Evaluating the Likely Temporal Variation in Electric Vehicle Charging Demand at Popular Amenities using Smartphone Locational Data

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Abstract: 'Destination charging' – the opportunity for drivers to charge their battery electric vehicles (EVs) while parked at amenities such as supermarkets, shopping centres, gyms and cinemas – has the potential to accelerate the rate of EV uptake. This paper presents a Monte Carlo (MC)-based method for the characterisation of EV destination charging at these locations based on smartphone users' anonymised positional data captured in the Google Maps Popular Times feature. Unlike the use of household and travel surveys, from which most academic works on the subject are based, these data represent individuals' actual movements rather than how they might recall or divulge them. Through a fleet EV charging approach proposed in this paper, likely electrical demand profiles for EV destination charging at different amenities are presented. Use of the method is presented firstly for a generic characterisation of EV charging in the car parks of gyms, based on a sample of over 2,000 gyms in around major UK cities, and secondly for a specific characterisation of hypothetical EV charging infrastructure installed at a large UK shopping centre to investigate the impact of varying the grid and converter capacity on the expected charging demand and level of service provision to the vehicles charging there.

Nomenclature

Sets

$\mathbb{I}_j$	Set of EVs in car park at the beginning of the j^{th} timestep, indexed by i
$\mathbb{J}$	Set of timesteps, indexed by j

Variables

λ	Arrival rate of vehicles into car park (per hour)
C_i	Battery capacity of i^{th} EV (kWh)
CR_{ij}	Charge rate of i^{th} EV evaluated at the beginning of the j^{th} minute (kW)
N	Car park occupancy
n_j	Number of EVs in car park at the beginning of the j^{th} minute
P_C	Power rating of converter (kW)
P_{EV}	Power rating of EV (kW)
P_G	Available grid capacity (kW)
PCR_{ij}	Potential charge rate of i^{th} EV evaluated at the beginning of the j^{th} minute (kW)
SoC_{ij}	Battery state of charge of i^{th} car evaluated at the beginning of the j^{th} minute (kW)
T	Mean parking duration (hours)
TER_j	Total energy requirement of car park evaluated at the beginning of the j^{th} minute (kWh)

1. Introduction

1.1. Motivation

The UK's Committee on Climate Change (CCC) has stated that in order for the Government to achieve net zero carbon dioxide emissions, all new cars and vans sold in the UK must be electric by 2035 at the latest, with cost savings projected as a result of an earlier switch [1]. Given the current market dominance of battery Electric Vehicles (EVs) over other EVs 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.

While it is often assumed 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 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.

As the EV market continues to grow, it is likely that destination charging will become a significant part of overall EV charging infrastructure because, as has been shown in [6] and [7], EV drivers are likely to actively seek out destinations that offer charging opportunities, even at the expense of lengthening their own journeys: this places an incentive on the proprietors of these destinations to install charging infrastructure in order to attract more custom. this is demonstrably already happening: in 2018, one of the UK's largest supermarket chains announced plans to install free-to-use EV charging infrastructure at 600 of its stores by 2020 [8].

1.2. Mobility Data

In order to characterise EV charging demand of any sort, one must assume a rate of arrival and length of stay of the vehicles that require charging. In the majority of works on the subject, these are derived from individuals' responses to household or travel surveys [9]–[12]. Although a wide variety of simulation methods are demonstrated, use of such surveys as input data introduces systematic unreliability to these studies, as they are based on how individuals recall or divulge their activities. In contrast, this paper presents a model based on anonymous data obtained from individuals' smartphones, representing a realistic impression of their movements.

There are works that, as in this paper, use alternative forms of mobility data. In [13], authors present analysis of the temporal variation of EVs passing through a fast charging station based on the frequency and duration at which conventional vehicles are visiting petrol stations, which is analogous to how data are collected for charging destinations in this study. However, as the data are manually collected, the sample size is small (four petrol stations). The authors in [14] use traffic flow data to drive an EV charging demand model at various charging stops, which although uses real data as in this paper, a dependency is assumed between traffic (vehicles being on the roads) and their seeking to stop and charge. It is suggested that in reality, the likelihood of individual drivers stopping to charge is related to their remaining range and the time of day (and hence the EV charging activity in relation to other planned activities in the day). In [15], a model is presented which analyses the likely demand for en route EV charging stations based on a large dataset of over a million mobile phone call records over a four-month period. While the approach of using a large-scale mobile phone-based dataset is similar to that proposed in this paper, it is suggested that call records are of limited value when analysing individuals' mobility: aside from it generally being against the law to use a mobile phone while driving, use of mobile phones for calling is in significant decline in favour of internet-based communication apps such as WhatsApp and Facebook (whose usage would not be recorded in call records), with a quarter of UK smartphone users reportedly using their phones to make calls less than once per week [16].

It is proposed that the method presented in this paper can be used to grow the body of knowledge in the topic of EV charging demand characterisation. The method of using large-scale smartphone locational data from such a ubiquitous source as Google Maps to inform the models represents a shift towards utilising big data in the effective planning of transport and energy systems.

1.3. Objective

The objective for this work is to present a method for the characterisation of EV destination charging from a Monte Carlo (MC) method based on the activity of amenities at which it is likely to exist, derived from data in the Google Maps 'Popular Times' feature. The method can be used by transport and energy system planners to understand the likely temporal variation in demand from EV charging at various locations; either considering a general characterisation based on a given type of amenity, or a specific characterisation on a particular business. The use of the method for both types of analysis is presented in this paper via the following studies:

1 Characterisation 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 UK cities.
2 Characterisation 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.

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

2.1. Google Maps Popular Times Data

The Popular Times feature [17] 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.

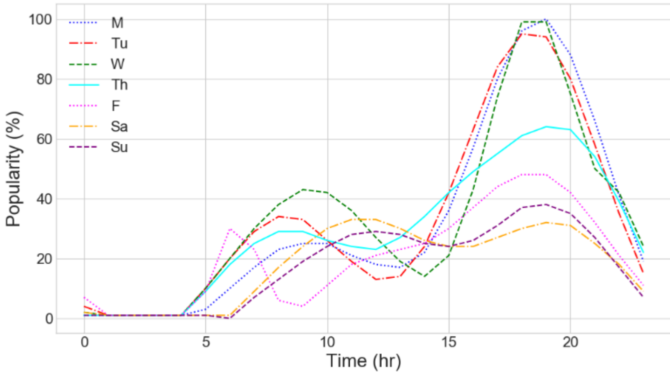

Fig. 1. Example of Google Maps Popular Times data for a particular large gym in the West of Scotland

Aside from displaying occupancy, the data also contains the average recorded duration of stay at a given business. Fig. 2 shows the variation in stay duration for a sample of 50 supermarkets, 50 gyms and 20 large shopping centres in the UK. All amenities chosen were with car parks at which EV charging infrastructure could reasonably be installed.

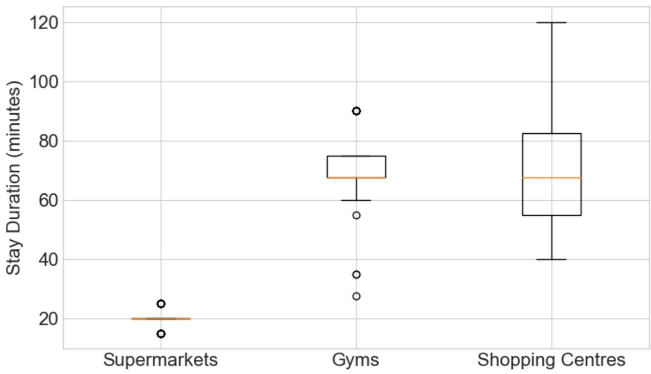

Fig. 2. Box plot showing variation of stay duration between supermarkets, shopping centres and gyms according to Google Maps Popular Times

Fig. 1 and Fig. 2 exemplify the extent to which the arrival times and parking durations of vehicles at these amenities are predictable. Fig. 1 shows that there is clear difference between weekday and weekend behaviour at that particular gym, with the weekly peak likely to occur in the evening in the beginning of the week (Monday-Wednesday). Fig. 2 shows that the distribution of stay duration at different businesses varies; at supermarkets, the majority queried reported typical stay durations of 20 minutes. Gyms have a tight distribution of stay duration about their median of 69 minutes; the interquartile range representing 7 minutes. Although the median stay duration queried from shopping centres was the same as for gyms, they are shown to have a wider distribution; typically, large out-of-town shopping centres reported longer stay durations up to 2 hours.

2.2. 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. In this paper, it is assumed that the throughflow of smartphones with Google Maps installed on them through an amenity is proportional to the throughflow of vehicles. It is noted that this could lead to inaccuracies due to some people taking alternative means of transport to these amenities, or some vehicles containing more than one – or zero – Google Maps-connected smartphones. However, the advent of EV charging and route-planning apps, many of which connect to Google Maps (e.g. the Zap-Map Journey Planner [18]), could make it possible for planners and charging operators to use data from these apps to develop a more accurate impression of the destination charging habits of EV drivers.

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 5, 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.

2.3. 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 fleet charging algorithm (section 3.4), 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).

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

T was fixed depending on the amenity in question. For MC analysis based on gyms presented in section 4, the mean parking duration was assumed as 69 minutes, based on the result presented in Fig. 2. For the case study based on Braehead shopping centre presented in section 5, the mean parking duration was taken as 134 minutes from [19].

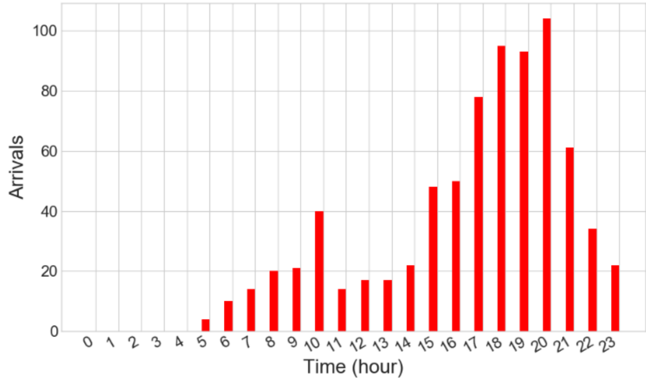

Fig. 3. Example arrivals profile based on Monday data for a particular large gym in the West of Scotland with 100 EV charging spaces

3. Electric Vehicle Fleet Charging

3.1. Charging Philosophy

'Smart' (i.e. controlled) EV charging can be used to minimise stress to the network [20], match times of high charging demand to times of low energy cost [21] or high renewable output [22], [23], or maximise service provision to the EV user [24].

Proposals for smart charging presented in [20]–[24] 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 [22] to having the EV user enter four separate 'preference parameters' upon parking [24]. 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 [25]. For example, users could 'game' the system by entering a false intended stay time in [22] 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 [26], 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 EV fleet 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 3.4.

3.2. 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 [23], [27] and replicated in Fig. 4.

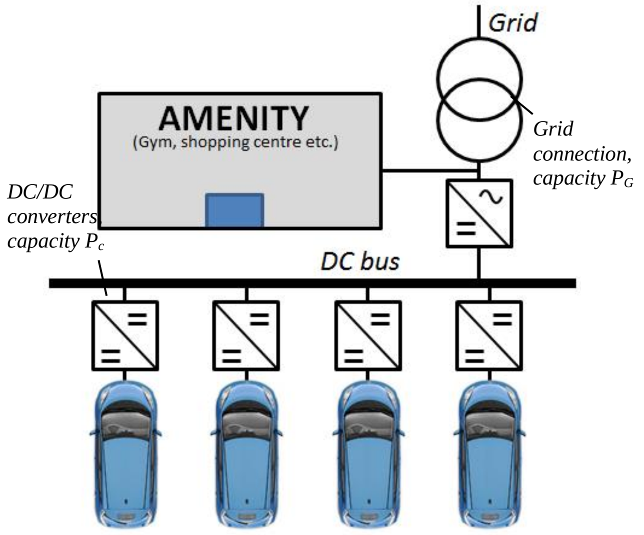

Fig. 4. Proposed topology for EV destination charging car park

3.3. Simulation of EV Parameters

Following the arrivals profile synthesised from the method described in section 2.3, an array of EVs equal in size to the height of the bars in Fig. 3 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 sections 3.3.1-3.3.4 below.

3.3.1. Arrival Time (within the hour)

Within the hour from which the EV instance was instantiated (Fig. 3), the EV's arrival minute was randomly assigned an integer between 0 and 59.

3.3.2. Battery Capacity

The EV is assigned a battery capacity randomly sampled from the distribution of EV battery capacities (kWh) for UK sales in 2017 [28] (Fig. 5). Two series are shown; one for all EVs, including plug-in hybrid EVs (PHEVs) and battery EVs (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. Furthermore, this distribution can be changed to reflect any credible future scenario of EV battery capacities; this is suggested as a piece of further work in section 6.

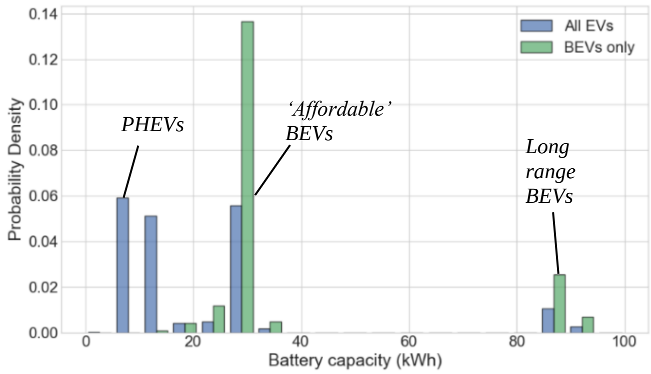

Fig. 5. Histogram showing distribution of battery sizes for UK EV Sales, 2017 – data from [28]

3.3.3. State of Charge (SoC) on Arrival

The battery's State of Charge (SoC) upon starting and finishing charging is often modelled by a Gaussian distribution as in [29]. However, the authors in [30] present $\chi 2$ test results to argue that a Beta distribution offers a better goodness of fit to real charging behaviour than a Gaussian distribution does. Furthermore, the fact that the domain of a Beta distribution is constrained to [0,1] means that there are no 'lost' values as there would be in a Gaussian distribution, which would allow sampling outside of that region.

The Beta distribution is characterised by two shape parameters α and β. For this work, they are derived using a 'method of moments' estimation [31] from data of the SoC at the start of charging for 2,494 charging events at 'public' locations monitored as part of the SwitchEV electric vehicle trial [32], which ran from March 2011 to May 2013 in Newcastle & Northeast England to provide insight on how individuals use and charge EVs, with an emphasis on workplace and public charging. Based on this data, the Beta distribution parameters are set at α = 2.27, β = 2.18 which derives a mean SoC on plugin of 51%. A probability distribution function (PDF) of this Beta distribution is shown in Fig. 6.

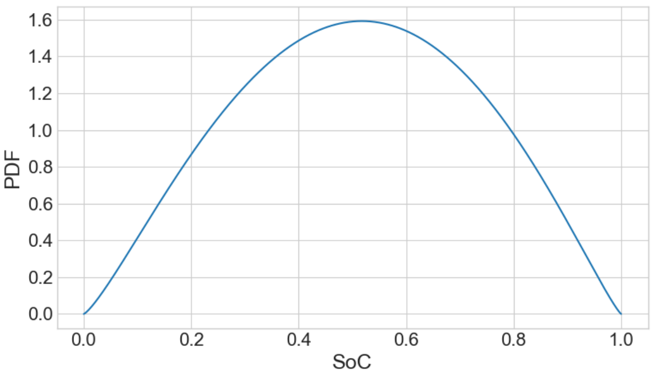

Fig. 6. Beta distribution (α=2.27, 2.18) used for modelling SoC on arrival

3.3.4. Parking Duration

The length of time the EV spends in the car park was modelled by a Poisson distribution, a method taken from [33] which uses the distribution to model an analogous quantity – the length of stay of patients 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 2.3).

3.4. Proposed EV Fleet Charging Algorithm

From the set of vehicles each with parameters from section 3.3, the EV fleet charging algorithm can be applied. For the j^{th} minute of the day, ($j \in \mathbb{J}, 0 \leq j < 1440$), and the i^{th} car in the car park, out of a total of n_j cars present in the car park at the beginning of the j^{th} minute, ($i \in \mathbb{I}_j, 0 < i \leq n$), TER_j is the total energy requirement of all cars in the car park at the beginning of the j^{th} minute (2).

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

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.

PCR_{ij} is the potential charge rate 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 a constant current-constant voltage (CC-CV) charge profile P_{EV}, taken from [24] (Fig. 7). Below an SoC of 90%, the charger will operate in constant current mode and the power is not limited. Above 90%, the charger switches to a constant voltage mode, and the power drawn will linearly decrease to zero at 100%.

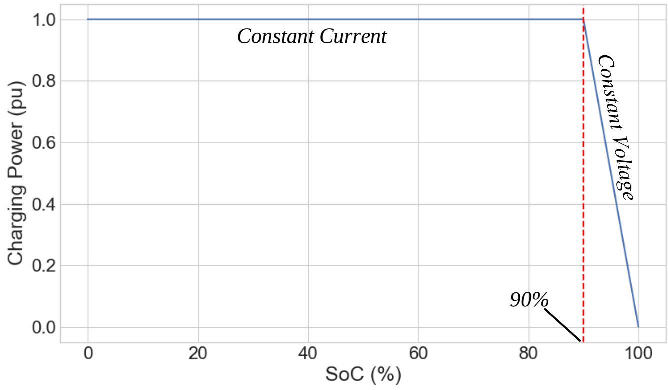

Fig. 7. Charging profile used for P_E

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 [34], [35]. It is noted that there is no consideration given to the effects of temperature or battery age on the charge rate of vehicles.

CR_{ij} is the actual charge rate of the i^{th} car in the j^{th} minute, given by (4).

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

The SoC of the i^{th} vehicle at the beginning of the next $(j+1)^{th}$ minute is then calculated in (5), where Δt is the timestep (1 minute).

$$SoC_{ij+1} = SoC_{ij} + CR_{ij}\Delta t \qquad (5)$$

The fleet charging method presented requires real-time monitoring and feedback to work on the basis of 1-minute timesteps. While the information required is likely to be possible to ascertain (based on the SoC at the start of charge – which could be estimated using a method such as in [36], the arrival time and the EV's power rating P_{EV}), any computational burden could be reduced by increasing the timestep. Investigation into the sensitivity of the model to this parameter is suggested as a piece of further work in section 6.

3.5. Queueing Model

If a car arrives such that n_j 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; it is assumed that its parking duration and all other parameters remain the same.

4. Characterisation of EV Charging at Gym Car Parks

4.1. 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 [37], 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 2.3 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.

4.2. Results

Results are presented in terms of a CDF plot for simulations based on the sample of gyms for Monday (Fig. 8) and Saturday (Fig. 9) popularity data.

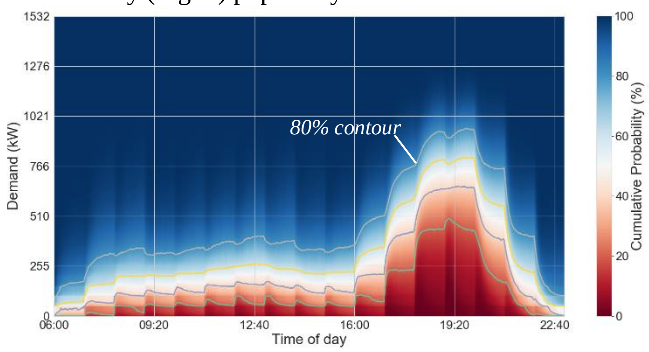

Fig. 8. CDF for MC simulation of EV charging at gym car park from Monday popularity data

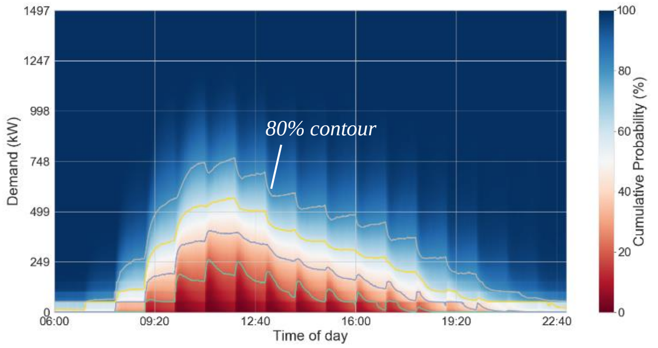

Fig. 9. CDF for MC simulation of EV charging at gym car park from Saturday popularity data

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 (lesser) weekend charging demand is most likely to peak in the late morning/noon around 10:00-13:00.

The method demonstrated provides a probabilistic evaluation of the likely EV charging demand at a given type of amenity. For example, Fig. 8 shows a 20% probability that the charging demand peak on a Monday will be greater than approximately 1000 kW between the hours of 18:00-20:00. 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 between EV charging in different locations and between EV charging and the pre-existing network demand.

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

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 [19], it is reported that customers spend an average of 134 minutes there. Using $T = 134$ minutes in (1), the Google Popular Times data (Fig. 10) can be used with the smart charging algorithm (section 3.4) to produce an expected demand profile for the period of interest (i.e. when the shopping centre is open).

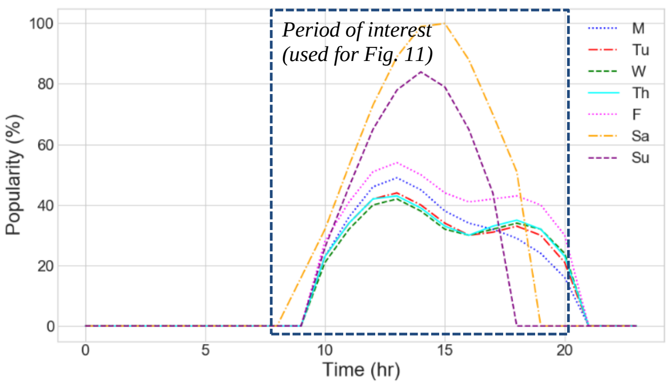

Fig. 10. Google Maps Popular Times data for Braehead shopping centre

Two values for P_G and three values for P_C were used to examine the effect of the car park parameters (Fig. 4) on peak demand and service provision (Table 1). Combining the values gives six 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

Parameter	*Low*	*Medium*	*High*
P_G	10 MW	-	25 MW
P_C	10 kW	20 kW	50 kW

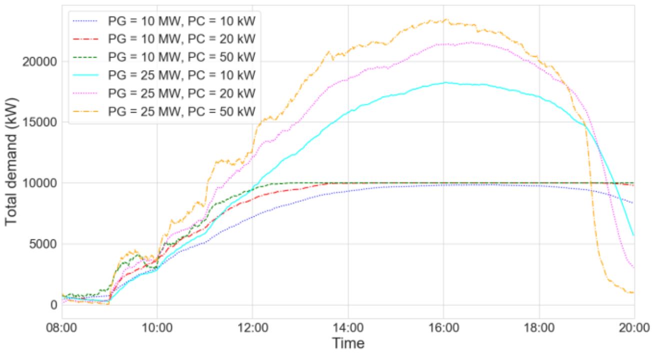

Fig. 11. Variation of demand profile with parameters P_G and P_C

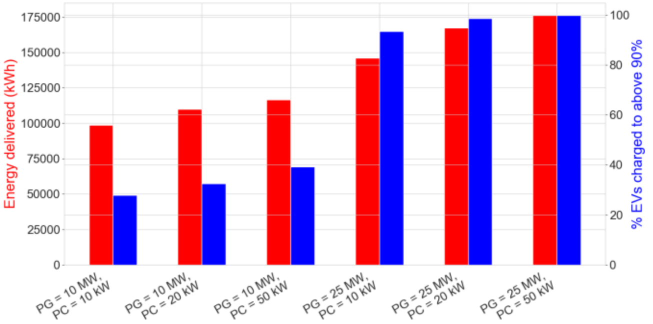

Fig. 12. Variation of service provision with parameters P_G and P_C

Figs 11 and 12 show that only P_G = 25 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 = 10 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 [38], 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 [39]. Multiplying 9 p/kWh by the energy delivered (kWh) enables a potential Saturday revenue to be calculated: this varies between around £8,900 for the P_G = 10 MW, P_C = 10 kW option to £15,900 for the P_G = 25 MW, P_C = 50 kW option. By integrating the curves in Fig. 10, 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 £2-4 million per 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. 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.

6. Conclusion and Further Work

In this paper, a MC-based method for characterising 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 a case study 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.

Evidenced through the findings in this paper, 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.

To improve the accuracy of the model presented in this paper, the following pieces of further work are suggested: (1) a sensitivity study of the effect of the assumed distributions of EV battery capacity (Fig. 5) and SoC on arrival (Fig. 6) on the resulting demand from destination charging and (2) a sensitivity study of the effect of a relaxed timestep in the fleet charging simulation (section 3.4) on the resulting charging demand.

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.

7. References

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