Abstract: The increasing penetration of electric vehicles (EVs) brings challenges and opportunities for power systems. One particular opportunity concerns the use of parked EVs to provide energy and associated services to the grid. In this work, the potential energy storage capacity of parking lots (PLs) of EVs is computed using the proposed stochastic model which considers the sporadic nature of the EV’s behaviours (i.e. arrival/departure, battery degradation, travel pattern, charge/discharge rates). The analysis was performed for two types of PLs with very different occupancy distributions, i.e. a shopping centre PL, and a workplace PL. In both cases, the available energy storage capacity of EVs was estimated hourly using real household travel data, i-MiEV data and car park occupancy records. The results show that the aggregated energy storage capacity closely follows the occupancy of EVs in the PLs, and is substantial, with little sensitivity to charging rate. The proposed stochastic modelling considered the variations in energy consumption, battery degradation, and user behaviour, predicted 13.4% less peak capacity than deterministic modelling. Moreover, the authors conclude that the shopping centre PL is a viable energy resource to the grid, with their scale and throughput compensating for the relatively low occupancy.

1 Introduction

Battery-powered zero-emission electric vehicles (EVs) are expected to significantly reduce CO2 emissions [1]. Although the internal combustion engine vehicles are currently the dominant source of transportation, electrification in the transportation sector is increasing rapidly [2, 3]. EVs can be charged by plugging into electrical outlets available at home, hospitals, shopping centres, workplace and community centre car parks. The increase in load demand due to the charging of EVs may create reliability and stability issues in the existing power system [4]. However, their associated battery storage brings opportunities as well. By enabling vehicle to grid (V2G) and vehicle to vehicle mode extending the life time of EV’s battery [5]. Moreover, EVs can provide ancillary services (e.g. peak shaving, voltage and frequency regulation) to support the grid [6].

EVs are moveable sources of energy storage and the arrival and departure times of EVs depend on the usage of the vehicle and where it is parked. For example, workplace (office) parking lots (WPLs), usually have very well-defined arrival and departure times. Normally, people spend an extended time at their workplace (i.e. more than 5 h per day) [7]. The periodic arrival/departure pattern and long occupancy time of commuter vehicles, if aggregated, make WPLs a potentially significant future energy storage resource. Conversely, in shopping centre parking lot (SCPL), the arrivals and departures of EVs are scattered throughout the day, and most vehicles stay for less than an hour. The widespread distribution in arrival and departure times together with the shorter occupancy vehicles in SCPLs is expected to make it challenging to estimate the available energy storage capacity.
EVs in PLs, many authors considered deterministic model whereas EV's battery degradation in calculating the storage capacity. This is an open access article published by the IET under the Creative Commons Attribution License (http://creativecommons.org/licenses/by/3.0/). In private company's WPLs [13]. Estimation of the aggregated effect of driving style on energy consumption per kilometre of EVs rated battery capacity, energy consumption per kilometre). An V2G capability can be a significant energy resource for VPP. In developed in [15, 16]. In [17], a stochastic model was developed to estimate the available aggregated ESC of EVs in SCPL/WPL. The proposed model mapped each EVs parameter (i.e. $d_i$, $K_i$, $BC_i$, $R_i$) in an appropriate probability distribution with quantified uncertainty.

The novelty lies in the fact that the proposed model effectively simulated the scattered occupancy pattern of vehicles in the SCPL. Moreover, this work incorporated (i) the effect of driving style on energy consumption of EVs and (ii) EVs battery degradation while estimating the ESC of EVs in the PL. As per authors' knowledge, modelling of EV occupancy pattern and estimation of available energy resources in shopping centre car parks has not previously been reported yet. The model is developed based on real data provided by (i) Macquarie shopping centre, (ii) i-MiEV usage data and (iii) on Victoria household travel surveys (HTSs). Furthermore, it can easily be extended to any size of the PL with different occupancy pattern and usage.

The remainder of the paper is organised as follows: Section 2 describes a potential charging/discharging architecture for the PL, whilst Section 3 presents the modelling of energy storage capacity. The results are discussed in Section 4, Section 5 presents a sensitivity analysis of the proposed model, and Section 6 concludes the paper.

2 Architecture of a PL incorporating EVs

Fig. 1 shows the conceptual architecture of a PL incorporating charging/discharging infrastructure for EVs. Every vehicle has a dedicated DC–DC bidirectional converter. These converters manage the rate of charging and discharging of EVs and connect EVs with the DC bus. The control switches enable PLA to control charging/discharging of the EVs. The DC bus of the PL connects to the utility grid (i.e. the AC bus) through a bi-directional AC–DC power converter. The distribution transformer supplies the desired level of voltage to the PL. The control switch at the point of common coupling (PCC) enables PLA and system operator to operate PL in either islanded mode or grid-connected mode. The control switches enable the PLA and system operator to schedule the charging/discharging of EVs. Vehicle-to-vehicle (V2V) and V2G power transfer is also possible via the DC bus and control switches but is not considered in this work.

3 Stochastic modelling of EV storage availability

3.1 Data collection

The availability of EVs in PLs is dependent upon the EV owners’ travel patterns and usage. It is essential to develop a comprehensive model to determine the availability of EVs in PLs. In the proposed

| Papers | Daily distance travel | Arrival & Dept. time | Rate of charging | Human behaviour (i.e. EV owner) | Market penetration | EVs battery degradation | Types of EVs | Real data SCPL |
|--------|-----------------------|----------------------|------------------|---------------------------------|--------------------|------------------------|--------------|--------------|
| [8, 9, 13] | ✓ | ✓ | Fixed | ✓ | Fixed | ✓ | ✓ | ✓ | ✓ |
| [18] | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| [14, 19] | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| [10, 12] | ✓ | ✓ | Fixed | ✓ | ✓ | ✓ | ✓ | ✓ |
| [20, 21] | ✓ | ✓ | Fixed | ✓ | ✓ | ✓ | ✓ | ✓ |
| this paper | (5) and (2) | (8) | (3) | (14)–(16) | (4) | (4) | ✓ | ✓ |

Legends: ✓ = Considered as stochastic parameter, Fixed = Considered as rated/fixed parameter, ✘ = Not considered.

SCPL, the scattered arrival/departure pattern and shorter occupancy time of vehicle make SCPLs a less obvious resource of energy storage for VPPs. However, in this work, we show that the scale of SCPLs is likely to make it worthwhile.

Deterministic model considers fix parameters, whereas EV usage (driver's behaviour) contains some uncertain parameters. These uncertain parameters often follow a probability distribution. Therefore, stochastic approach approximates the uncertain parameters by mapping them with probability distribution functions (PDFs). In this work, the stochastic model is proposed to estimate the available aggregated ESC of EVs in SCPL/WPL. The proposed model mapped each EVs parameter (i.e. $d_i$, $K_i$, $BC_i$, $R_i$) in an appropriate probability distribution with quantified uncertainty.

Fig. 1 Conceptual architecture of PL

1.1 Literature review

Various methods have been reported to estimate the energy storage capacity associated with EVs and the availability of vehicles in PLs. The model proposed in [8, 9] calculated the storage capacity of WPLs. It also incorporated the intermittent usage of EVs, however, considered fixed values of the critical parameters (e.g. rated battery capacity, energy consumption per kilometre). An intelligent charging/discharging method has been proposed to use the available energy storage capacity of EVs in the PLs [10]. Particle swarm optimisation was used to calculate the best charging/discharging time for EVs and plug-in hybrid electric vehicles (PHEVs), however, deterministic values were used to calculate the storage capacity of EVs providing limited insight into the likely variation in storage available at any point in time. Comparative analysis between the energy market and reserve market was carried out in [11] to determine the optimal behaviour of PLs incorporating EVs. In [12–14], the authors analysed the aggregated impact of EVs on the distribution grid but they did not consider battery degradation. The impact of arrival and departure patterns was analysed to determine the storage capacity of public and private company's WPLs [13]. Estimation of the aggregated storage capacity of EVs using a stochastic modelling approach was developed in [15, 16]. In [17], a stochastic model was developed to estimate the occupancy behaviour and arrival/departure pattern of EVs in WPLs using Markov chain analysis.

A summary of the literature review is shown in Table 1. It can be observed in Table 1 that most of the latter works neglected the effect of driving style on energy consumption per kilometre of EVs and EV’s battery degradation in calculating the storage capacity/load demand of EVs. Moreover, to determine the sporadic nature of EVs in PLs, many authors considered deterministic model whereas the EV charging load is entirely dependent on its variable usage. Detailed modelling is still an issue in determining vehicle availability, available energy resources and EVs charging demand, which depends on the needs, usage and travel preferences of EV owners.

Virtual power plants (VPPs) aggregate the heterogeneous distributed energy resources to support the grid [16]. EVs with V2G capability can be a significant energy resource for VPP. In

Table 1 Literature review, categorised by EV behaviour modelling for estimating ESC of EVs in the PLs

Legend: ✓ = Considered as stochastic parameter, Fixed = Considered as rated/fixed parameter, ✘ = Not considered.
model, EV usage is characterised by five parameters (i.e. $d_i$, $d'_i$, $BC_i$, $R_i$, $KM_i$).

All parameters are stochastic variables with their PDFs derived from real data. In this work, two types of PLs are considered: (i) an SCPL with space $(N_{ev})$ for 4500 vehicles; and (ii) a WPL with space $(N_{ev})$ for 1000 vehicles.

The aggregated occupancy of the SCPL was modelled using hourly data collected over a month from a nearby suburban shopping centre (the Macquarie Centre). On average, $(N_{ev}) 17,000$ vehicles visited the SCPL per day. Fig. 2 shows that in this SCPL $>23\%$ vehicles were parked for $<30$ min and almost $92\%$ of vehicles departed within $3$ h (Note: a parking fee applied for stays longer than $3$ h and all shops in the shopping centre close at 10:00 PM).

The aggregated occupancy of a WPL and daily distance travelled was derived from vehicle travel survey data obtained from 25,443 people in 9715 households across the Victoria State (Australia) over a period of 3 years [7]. The data reported 1.1 million trips on weekdays and 8.6 million trips on weekends, including information about the origin of travel, departure time from the origin, destination point, arrival time at destination, the purpose of travel etc. The data was filtered to consider only commuters who (i) travelled $<100$ km per day, (ii) travelled within the city of Sydney, and (iii) used their own cars for commuting. We analysed the travel pattern of the Sydney region from the filtered HTS data. We concluded that on average, vehicles in Sydney travel $\sim11,650$ km per annum (i.e. $\sim32$ km/day). About $88\%$ of vehicles drive $<30$ km per day, and $\sim95\%$ vehicles travel $<45$ km per day. These results are comparable to the travel patterns studies in other works, e.g. [12, 17, 22, 23].

We have been driving the i-MiEV EV in Sydney since 2017 and precisely analysing the factors affecting the energy consumption and battery health of EV. We observed that the energy consumption per kilometre of EV $(R_i)$ is mainly affected by the driving style, number of passengers, atmospheric temperature and battery ageing. The minimum energy consumption of i-MiEV is obtained by smoothly driving the vehicle (see Fig. 3a). Whereas Fig. 3b shows the energy consumption of EV while aggressively driving the vehicle. It can be seen in Fig. 3 that due to different driving styles, the energy consumption of i-MiEV varies in-between $159$ and $211$ Wh/km. The state of health of EVs’ battery is significantly affected by EV usage, calendar ageing and charging/discharging pattern [24–26]. We observed that within 3 years the battery capacity $(BC_i)$ of our EV (i.e. i-MiEV) is reduced from 16 to 14.3 kWh.

### 3.2 Data fitting

The distribution of arrival times $(a_i)$ and departure times $(d_i)$ of vehicles to/from the PLs was modelled by PDFs chosen to give the best fit to the data. The departure time of EVs in WPL/SCPL was best fitted with a log-normal distribution, whilst the arrival time of WPL/SCPL was best fitted with an extreme-value distribution. In both cases the distributions were truncated (positive skewed and negative skewed). Moreover, occupancy time of vehicles in the SCPL was incorporated in the model by using discrete random variables having mean $= 1.537$ and standard deviation $= 1.093$. The arrival and departure pattern of SCPL are synthetically generated from (1) to (2) and are shown in Fig. 4.

$$d'_i = \text{log normal}(\mu_p, \sigma_p) \quad \forall i, c$$  

$$d'_i = \text{extreme value}(\mu_p, \sigma_p) \quad \forall i, c$$

The values of the mean, $\mu_p$, and standard deviation, $\sigma_p$, for each distribution are listed in Table 2.

Form Fig. 3 we generalised that due to driving style the energy consumption of EV varies up to $33\%$ of its rated value and, the battery capacity degraded up to $11\%$ of its rated capacity. These results are comparable to the EV range estimation studies in other work, e.g. [27, 28]. It is assumed that every vehicle owner has

![Fig. 2 Occupancy pattern of cars in SCPL](image)

**Fig. 2** Occupancy pattern of cars in SCPL

![Fig. 3 Energy consumption per km of EV](image)

(a) Smoothly driving, (b) Aggressively driving i-MiEV

**Fig. 3** Energy consumption per km of EV

(a) Smoothly driving, (b) Aggressively driving i-MiEV

![Fig. 4 Arrival and dept. pattern of EVs in SCPL](image)

**Fig. 4** Arrival and dept. pattern of EVs in SCPL

| Table 2 | Statistical parameters |
|---------|------------------------|
| **Parking lots** | **Arrival time $(a'_i)$** | **Dept. time $(d'_i)$** |
| | $\mu_p$ | $\sigma_p$ | $\mu_p$ | $\sigma_p$ |
| office PL | 12.1769 | 0.32 | 16.998 | 3.471 |
| SCPL | 12.5368 | 0.293 | 16.89 | 2.414 |
different driving style and usage pattern. In order to accurately estimate the ESC of EV, it is necessary to incorporate EV owner’s driving style and battery degradation of each EV. The energy consumption per kilometre driven $R^i_c$ and battery capacity $BC^i_c$ were best fitted with truncated gumbel-min and normal distributions, respectively. These distributions having a lower and upper limit specified by $R_{\text{min}}, R_{\text{max}}$ and $BC_{\text{min}}, BC_{\text{max}}$, respectively.

The limits of $R^i_c$ and $BC^i_c$ in (3) and (4) are listed in Table 3. In (3), $\mu_T = R_{\text{min}}$ and $\sigma_T = 7.034$ whereas, in (4) $\mu_B = BC_{\text{min}}$ and $\sigma_B = 0.4512$. The truncated PDFs computed by using (3) and (4) are shown in Figs. 5 and 6, respectively

$$R^i_c = \text{gumbel min} \left( \mu_T, \sigma_T | R_{\text{min}} \leq R^i_c \leq R_{\text{max}} \right) \quad (3)$$

$$BC^i_c = \text{normal} (\mu_B, \sigma_B | BC_{\text{min}} \leq BC^i_c \leq BC_{\text{max}}) \quad (4)$$

The other important factor of EV usage is the daily distance travelled. It was analysed from HTS data that about 95% vehicles travel <45 km per day. However, we are only interested in the distance travelled by EV before arriving at SCPL. From HTS data we analysed that people usually do shopping from their closest shopping centre, which are normally 5–30 km away from their homes. The PDF for distance travelled before arriving at SCPL was best fitted by a Weibull distribution with shape parameter $\sigma_{\text{MD}} = 13$ and scale parameter $\mu_{\text{MD}} = 1.9$

$$\text{KM}^i_c = \text{Weibull}(\sigma_{\text{MD}}, \mu_{\text{MD}}) \quad \forall i, c \quad (5)$$

The probability distribution generated by using (5) is shown in Fig. 7.

### 3.3 Energy storage capacity calculation

Equations (1)–(5) are used to calculate the distribution of states of charge of vehicles arriving at the car park, i.e. assuming all vehicles are electric, and their travel patterns are the same as in the HTS [7]. For example, the energy required to charge the $i$th EV while parked in the PL is given by

$$E^i_c = \begin{cases} 
BC^i_c & \text{if } \text{KM}^i_c = D_{c, \text{max}} \\
\text{KM}^i_c & \text{otherwise}
\end{cases} \quad \forall i, c \quad (6)$$

Now, we can calculate: (i) the charging rate required for a typical EV battery, $P^i_{\text{charge}}$; (ii) the time required for charging, $T^i_{\text{charge}}$; (iii) the aggregated load demand of EVs; (iv) the hourly ESC of EVs in the PLs; and (v) total number of EVs. Equations for the latter are described in (6)–(13). Where ‘$i$’ is the EV class, ‘$h$’ is the hour and ‘$c$’ is the EV class. A level 2 charger of 3.6 kW (i.e. $V = 240 \, \text{V}_{\text{RMS}}$ and $I = 15 \, A_{\text{RMS}}$) is used to charge EVs in SCPL and WPL

$$A^i_c = \min \left( \frac{E^i_c}{V^h_{\text{RMS}} \times i_{\text{charger}}} \right) \quad (7)$$

here $T^c_{\text{dwell}}$ is the occupancy time of vehicles in the PLs and it is derived from arrival/departure time of EVs. $I$ and $V$ are the rated current and voltage of EV charger, respectively. The rate of charging $P^i_{\text{charge}}$ of EV is computed as follows:

$$P^i_{\text{charge}} = V \times A^i_c \times i_{\text{charger}} \quad (8)$$

The total number of hours needed to fully charge the battery, $T^i_{\text{charge}}$, is

$$T^i_{\text{charge}} = E^i_c / P^i_{\text{charge}} \quad (9)$$

The charging load of EVs at any given time is calculated using (10) and (11)

$$P^i_{\text{EV}}(h) = \sum_{i=1}^{\text{EV}} P^i_{\text{charge}}(h) \quad (10)$$

### Table 3  EV specifications

| EV Class | Nissan Leaf | i-MiEV |
|----------|-------------|--------|
| $R_{\text{max}}$, kWh/km | 0.164 | 0.159 |
| $R_{\text{min}}$, kWh/km | 0.219 | 0.211 |
| $BC_{\text{max}}$, kWh | 36 | 14.3 |
| $BC_{\text{min}}$, kWh | 40 | 16 |
| $D_{c, \text{max}}$, km | 243 | 130 |
| $\eta_{\text{charger}}$ | 0.94 | 0.94 |
| $P_{\text{EV}, c}$ | 0.97 | 0.03 |
The ESC of each EV can be calculated by subtracting the battery capacity of EV with its load demand. In this paper, we are interested in finding the aggregated ESC of the EVs that can be utilised to support the grid. The maximum available aggregated ESC of parked EVs may be calculated using (12) and (13)

\[Q_{\text{EV}}(b) = \text{SOC}_{i, c}^\text{int} + P_{\text{EV}}(b)\]  \hspace{1cm} (12)

where \(\text{SOC}_{i, c}^\text{int} = BC_{i, c} - E'_{i}\)

\[Q_{\text{tot}} = \sum_{i=1}^{N_{\text{ev}}} \left[Q_{\text{EV}}^{i1} Q_{\text{EV}}^{i2} \cdots Q_{\text{EV}}^{iN_{\text{c}}}ight]\]  \hspace{1cm} (13)

Here \(Q_{\text{EV}}\) is the SOC of each EV, and \(Q_{\text{tot}}\) is the aggregated hourly ESC of all EVs in the PL.

For simplicity, we assumed that all cars are fully electric (i.e. 100% EVs) and belong to two classes of EVs (i.e. Nissan Leaf and Mitsubishi i-MiEV), however, this is not a limitation of the model. By using (14)–(16), this model can consider different types and different penetrations of EVs, ranging from 0 to 100% relative to conventional vehicles

\[N_{i} = \text{normal}(\mu_{c}, \sigma_{c})\] \hspace{1cm} (14)

\[\mu_{c} = N_{\text{ev}, c} \times P_{\text{ev}, c}\] \hspace{1cm} (15)

\[\sigma_{c} = 0.01 \times \mu_{c}\] \hspace{1cm} (16)

Here \(P_{\text{ev}, c}\) is the probability of different classes of EV. \(N_{\text{ev}}\) is the total number of EVs and is assumed to be by a normal distribution having mean \(\mu_{c}\) and standard deviation \(\sigma_{c}\) [29]. In this work, we assume that all vehicles are electric and belong to two class, so, \(N_{\text{tot}} = N_{\text{ev}}\). Penetration \(P_{\text{ev}, c}\) of both classes is considered as per the current market participation/sale of both EVs (see Table 3).

### 3.4 Energy storage capacity algorithm

This section of the paper describes the step by step method to estimate ESC of EVs (see Fig. 8). First, collect the data of travel pattern, arrival/departure time, energy consumed per kilometre driven and degraded battery capacity. Then select appropriate PDFs for each parameter based on their goodness of fit. In the second step, stochastically generate the values of the above-mentioned parameters by using PDFs. Finally, calculate the available ESC of EV. Repeat this algorithm ‘\(n\)’ times (i.e. \(n = 2000\)) using non-sequential Monte Carlo simulation.

### 4 Results

In this section, the results of modelling to obtain the state of charge, and hence energy required by (or available from) the aggregated EVs in the PL are presented. Two types of car park (i.e. SCPL and WPL) of different size and occupancy patterns were considered. The rate of change of availability of vehicles and departures of vehicles are dispersed throughout the day as depicted in Fig. 9. Each cross represents the arrival of EV, and each circle indicates the departure of EV. It can be observed in Fig. 9 that the SOC of EVs when arriving at SCPL varies between 70 and 95%. The dense cluster in Fig. 9 between 1000 and 1800 h show that the number of vehicles in the SCPL is significantly higher. The SOC level of EVs at departure time is higher than arrival SOC. However, due to shorter dwell time and slow charging rate, ~4% vehicles are charged up to 100%.

Fig. 10 represents the box plot of aggregated ESC of EVs in the SCPL. The upper bound (blue line) represents the maximum energy available and it is calculated by assuming 100% initial SOC of EVs. Whereas, the lower bound (orange line) is estimated by assuming 50% initial SOC of EVs. The interquartile range between them is the feasible region of available ESC and the red lines are the median values. It can be observed in Fig. 10 that the availability of ESC in SCPL is from 0800 to 2300 h (i.e. 4 h more than WPL). To provide ancillary to the grid, PLA must commit hourly ESC and failure to provide the committed power will result in paying the penalty. As the availability of ESC is dependent on uncertain usage of EVs. It is proposed that the PLA may commit with 80% of the maximum energy capacity available at respective time-of-day, which we refer in Fig. 10 as a safety margin (black line). It could be inferred from the graph that the safety margin in terms of energy available is higher during the day (i.e. from 0900 to 1600 h). This shows that with the proposed safety margin, the...
chances of getting penalised would reduce significantly for an aggregator and it would have a flexible range of certainty in making energy commitments with the grid. The aggregator has to be more careful in committing energy during the times when the energy availability margins are significantly lower compared to the day-times (i.e. from 0900 to 1600 h).

4.2 Workplace parking lot

The pattern of arrival and departure of EVs are more predictable as it is associated with the office timings (i.e. 0900 to 1700 h.). This pattern is presented mathematically in (1) and (2). Fig. 11 represents the SOC of EV batteries at arrival (blue cross) and departure (orange circles) in the WPL. The dwell time of individual EV is much higher in the WPL compared to the SCPL. Therefore, most EVs in the WPL are charged up to 90% before departing.

In Fig. 12, it is clearly seen that the estimated ESC in WPL closely follows the real data. The ESC is available between 0500 and 2100 h. Between 0800 and 1800 h aggregated ESC of EVs in WPL is >30% (i.e. 12 MWh) of its maximum ESC. In this period, WPL aggregator may use the available ESC to support the grid. It could also be inferred that it is risky for PLA to make energy commitments during the times when the energy availability is significantly lower compared to the day-times (i.e. from 0900 to 1600 h).

4.3 Comparison with literature

Driving style, road conditions, travel pattern and atmospheric temperature affect the energy consumption ($R_c^{i}$) of EVs [25, 28, 30]. Moreover, ageing of battery and charging/discharging patterns are significantly reducing the battery health of EVs [5]. Because of the above-mentioned factors, the energy consumed per kilometer ($R_c^{i}$) and the battery capacity ($BC_c^{i}$) of the vehicles varies significantly. However, the charging/discharging behaviour models of EVs reported in the literature considered the rated/fixed values of $R_c^{i}$ and $BC_c^{i}$.

To analyse the impact of $R_c^{i}$ and $BC_c^{i}$ on ESC, simulation was performed by choosing the rated values of Nissan Leaf and i-MiEV, specified by the manufacturer (i.e. $R_c^{i}$ = 0.164 kWh/km and 0.125 kWh/km and $BC_c^{i}$ = 40 and 16 kWh, respectively). It can be seen in Fig. 13 that using the rated/fixed values of $R_c^{i}$ and $BC_c^{i}$ for each vehicle compute 13.4% higher value of ESC in the peak hours. We conclude that considering deterministic values of stochastic parameters leads to an inaccurate estimation of ESC.

5 Sensitivity analysis

This section presents the sensitivity analysis of parameters that effect the aggregated ESC of EVs in the SCPLs. Following is a list of those parameters:

(i) Availability of EVs (as a function of arrival/departure/ dwell time).
(ii) Rate of charging (as a function of charging power capacity).

The aggregated ESC of EVs was calculated by considering (i) 100% EVs in SCPL and (ii) 100% initial SOC of EVs at the point of departure is considered as the base-case.

5.1 Availability of EVs

The arrival/departure pattern and dwell time of vehicles in the PLs is dependent on EV usage and travel preferences of EV owners. Simulation is done by changing the arrival pattern of EVs (i.e. $\sigma_p = 0.293$ and $\mu_p = 2.45$) and the resulting aggregated ESC is shown together with the base case in Fig. 14. The deviation of ESC with the base case is shown in the shaded area. It seems clear that the arrival/departure pattern and dwell time significantly shifts the time of availability and magnitude of ESC of EVs. If there is a need to shift the availability of ESC of EVs, the PLA can modify

Fig. 10 Aggregated ESC of EVs in SCPL

Fig. 11 Arrival and departure SOC of EV in WPL

Fig. 12 Hourly estimated ESC of EVs in WPL

Fig. 13 Effect of using deterministic values on ESC
It is very costly to install a single charger for each vehicle. If the PLA only wants to charge EVs then one charger for three EVs seems an economical option. However, if the PLA wants to participate in the electricity market, then a dedicated charger for each parking spot is needed. Simulation is performed by upgrading the rate of charging from 3.6 to 6.6 kW and its impact on ESC is shown together with the base case in Fig. 15. It can be observed that because of the presence of a large number of vehicles, the ESC increases 3–4% in the middle of the day. It is because of the shorter occupancy time of the vehicles in the SCPL. Moreover, we are not considering dumb charging so all vehicles are not charged at their maximum charging rate. So the available ESC is not increasing significantly. It can be inferred from Fig. 15 that small shift in charging rate (i.e. from 3.6 to 6.6 kW) does not have a considerable impact on the ESC, but DC fast charger may significantly affect the ESC.

6 Discussion

It can be observed that the maximum available ESC in SCPL is 61.9% of the maximum ESC of SCPL and in WPL, the maximum ESC available is 26.4 MWh, i.e. 66% relative to maximum ECS of WPL. However, PLA cannot utilise all of the available ESC due to charger limitation. In this paper, level 2 charge of 3.6 kW was considered for each EV. So, the maximum ESC that can be utilised in SCPL and WPL is 16.2 and 3.6 MWh, respectively. To fully utilise the available ESC, DC fast charger is needed. It is also observed that even the initial SOC of Nissan Leaf is 50%, it fulfils the daily travel requirement.

The results show that the individual vehicle occupancy time duration for the WPL is higher and more predictable compared to the SCPL. However, the aggregated energy storage capability in the SCPL is significantly higher compared to the WPL for a given day. It could be inferred that the SCPL compensates the variability of vehicle occupancy with its higher aggregated energy storage capability. The SCPL is also capable of providing aggregated energy storage services after office (Workplace) hours. Moreover, the peak ESC per parking space in both PLs is approximately similar, despite the difference in occupancy pattern, usage, the magnitude of PL and number of vehicles visit per day. In terms of availability of aggregated ESC, we concluded that SCPL is a more promising resource of energy storage for VPP compared with WPL.

The activation of ancillary services is stochastic and will have a significant impact on the estimation of the ESC of EVs in the PLs. However, the main objective of this paper is limited to estimating the potential energy available in PLs to support the electrical network. Currently, we do not have real data to model the ancillary services activation behaviour in the context of uncertain aggregated energy resources. However, modelling ancillary services requirements and its impact on ESC estimation will be considered in future work.

7 Conclusion

A generic model incorporating five stochastic variables for estimating the aggregated storage capacity and charge available (or needed) in PLs with EVs was presented. Real HTS data and shopping centre occupancy data were used to provide realistic measures of uncertainty for each parameter. The model should assist planning and optimisation of future grids with high penetrations of EVs.

Results showed that the estimated aggregate storage capacity of PLs closely follows the occupancy of EVs and is relatively insensitive to the charging rate. However, stochastic modelling reduced the estimated peak storage capacity by 13.4% relative to deterministic modelling. It was also found that the average peak storage capacity per PL space was almost independent of the use case, despite significant differences in period for which individual vehicles were parked. Consequently, shopping centre car parks were found to be potentially significant candidates for providing aggregated services to the grid, with their scale and throughput compensating for the lower occupancy.

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