Estimation of Vehicle-to-Grid Service Capacity at Business Premises Using Aggregate Model

Md Shariful Islam, Junainah Sardi, Awan Krismanto, N. Mithulananthan
School of Information Technology and Electrical Engineering
The University of Queensland
Brisbane, Queensland
m.islam1@uq.edu.au, j.sardi@uq.edu.au, a.krismanto@uq.edu.au, mithulan@itee.uq.edu.au

Abstract*—Large number of electric vehicles (EV) at the same location can act as energy storage to provide various vehicle-to-grid (V2G) services, such as participating in energy arbitrage and providing ancillary services to the grid. The bulk of the existing V2G capacity models is intended for home charging that mainly considers the parameters related to the arriving EV population only. However, a significant EV population is expected to be charged at business premises (e.g., office, university, hospital, shopping mall, etc.) during the daytime. Since the duration of stay is relatively low at business premises compared to home charging, the parameters associated with the departing EV population and willingness to provide V2G service in addition to those related to arriving EV population could play a pivotal role in the V2G capacity. Therefore, this paper proposes a V2G capacity model by incorporating these aspects. The proposed model has been applied and tested on the University of Queensland Parking lots, which shows that the V2G capacity calculated using the proposed model can be significantly different from that calculated from the conventional models in regards to parameters related to the willingness factor.

Keywords— aggregate EV model; business premises; service capacity; vehicle-to-grid (V2G); willingness factor.

I. INTRODUCTION

Electric vehicles (EVs) have shown great potential in lowering the greenhouse gas (GHG) emission, which can halt the growth on the global warming [1]. Governments and various bodies across the world have taken the cognizance of this promise and accordingly, have been promoting the proliferation of the EVs through enacting legislation and policies [2]. In addition to these long-term benefits, EVs can cater many immediate remunerations as well as they can enable various technical capabilities. Vehicle-to-grid (V2G) service is one of such frequently advocated technical capabilities that can be enabled under the currently enforced grid frameworks [3]. The V2G includes services ranging from arbitraging energy in the market to providing ancillary services such as frequency and voltage support [4]. For the purpose, an EV population can be lumped together under the control of an aggregator, which can act as a big virtual energy storage [5]. The aggregator can control the charging and discharging (V2G) of the aggregated EV population under the instructions of the grid owner regarding the grid constraints and costs. However, to be able to control the charging and discharging efficiency, the grid and aggregator must develop a foreknowledge about the aggregated charging and discharge (V2G) power capacities.

In one of the precursors of the V2G capacity evaluation methods, authors in [6] have shown how a single EV can communicate with the grid to provide V2G service. In addition, they have given a detailed account of all the costs involved in this process. However, given the minuscule capacity of the energy and power of a single EV, an aggregator would require a large EV population to be able to provide a tangible amount of V2G capacity. As such, the authors in [7] have employed the queuing theory in conjunction with an exponential load demand model for evaluating the V2G capacity for a large EV population. Though different samples of the parameters related to arriving and departing of EV population have been incorporated in this model, the diurnal evolution of the EV load demand with respect to the arriving and departing EV population, and delivered power has not been considered. In [8], the authors have proposed that the V2G capacity is proportional to the number of units in the EV population. However, contrarily, the achievable V2G capacity depends not only on the number of EVs but also on their combined state of charge (SOC). The SOC, on the other hand, sturdily hinge on the parameters associated with the arriving and departing EV population, and delivered SOC by the chargers [9]. Though the V2G capacity, therefore, is largely delimited by these parameters, they have not been encompassed in [8]. In addition, these V2G capacity models in [6-8] are intended for home charging only.

In contrast, the evolution of SOC regarding the arriving and departing EV population, and delivered SOC has been taken into account for V2G capacity models for both home and business charging in [10]. However, the charging and discharging of the EV population have been proposed to be controlled individually, which could be computationally costly for a large EV population [11]. To eradicate such shortcoming, an aggregate model incorporating the arriving EV population has been proposed for the home charging in [12]. However, the nature of the aggregate model has not been explicitly mentioned in that work. Moreover, neither the departing EV population nor the business charging has been considered. In addition, the willingness to provide the V2G service has not reflected in the V2G capacity models in [6-8, 10, 12].

Therefore, an aggregate V2G capacity model is proposed in this paper for business charging by taking into account the di-

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urnal evolution of the aggregate SOC of the EV population. The diurnal evolution of the aggregate SOC is estimated with respect to the parameters associated with the diurnal arriving and departing EV population, delivered SOC and willingness to provide V2G service.

The rest of the paper is organized as follows: an overview of the proposed methodology is outlined in Section II. The V2G capacity model by incorporating the diurnal evolution of the aggregated SOC is depicted in Section III. A case study is carried out on the University of Queensland (UQ) parking lots in Section IV. Finally; the concluding remarks are presented along with the future directions of this works in Section V.

II. Overview of the Methodology

Fig. 1 briefly illustrates the overview of the method proposed in this paper. The time horizon is first divided into equally spaced timeslots (samples). The aggregate SOC is updated at the beginning of each sample by taking into account the aggregate SOC of the previous sample and the departing and arriving EV populations as well as the willingness to provide the V2G services. Each sample is then divided into equally spaced sub-samples. A charging/discharging strategy decides whether a certain EV should charge or discharge in a given sub-sample based on its SOC. The V2G capacity is calculated on the basis of this decision, and the aggregate SOC is updated accordingly.

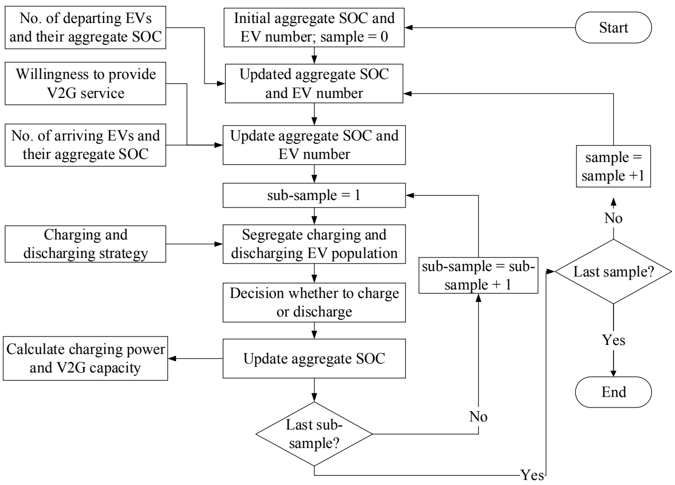

Fig. 1. Overview of the proposed methodology.

III. Methodology

Let, the time horizon, 24 hours, in this case, be divided into $24/T_S$ equally spaced timeslots with spacing T_S and indexed by k. In addition, let, T_S be subsequently divided into T_S/T_C equally spaced sub-timeslots and indexed by j. Since the V2G capacity depends on the aggregate SOC and number of EV, their evolution through time horizon must be dynamically updated with respect to the arriving and departing EV population, willingness to provide the V2G services and delivered SOC as in Fig. 1. For the purpose, the aggregate SOC and number of EV are updated after every T_S hour, while the charging and discharging (V2G) powers are dispatched, and subsequently, only the aggregate SOC is updated for every T_C hour. Suppose, X denotes the aggregate SOC of the EV population. Its value for the k-sample (X_k) is the dynamically weighted summation of the arriving ($X_{A,k}$) and departing ($X_{D,k}$) aggregate SOC and delivered SOC ($X_{del,k}$). Referred to Fig. 1, the probability density function (PDF) of X_k is contingent on X_{k-1}, $X_{A,k}$, $X_{D,k}$ and $X_{del,k}$. According to the authors in [13], the SOC PDF of a single EV follows a Lognormal distribution. Therefore, the aggregate PDF of the initial SOC (X_0) must also be a Lognormal distribution. Likewise, the practical arrival and departure aggregate SOC data provided in [14] show that they can be fitted by Lognormal PDFs too. Therefore, if $X_{del,k}$ is constant or Lognormal, X_k can be approximately presented by a Lognormal for all the timeslots. The diurnal evolution of such a Lognormal X_k and the evolution of the number of EV (N_k) are updated as follows.

A. Updating X_k and N_k after departure

Suppose, the aggregate SOC just before the departure of $N_{D,k}$ number of EVs be denoted by $X_{k\text{-}}$. If the probability that the i-th EV with SOC $x_{k\text{-},i}$ will not depart is given by $p_{k\text{-},i}$, the mean (μ_k) and variance (σ_k^2) of aggregate SOC X_k can be updated as

$$\mu_k = \frac{\sum_{i=1}^{N_{k-1}} \left(p_{k-,i} x_{k-,i}\right)}{\sum_{i=1}^{N_{k-1}} p_{k-,i}}; \sigma_k^2 = \frac{\sum_{i=1}^{N_{k-1}} \left[p_{k-,i}\left(1-p_{k-,i}\right)\left(x_{k-,i}-\mu_{k-1}\right)\right]^2}{\sum_{i=1}^{N_{k-1}} \left[p_{k-,i}\left(1-p_{k-,i}\right)\right]}. \quad (1)$$

Equation (1) can be solved in closed-form as

$$\begin{aligned} \mu_k &= e^{m_{k-}+0.5 s_{k-}^2+\rho_{k-} s_{k-} s_{p,k-}} \\ \sigma_k &= \sqrt{e^{2 m_{k-}+s_{k-}^2+\rho_{k-} s_{k-} s_{p,k-}}\left(e^{s_{k-}^2+\rho_{k-} s_{k-} s_{p,k-}}-1\right)} \end{aligned} \quad (2)$$

where, $\rho_{k\text{-}}$ is the bias of $p_{k\text{-},i}$ towards higher SOC and it remains within the range of -1 to +1; usually it should attain a negative value, i.e., an EV with lower SOC will be more likely to stay at the charging facilities to consolidate the SOC; and

$$m_{k-} = \ln\left(\frac{\mu_{k-}^2}{\sqrt{\mu_{k-}^2+\sigma_{k-}^2}}\right); s_{k-} = \sqrt{\ln\left(\frac{\sigma_{k-}^2}{\mu_{k-}^2}+1\right)};$$
$$s_{p,k-} = \sqrt{\ln\left(\frac{\sigma_{p,k-}^2}{\mu_{p,k-}^2}+1\right)}$$

where, the mean ($\mu_{p,k\text{-}}$) and standard deviation ($\sigma_{p,k\text{-}}$) of $p_{k\text{-},i}$ is calculated as

$$\begin{aligned} \mu_{p,k-} &= \frac{1}{N_{k-1}} \sum_{i=1}^{N_{k-1}} p_{k-,i} = \frac{N_{k-1}-N_{D,k}}{N_{k-1}} \\ \sigma_{p,k-} &= \sqrt{\frac{1}{N_{k-1}} \sum_{i=1}^{N_{k-1}} \left(p_{k-,i}-\mu_{p,k-}\right)^2}. \end{aligned}$$

It is noted that though the values of $m_{k\text{-}}$ and $s_{k\text{-}}$ can be estimated directly from the EV population, that of $s_{p,k\text{-}}$ and $\rho_{k\text{-}}$ cannot be calculated separately in a similar manner. However, if the relevant historical data are supplied in advance, their product $s_{p,k-}\rho_{k-}$ can be estimated using (2). Nonetheless, it has been assumed that $s_{p,k-}$ and ρ_{k-} are known in this paper. On the other hand, the EV number (N_k) is updated as

$$N_k = N_{k-1} - N_{D,k} = \mu_{p,k-} N_{k-1}. \tag{3}$$

The updated X_k and N_k are used in the next step in Section IIIB.

B. Updating X_{k+} and N_{k+} after arrival

Out of $N_{A,k}$ arriving EVs with an aggregate SOC of $X_{A,k}$, only a portion of it would be willing to provide the V2G service. Let, the willingness factor that the i-th EV with an arriving SOC $x_{A,k,i}$ will be willing to provide the V2G service be given by $w_{k,i}$. Then, the mean ($\mu_{W,k}$) and variance ($\sigma_{W,k}^2$) of aggregate SOC $X_{W,k}$ of the willing EV population can be updated as

$$\mu_{W,k} = \frac{\sum_{i=1}^{N_{A,k}} \left(w_{k,i} x_{A,k,i} \right)}{\sum_{i=1}^{N_{A,k}} w_{k,i}}; \sigma_k^2 = \frac{\sum_{i=1}^{N_{A,k}} \left[w_{k,i} \left(1 - w_{k,i}\right)\left(x_{A,k,i} - w_{k,i}\right) \right]^2}{\sum_{i=1}^{N_{A,k}} \left[w_{k,i} \left(1 - w_{k,i}\right) \right]}. \tag{4}$$

Equation (4) can be solved in closed-form as

$$\begin{aligned} \mu_{W,k} &= e^{m_{A,k} + 0.5 s_{A,k}^2 + \rho_{W,k} s_{A,k} s_{W,k}} \\ \sigma_{W,k} &= \sqrt{e^{2m_{A,k} + s_{A,k}^2 + \rho_{W,k} s_{A,k} s_{W,k}} \left(e^{s_{A,k}^2 + \rho_{W,k} s_{A,k} s_{W,k}} - 1 \right)} \end{aligned} \tag{5}$$

where, $\rho_{W,k}$ is the bias of $w_{k,i}$ towards higher SOC and it remains within the range of -1 to +1; usually it should attain a positive value, i.e., an EV with higher arriving SOC will be more willing to provide V2G service; and

$$m_{A,k} = \ln\left(\frac{\mu_{A,k}^2}{\sqrt{\mu_{A,k}^2 + \sigma_{A,k}^2}} \right); s_{A,k} = \sqrt{\ln\left(\frac{\sigma_{A,k}^2}{\mu_{A,k}^2} + 1 \right)};$$
$$s_{W,k} = \sqrt{\ln\left(\frac{\sigma_{W,k}^2}{\mu_{W,k}^2} + 1 \right)}$$

where, the mean ($\mu_{W,k}$) and standard deviation ($\sigma_{W,k}$) of $w_{k,i}$ is calculated for the willing EV number $N_{W,k}$ as

$$\mu_{W,k} = \frac{1}{N_{A,k}} \sum_{i=1}^{N_{A,k}} w_{k,i} = \frac{N_{W,k}}{N_{A,k}}$$
$$\sigma_{W,k} = \sqrt{\frac{1}{N_{A,k}} \sum_{i=1}^{N_{A,k}} \left(w_{k,i} - \mu_{W,k} \right)^2}$$

It is noted that though the values of $m_{A,k}$ and $s_{A,k}$ can be estimated directly from the arriving EV population, that of $s_{W,k}$ and $\rho_{W,k}$ cannot be calculated separately in a similar manner. However, if the relevant historical data are supplied in advance, their product $s_{W,k}\rho_{W,k}$ can be estimated using (5). Nonetheless, it has been assumed that $s_{W,k}$ and $\rho_{W,k}$ are known in this paper. On the other hand, the willing EV number ($N_{W,k}$) is updated as

$$N_{W,k} = \mu_{W,k} N_{A,k}. \tag{6}$$

Therefore, the mean (μ_{k+}) and standard deviation (σ_{k+}) of the aggregate SOC of the EV population (X_{k+}) after updating the arriving EV population is given by (7). Here, the assumption is that X_k and $X_{A,k}$ are uncorrelated.

$$\begin{aligned} \mu_{k+} &= \mu_k \frac{N_k}{N_k + N_{W,k}} + \mu_{W,k} \frac{N_{W,k}}{N_k + N_{W,k}} \\ \sigma_{k+} &= \ln\left[\frac{e^{\left[2m_k + 2\ln\left(\frac{N_k}{N_k + N_{W,k}}\right) + s_k^2\right]} + e^{\left[2m_{W,k} + 2\ln\left(\frac{N_{W,k}}{N_k + N_{W,k}}\right) + s_{W,k}^2\right]}}{\left(e^{\left[m_k + \ln\left(\frac{N_k}{N_k + N_{W,k}}\right) + \frac{s_k^2}{2}\right]} + e^{\left[m_{W,k} + \ln\left(\frac{N_{W,k}}{N_k + N_{W,k}}\right) + \frac{s_{W,k}^2}{2}\right]} \right)^2} + 1 \right] \end{aligned} \tag{7}$$

where,

$$m_k = \ln\left(\frac{\mu_k^2}{\sqrt{\mu_k^2 + \sigma_k^2}} \right); s_k = \sqrt{\ln\left(\frac{\sigma_k^2}{\mu_k^2} + 1 \right)};$$
$$m_{W,k} = \ln\left(\frac{\mu_{W,k}^2}{\sqrt{\mu_{W,k}^2 + \sigma_{W,k}^2}} \right); s_{W,k} = \sqrt{\ln\left(\frac{\sigma_{W,k}^2}{\mu_{W,k}^2} + 1 \right)}.$$

The EV number (N_{k+}) is updated as

$$N_{k+} = N_k + N_{W,k}. \tag{8}$$

The V2G capacity is estimated based on these updated values in (7) – (8) with the help of a charging strategy in Section IIIC.

C. Estimating V2G capacity with the help of a charging strategy

As discussed at the beginning of this section, the time between two samples k and $k+1$ (i.e. T_S) is now divided into T_S/T_C sub-timeslots and the charging and discharging is successively performed in these sub-timeslots and μ_{k+} and σ_{k+} are updated accordingly. The updated μ_{k+} and σ_{k+} for the j-th sub-timeslot (i.e. sub-sample) are, respectively, denoted by $\mu_{k,j}$ and $\sigma_{k,j}$. An aggregate SOC based charging strategy is proposed in this paper based on $\mu_{k,j}$ and $\sigma_{k,j}$ as in Fig. 2. This strategy guarantees that the EV population that is departing at the beginning of the next timeslot (i.e., $k+1$-th timeslot) will be delivered with a minimum SOC of $X_{Des,del}$. That is the mean of arrival SOC will be increased by $X_{Des,del}$ during the duration of stay at the charging facilities. The mean ($\mu_{Des,del}$) of $X_{Des,del}$ can be dynamically optimized with respect to the grid constraints and costs. However, in this paper, it is assumed that $\mu_{Des,del}$ is predefined and calculated using (9).

$$\mu_{Des,del} = \frac{d_d}{d_R} \times 100. \tag{9}$$

where, d_d and d_R, respectively, are the daily driving distance and the driving range of EV. Thus, the V2G power ($P_{k,j}$) can be estimated as per Fig. 2 using (10).

$$P_{k,j} = \int_{x_{k,j}=\mu_A+\mu_{Des,del}}^{\infty} u_{1,k,j} P_C N_{k+} dx_{k,j}, \forall x_{k,j} \in X_{k,j} \tag{10}$$

where P_C is the rated charging power permitted by the EV charger in the stipulated level of charging [15]; and

$$u_{1,k,j} = \begin{cases} 1, & if\ discharging\ (V2G) \\ 0, & else \end{cases}; \begin{array}{l} \mu_A = Max\left(\mu_{A,k}\right), \forall \mu_{A,k} \\ X_{k,1} = X_{k+} \end{array}.$$

Equation (10) can be evaluated in closed-form as

$$P_{k,j} = u_{1,k,j} P_C N_{k+} \left[\frac{1}{2} - \frac{1}{2} erf\left(\frac{\ln\left(\mu_A + \mu_{Des,del}\right) - \mu_{k,j}}{\sqrt{2}\sigma_{k,j}} \right) \right] \tag{11}$$

where, *erf (…)* is an Error function, and its purpose is to calculate the value of the cumulative distribution function (CDF) for a given value of $x_{k,j}$ [16]. Due to the charging and discharging $\mu_{k,j}$ and $\sigma_{k,j}$ are going to evolve over the course of the timeslot between sub-sample *j*-th and *j+1*-th to $\mu_{k,j+1}$ and $\sigma_{k,j+1}$, and they are updated as

$$\mu_{k,j+1} = \frac{u_{2,k,j} P_C T_S}{0.01 B T_S} \left[\frac{1}{2} + \frac{1}{2} erf\left(\frac{\ln\left(\mu_A + \mu_{Des,del}\right) - \mu_{k,j}}{\sqrt{2}\sigma_{k,j}} \right) \right] + \frac{u_{1,k,j} P_C T_S}{0.01 B T_S} \left[\frac{1}{2} - \frac{1}{2} erf\left(\frac{\ln\left(\mu_A + \mu_{Des,del}\right) - \mu_{k,j}}{\sqrt{2}\sigma_{k,j}} \right) \right] + \mu_{k,j} \tag{12}$$

$$\sigma_{k,j+1} = \sigma_{k,j};$$

where, B is the battery capacity and $u_{2,k,j}$ is defined as

$$u_{2,k,j} = \begin{cases} 1, & if\ charging \\ 0, & else \end{cases}.$$

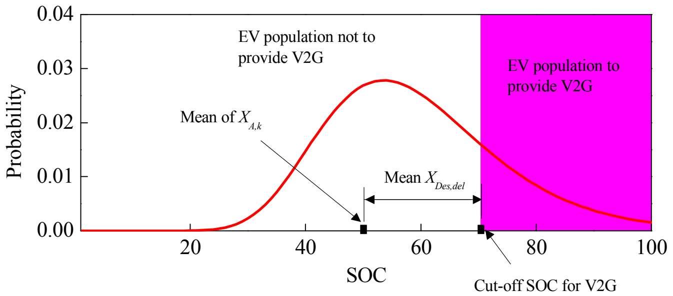

Fig. 2. An aggregate SOC based charging and discharging (V2G) strategy.

It is worthwhile to mention that the values of $u_{1,k,j}$, $u_{2,k,j}$, and $\mu_{Des,del}$ have to be set optimally. This, however, entails elaborate mathematics optimization problem which has not been deemed as the part of the scope of this paper and left for the future works. The $\mu_{k,j+2}$ and $\sigma_{k,j+2}$ are then updated similarly until the last sub-sample has been reached. Their updated values for the last sub-samples are then assigned as μ_{k+1-} and σ_{k+1-} and the entire methodology in Sections IIIA – IIIC are repeated until the last sample has been reached.

IV. Case Study

The proposed methodology to estimate the V2G capacity has been tested on the parking lots of the University of Queensland (UQ), St Lucia campus.

A. Inputs and Assumptions

UQ, St Lucia campus has a combined parking capacity of 4,800 parking spots [17]. The strength of the diurnal arriving and departing populations and the total strength of the diurnal EV population are depicted in Fig. 3. The other assumption made regarding Fig. 3 is that the penetration level of EV is 100%. The values of various parameters required in (1) – (12) are tabulated in Table I. Among these values, μ_{0-}, $\mu_{A,k}$, σ_{0-}, and $\sigma_{A,k}$ have been collated from [14]. The values of d_d, d_R, P_C, and B have been obtained from [15]. The other values have been appropriately chosen. The values of the remainder of the parameter that are not presented in Table I are dynamically derived from the values presented in Table I.

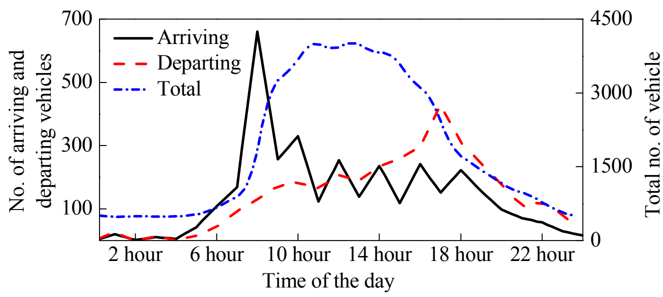

Fig. 3. The number of arriving, departing and total vehicles at UQ [17].

TABLE I. Various Paramters Required in (1) – (12)

Parameter	Value	Parameter	Value	Parameter	Value
ρ_{k-}	- 0.20	$\rho_{W,k}$	0.20	μ_{0-}	70%
σ_{0-}	28%	$\mu_{A,k}$	70%	$\mu_{W,k}$	0.6
$\sigma_{p,k-}$	0.20	$\sigma_{A,k}$	28%	$\sigma_{W,k}$	0.20
d_d	36.2 km	d_R	190 km	P_C	3.3 kW
B	27 kWh	T_S	¼ hour	T_C	1/60 hour

B. Results

The diurnal V2G capacity ($P_{k,j}$) for the UQ parking lots has been calculated as per (11) using the inputs as in Section IVB and depicted in Fig. 4. It can be observed from Fig. 4 that the V2G capacity closely resembles with the total diurnal EV number profile in Fig. 3. The other observation is that the peak V2G capacity can be achieved during 12 pm to 4 pm. However, it will be seen later that this peak hour could be altered by changing the values of the parameters in Table I.

To illustrate the significance of the proposed V2G capacity model, the V2G capacity for the conventional model is calculated and compared with that of the proposed model in Fig. 5. The conventional model can be defined as the model which considers that every EV will be willing to provide the V2G service with 100% certainty, i.e., $w_{k,I}$ = 1. This renders $\mu_{W,k}$ and $\sigma_{W,k}$, respectively, to 1 and 0 as per (5). In addition, $\rho_{W,k}$ becomes 0. Moreover, the conventional model assumes that every EV is equally likely to stay (or leave) at the charging facilities during the charging period, which results in the values of ρ_{k-} and $\sigma_{p,k-}$ becoming 0 too. Fig. 5 shows that the V2G capacity for the proposed method could be completely different compared to that for the conventional method. It will be seen later that this difference could magnified manifold depending on the values the parameters in Table I, which underscores the importance of the proposed method. Also, notice that conventional method overestimates the V2G capacity.

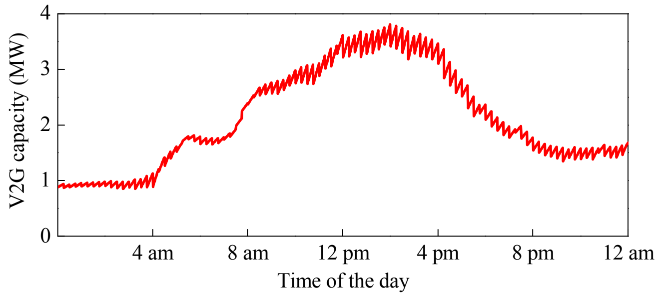

Fig. 4. The diurnal V2G capacity of UQ parking lots.

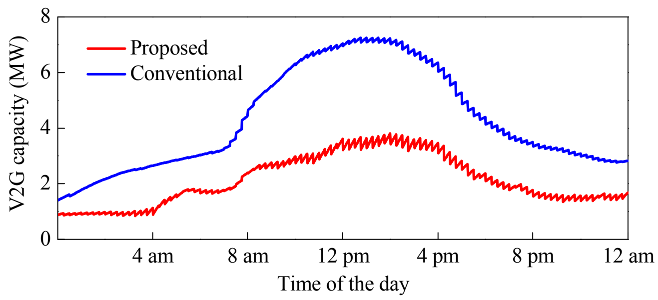

Fig. 5. The diurnal V2G capacity of UQ parking lots for the proposed method compared with that for a conventional method.

As per (11), $X_{Des,del}$, which is quantitatively estimated as (9) plays a major role in the V2G capacity estimation. To investigate its impact on the V2G capacity, its value is varied by a factor of 1.25 and 0.75, and the resulting V2G capacities are compared with the findings of Fig. 4 as in Fig. 6. The other involved parameters have been kept unchanged during this exercise. This figure shows that V2G capacity can be increased or decreased, respectively, by decreasing and increasing the value of $X_{Des,del}$. However, altering the value of $X_{Des,del}$ could alter the value of the quality of charging service (QoS) defined in [18, 19], in many cases, unfavorably. Such unfavorable QoS could be rendered as technically and economically infeasible [19]. Therefore, $X_{Des,del}$ must be optimized dynamically with respect to the costs involved and required QoS. However, it has been deemed as beyond the scope of this paper.

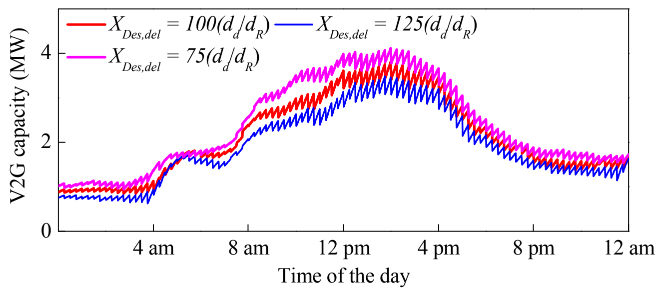

Fig. 6. Diurnal V2G capacities of UQ parking lots for various $X_{Des,del}$.

Among other parameters, the willingness factor ($\mu_{W,k}$), which is calculated as per (5), is one of the cornerstones of the proposed model. Referred to Fig. 4, the V2G capacities have been estimated for the proposed method for $\mu_{W,k}$ = 0.6. Therefore, this part of the exercise is carried out for $\mu_{W,k}$ = 0.4 and $\mu_{W,k}$ = 0.8 to calculate the respective V2G capacities, and compared with the findings in Fig. 4 in Fig. 7. The values of the other parameters involved are kept unchanged for this sensitivity analysis of the willingness factor. It can be observed from this figure that V2G capacity increases with respect to the augmented willingness factor, which can be perceived intuitively. However, the other observation from this figure is that the degree of increase of the V2G capacity is not exactly proportional to the willingness factor, which is counter-intuitive. Therefore, for accurate prediction of the day-ahead V2G capacity, the willingness factor must reflect in its employed model.

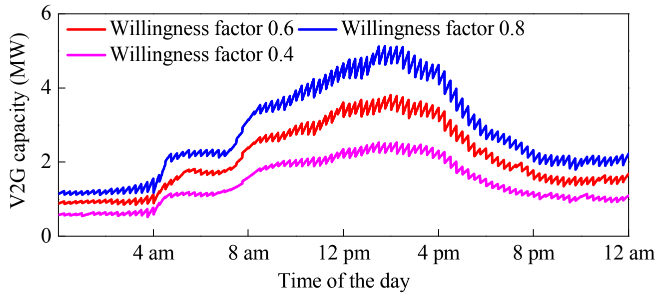

Fig. 7. Diurnal V2G capacities of UQ parking lots compared for various willingness factor.

Willingness to provide the V2G service may depend on various factors. One of the major factors that could influence the willingness factor is the state of the charge (SOC) of the EV. Intuitively, the EV with a higher SOC would be more willing to provide the V2G service. This bias of willingness towards higher SOC has been captured by the bias factor of willingness ($\rho_{W,k}$) in (5). Since the V2G capacity has already been calculated for a bias of willingness of 0.20 in Fig. 4, its values are further estimated for the values of bias of willingness of 0.00 and 0.10 and compared in Fig. 8. The values of other parameters have been imagined to have remained unchanged during these estimations. The results presented in this figure show that the V2G capacities are marginally different for different values bias of willingness. However, for the more accurate operation of the charging facilities, this factor must be incorporated into the V2G capacity model, which has not reflected in the conventional V2G capacity models.

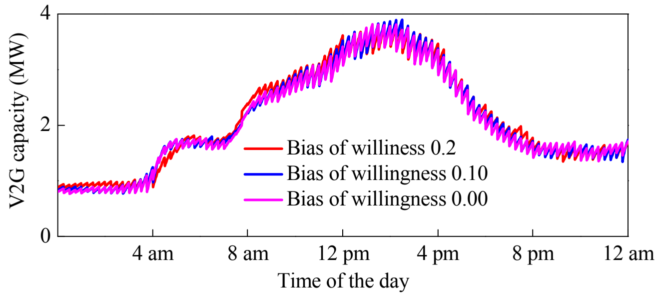

Fig. 8. Diurnal V2G capacities of UQ parking lots compared for various values of bias of willingness.

Ideally, the EV with a lower SOC would be more inclined towards staying in the charging facilities to consolidate the SOC further. This inclination has been modeled by the bias of departure (ρ_{k-}) in (2). Intuitively, ρ_{k-} usually would take a negative or zero value during the charging. Since the V2G capacity has already been calculated for a value of – 0.2 in Fig. 4, its values for 0.00 and – 0.10 also have been calculated while keeping the other parameters unchanged as a part of the sensitivity analysis and compared in Fig. 9. This figure shows that the V2G capacity heavily depends on the value of bias of stay towards lower SOC. As such, the conventional V2G model, which assumes that there is no bias towards lower SOC (i.e., ρ_{k-} = 0.00) yields the highest amount of V2G capacity. The other observation is that the V2G capacity decreases with the increase of the bias towards lower SOC. Despite this momentous importance, the bias towards lower SOC has not been modeled in the conventional V2G capacity models, which further reinforces the importance of the proposed V2G capacity model.

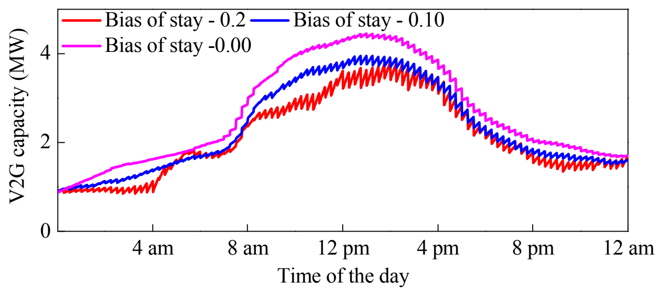

Fig. 9. Diurnal V2G capacities of UQ parking lots compared for various values of bias of departure.

V. Conclusions

Conventional V2G models have not comprehensively incorporated the parameters involved in arriving and departing EV population. Moreover, these models have not reflected the EV owners' willingness to provide the V2G services. In addition, various human traits such as the bias of willingness towards higher SOC and bias of consolidating charging towards lower SOC also have not been considered in any of these models. Therefore, a V2G capacity model has been proposed in this paper by encompassing these aspects of the EV charging. The proposed model has been tested on the parking lots of the University of Queensland (UQ). The obtained results show that these additional parameters can influence the achieved V2G capacity heavily, which underlines the importance of this proposed V2G capacity model.

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