2,221 gyms in and around major GB population centres. According to [25], this represents around a third of the total number of gyms in the UK. Based on this data, an MC-based approach was used to form Cumulative Distribution Functions (CDFs) of the percentage popularity for each hour of the day. From this, a Monte Carlo approach was used to derive a simulated popularity profile for any day of the week. This can then be translated to an arrivals profile using the same method as in Section II-C for a specified number of EV charging spaces. The simulation was run for 10,000 trials based on all gyms in the sample, for a 100-car capacity EV charging car park with a 2 MW grid capacity and 50 kW converter rating.

B. *Results*

Results are presented in terms of a CDF plot for simulations based on the sample of gyms for Monday (Fig. 7) and Saturday (Fig. 8) popularity data.

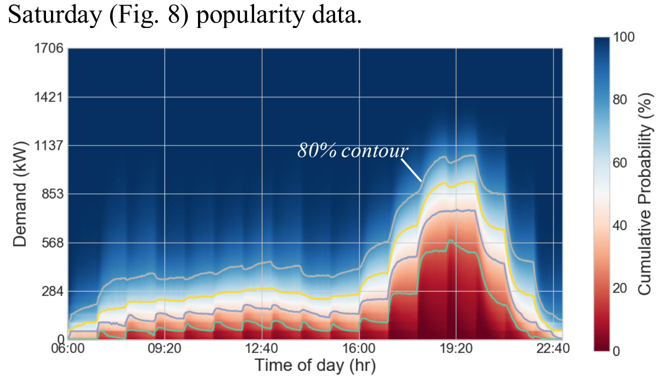

Fig. 7. CDF for MC simulation of EV charging at gym car park from Monday popularity data

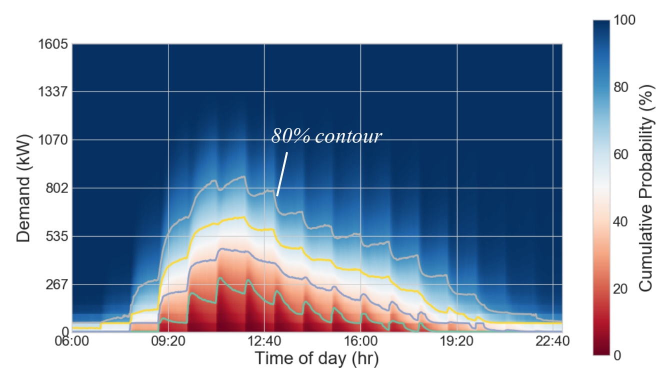

Fig. 8. CDF for MC simulation of EV charging at gym car park from Saturday popularity data

As exemplified by Figs. 7 and 8, the weekday demand profile for gym-based EV charging is most likely to peak in the evening around 18:00-20:00 whereas the weekend charging demand is most likely to peak in the late morning/noon around 10:00-13:00.

The method demonstrated provides an estimate of the likelihood that the charging peak will exceed a certain value on a given day. For example, Fig. 7 shows that there is a 20% probability that the charging demand peak on a Monday will be greater than approximately 1100 kW. The method also allows quantification of the duration for which demand is likely to be above a certain value. This temporal analysis could be invaluable in assessing the potential of smart grid technologies to provide a better utilised electricity network, exploiting the potential diversity in EV charging demand between locations.

V. Case Study 1: Transmission-Connected EV Destination Charging at Large GB Shopping Centre

A. Derivation of likely Destination Charging Demand Profile

Braehead is a large shopping centre and leisure complex in Glasgow, Scotland. Due to its proximity to the M8 motorway and its total of 6,500 car parking spaces, it has the potential to serve as a significant destination charging location. Its proximity to local transmission infrastructure means that it could be connected directly to a Grid Supply Point (GSP), affording the charging car park a large grid import capacity.

From [12], it is reported that customers spend an average of 134 minutes there. Using T = 134 minutes in (1), the Google Popular Times data (Fig. 9) can be used with the smart charging algorithm (Section III-D) to produce an expected demand profile for the period of interest (i.e. when the shopping centre is open) (Fig. 10). The simulation was run based on the Saturday data, as this is the day that contains the weekly peak.

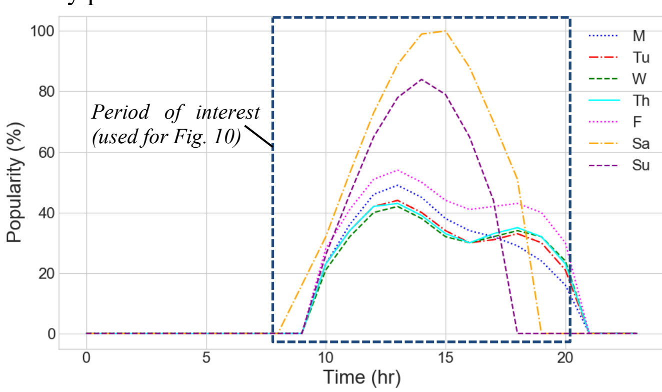

Fig. 9. Google Maps Popular Times data for Braehead shopping centre retrieved on 20th August 2018

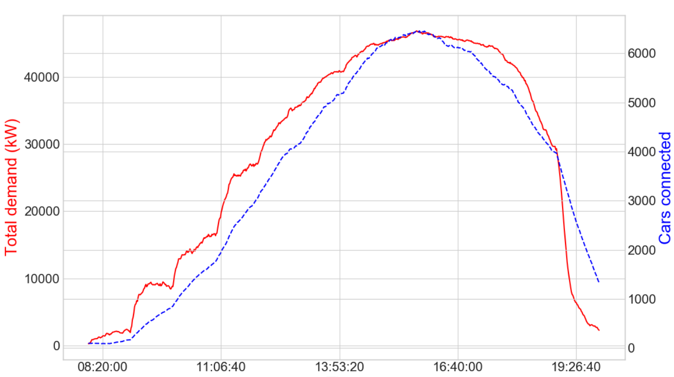

Fig. 10. Expected demand profile (red, solid) and car park occupancy profile (blue, dashed) for Saturdays at Braehead shopping centre with nominal values: P_G = 50 MW, P_C = 50 kW

The blue profile in Fig. 10 is dependent only on the Google data and the Poisson arrival distribution assumption (1). The demand profile (red) is also dependent on the variables chosen for the charging car park P_G and P_C. The effects of varying P_G and P_C are the peak demand drawn by the car park, the rate of change of demand and the service provision to the EVs parked there. The nominal values used for the profile in Fig. 10 (P_G = 50 MW, P_C = 50 kW) allow for 100% of visiting EVs to be charged above 90% during their stay (above which the charging rate slows and a value of exactly 100% is never achieved; Fig. 6). However, the expected peak at around 15:00 on a Saturday is above 45 MW, which would likely require a transmission connection. By varying these parameters, a trade-off between service provision and peak demand can be observed. This is explored in subsection B.

B. Sizing the car park infrastructure

Three values for P_G and P_C were used to examine the effect on peak demand and service provision (Table 1). Combining the values gives nine trials; for which the variation in demand profile (Fig. 11) and service provision (Fig. 12) are shown.

Table 1. Values of P_G and P_C used for Case Study 1

Parameter	*Low*	*Medium*	*High*
P_G	20 MW	35 MW	50 MW
P_C	20 kW	50 kW	80 kW

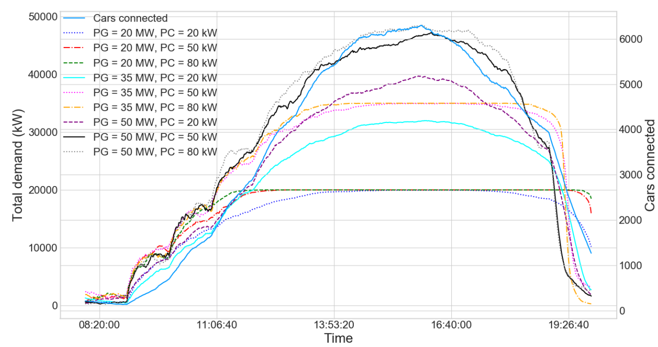

Fig. 11. Variation of demand profile with parameters P_G and P_C

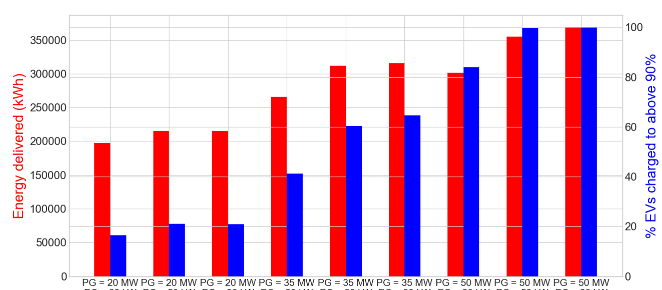

Fig. 12. Variation of service provision with parameters P_G and P_C

Figs. 11 and 12 show that only P_G = 50 MW allows fully unconstrained charging on a Saturday and, with sufficient P_C, allows all vehicles to charge to at least 90% SoC during their stay. As the grid capacity is reduced, the service provision and peak demand are reduced, but the time spent at the maximum demand increases, with the profiles in Fig. 11 for P_G = 20 MW at their upper limit for up to eight hours of the day.

The energy delivered (kWh) throughout the Saturday simulated is shown in Fig. 12. Taking the average tariff for a non-domestic customer as 10.8 p/kWh [26], the charging car park owner could make a profit of around 9 p/kWh if they were to match the 20 p/kWh rate currently offered by multiple public charging networks in the UK [27]. Multiplying 9 p/kWh by the energy delivered values enables a potential Saturday revenue to be calculated: this varies between around £17,700 for the P_G = 20 MW, P_C = 20 kW option to £33,200 for the P_G = 50 MW, P_C = 80 kW option. By integrating the curves in Fig. 9, it can be found that the Saturday footfall accounts for approximately 21% of the total. Therefore, it can be supposed that the potential annual revenues from such a scheme could be in the region of £8 million/year. This simplistic economic analysis ignores converter losses and equipment downtime as a result of maintenance, but enables the quantification of the potential inflows of finance from such charging schemes and provides grounding for more robust business case analysis.

From this potential revenue, the charging infrastructure owner would have to finance infrastructure capital, operation & maintenance and any connection reinforcement costs made necessary by the increase in demand. These costs would vary by grid and converter capacity, as would the potential revenue: therefore, the sizing of car park infrastructure in such applications will likely be a question of economics. If the charging is to provide an extra revenue stream to the amenity, then maximum service provision at an optimal trade off with infrastructure cost may be sought. However, if the amenity is using EV charging as a 'loss leader' (i.e. there purely to encourage more visitors) then a lower service provision may encourage customers to stay longer, which may be preferable in the instance of some amenities, such as shopping centres.

VI. Case Study 2: Distribution Network Impact of EV Destination Charging at Supermarket

A. Local Distribution Network Assets

This section concerns the network impact of a hypothetical installation of an EV charging car park at a branch of a large UK supermarket chain in the Southside area of Glasgow. From Geographical Information System (GIS) data obtained from SP Energy Networks, the Distribution Network Operator (DNO) of the area, the location of the supermarket (shown by a red rectangle) relative to local distribution assets was analysed (Fig. 13).

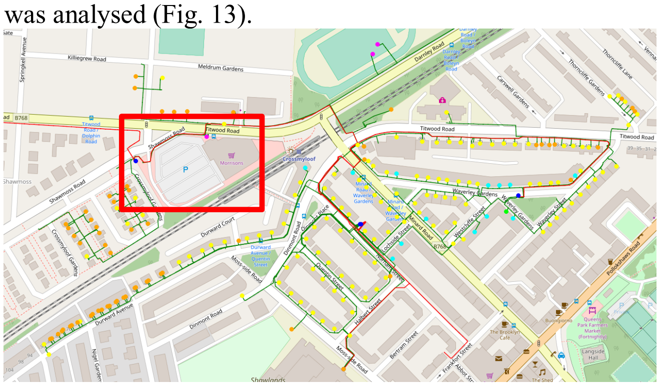

Fig. 13. Location of supermarket relative to distribution assets for EV destination charging case study

The assets shown in Fig. 13 represent one HV (11 kV) feeder from a primary (33/11 kV) substation to the left of what is displayed in the plot. The network in question is radial, but with normally open points sitting between this network and adjacent feeders which can be closed in the event of a fault to maintain power supply to the homes and businesses in the area. The HV (11 kV) network is plotted in red and the Low Voltage (LV) (0.4 kV) network is plotted in green. Busbars, shown by points in Fig. 13, represent the loads ordinarily served by this feeder. The colour of the busbars represents the number of residential customers (i.e. the number of loads) at that busbar; orange (1), yellow (2-9), cyan (10-19); magenta represents commercial customers' loads.

B. Modelling Likely Existing Domestic Demand

1) CREST demand model

In order to compare the demand profile of the EV charging car park to that of the existing domestic demand, an MC-based technique was developed to assign a demand profile to each residential property served by the feeder (Fig. 13) using the CREST demand model developed by McKenna and Thomson [29]. The model simulates electricity demand profiles of domestic dwellings based on stochastic simulation of the active occupancy of each dwelling, derived from the 2010 UK Time Use Survey. The output of the model is sensitive to the accommodation type (terraced/flat, semi-detached, detached) and the household size (number of residents; 1-4+). A sensitivity study of the model was conducted by running the model for 728 households under each household size and accommodation type combination (Fig. 14).

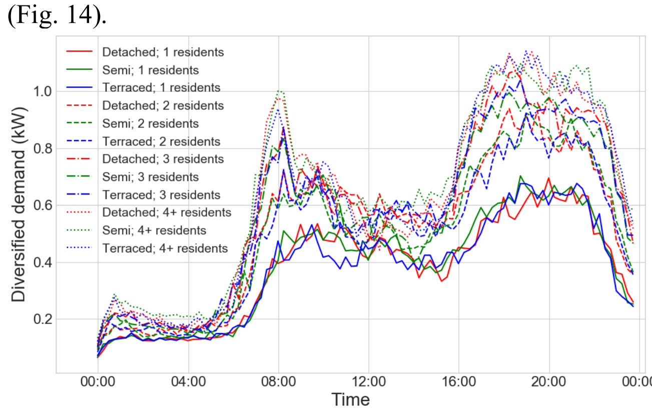

Fig. 14. Sensitivity study of CREST domestic demand simulation output to household size and accommodation type

To ensure effective implementation of the CREST model, each domestic property in the network (Fig. 13) was assigned an accommodation type and a number of residents. This is explained in subsections 2 and 3 respectively.

For each MC trial, the household size and accommodation type were established for each household and a single CREST simulation was run. For each time step, the corresponding active power load was applied at the relevant busbar with power factor 0.95.

2) Accommodation type

Each busbar was associated with a building type in the SP Energy Networks GIS data. In this analysis, that building type was applied to every property connected at that busbar. This is realistic, as one LV busbar tends to mean one dwelling (a house), or a series of dwellings (e.g. a block of flats) of the same building type.

3) Household size (number of residents)

2011 UK Census data for household size (number of residents) is available from the UK Data Service's Infuse webpage [28] for Scottish Small Output Areas, each containing around 50-100 households. The distribution of household size in the Small Output Area in which the busbar was contained was returned by matching up the GIS data of the network with the GIS data of the Census boundaries. For each MC trial, a household size was selected at random from the distribution of household sizes in that Small Output Area.

C. Derivation of Likely Destination Charging Demand Profile

The hypothetical charging infrastructure in this case study is connected directly to the HV (11 kV) network via a dedicated secondary transformer (or set of multiple transformers).

The supermarket car park in Fig. 13 has a capacity of around 200 spaces. Destination charging demand profiles are derived using the same method as in Section V for 50 EV charging spaces, whose occupancy is assumed to be the same as the supermarket itself. The Google Maps Popular Times data for this supermarket is shown in Fig. 15.

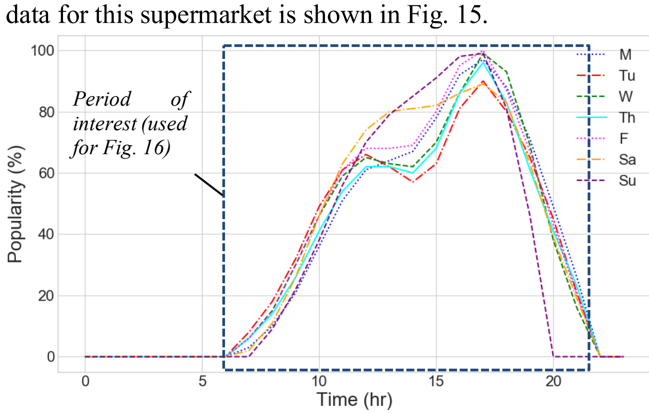

Fig. 15. Google Maps Popular Times data for Glasgow Southside branch of large UK supermarket chain retrieved on 20th August 2018

In this case study, the period of interest was 06:00-22:00 as this represents the time when both the domestic loads and the destination charging loads are likely to be greatest.

As in Section V, the charger ratings P_C and grid import capacities P_G are varied (Table 2). The P_C values are based on installations of individual secondary transformers each of capacity 800 kW.

Table 2. Values of P_G and P_C used for Case Study 2

Parameter	*Low*	*Medium*	*High*
P_G	800 kW	1600 kW	2400 kW
P_C	20 kW	50 kW	80 kW

From the Google data, it is reported that customers spend an average of 20 minutes at the supermarket. Using T = 20 minutes in (1), an expected demand profile can be produced using the same method as before (Sections II and III).

As the CREST model output is for a 'winter weekday', the Google data was extracted for a random weekday each time a trial was run rather than using a specific weekday.

D. Impact on the local distribution network

Due to the stochastic nature of the method by which the domestic property attributes are set (Section VI-B) and the destination charging profile was generated, the overall simulation (domestic profile plus destination charging load) was run 100 times and average results are reported. The simulation was run for each scenario for the time period 06:00–22:00 at a resolution of 15 minutes.

Fig. 16 shows the additional loading of the HV (11 kV) line upstream of where the charging car park would be connected with different scenarios taken from Table 2.

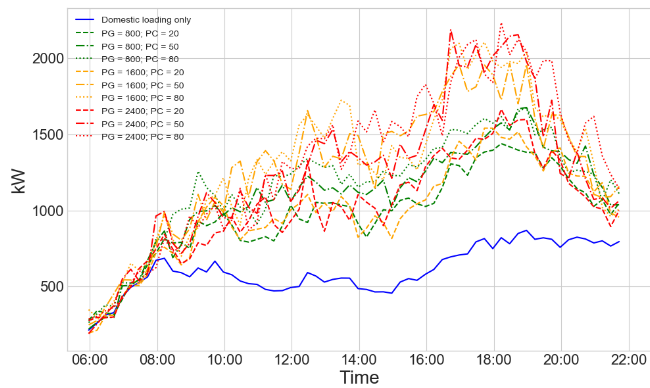

Fig. 16. Additional loading of HV line due to installation of EV destination charging car park

As shown in Fig. 16, the expected increase in line loading is sensitive to the parameters P_C and P_G. As in Section V, the specification of the charging infrastructure will be a compromise of cost to install the equipment versus revenue from selling energy to EV users or revenue from additional custom as a result of the presence of charging infrastructure. For all the values of P_C and P_G in Table 2, [] shows the variation in the average energy content gained (kWh) by cars visiting the chargers during their trips to the supermarket. As the energy gained will vary from when the charging facility is busy and when it is quiet, the results are presented for both 'peak' (between 14:00 and 18:00, when the supermarket is busiest according to data in Fig. 15) and 'off peak', which includes all other time for which the supermarket is open.

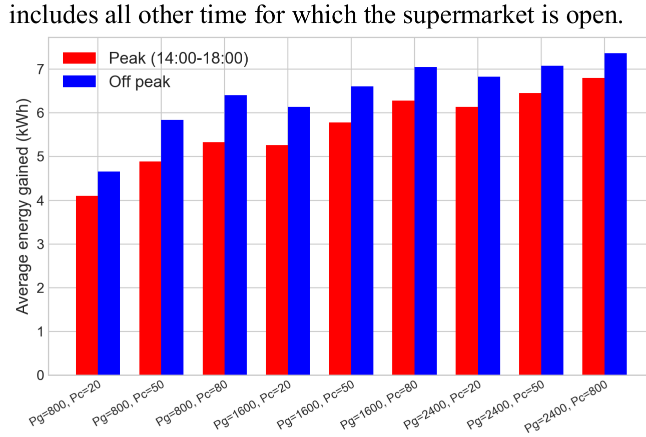

Fig. 17. Variation of average energy gained by EVs visiting supermarket charging facility by parameters P_C and P_G

Bearing in mind that typical EV electrical 'efficiencies' are of the order 17-20 kWh/100 km, the average energy content gained translates to a driveable range of 20-24 km for peak charging with P_C = 20 kW and P_G = 800 kW (the lowest specification of charging infrastructure) to 37-44 km for off peak charging with P_C = 80 kW and P_G = 2400 kW (the highest specification of charging infrastructure). As a sole method of charging an EV, this kind of range addition would likely not suffice. However, if destination charging infrastructure was commonplace at places where people left their cars for periods of time, then frequent and moderate 'top ups' like this could be an effective way of running an EV.

VII. Conclusion and Further Work

In this paper, a MC-based method for characterizing the likely demand profiles of destination charging at popular amenities has been presented. It has been applied to a generic gym based on a sample of gyms in GB and also to case studies of a real shopping centre, to explore the difference in likely EV charging demand at different types of amenities and the effect of infrastructure specification on service provision, and to a real supermarket, to explore the likely impact of destination charging on a residentially-dominated distribution network for a range of infrastructure specifications.

Evidenced through the findings in this study, it is shown that EV destination charging demand is likely to vary significantly depending on the type of amenity at which it is installed and the day of the week. For example, if charging is installed at a gym then the weekly peak is expected to occur on a weeknight evening, whereas if charging is installed at a shopping centre then the weekly peak is expected to occur on a weekend afternoon.

It is proposed that further work is carried out to model how the usage of destination charging installations at different amenities may interact with one another and how they might interact with other modes of EV charging, e.g. domestic and rapid charging. By building a robust system of modelling for this, insights on the overall impact to the electricity network from EV charging can be given and this can be used to form recommendations as to the policy of the development of EV charging infrastructure.

From these insights, modelling can be developed in which smart grid technologies and novel tariff arrangements can be assessed in their potential to enable an electricity system fit for the electrification of personal transport at the lowest possible cost to both the EV user and the energy consumer.

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