Battery Energy Storage Sizing Method for Parking Lot Equipped with Electric Vehicles' Chargers

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Abstract—**Parking lots (PLs) equipped with electric vehicles (EVs) chargers will be the most convenient spot for EV users to charge their cars. However, there is a high degree of unpredictability around how the car parks are used, especially shopping centre parking lots (SCPL). Moreover, the cluster charging of EVs in the PLs may destabilise the grid. Application of battery energy storage system (BESS) in the PLs is considered a way to reduce the impact of EV charging on the grid. This work proposes an approach to estimate the size of the stationary BESS for the PLs in a constrained grid. At first, intermittent charging demand of EVs is constructed by considering travel pattern, charging need and driver's behaviour of EVs. Then, a region reduction method combined with non-linear optimisation is proposed to estimate the optimal size of BESS such that the capital cost and operational cost of the SCPL are minimised. The proposed sizing method ensures 1) the maximum utilisation of the stationary BESS, 2) avoid over/under-sizing, 3) reduce the operational cost, 4) and maintain the reliability of the system. The applicability of the proposed method is shown by simulating different cases, characterised by real household travel survey data and shopping centre car park occupancy data.**

Keywords— Electric vehicle, Battery Energy Storage, Constrained grid, Shopping Centre Parking lots.

Indices

h	Hour
i	Electric vehicle index

Variables and Parameters

BC^i	Rated battery capacity of i^{th} EV.
KM^i	Distance travel by i^{th} EV in single charge.
A^i & D^i	Arrival & Departure time of i^{th} EV.
T^i_{charge}	Time required to fully charged the i^{th} EV
P^i_{charge}	Rate of charging required for i^{th} EV.
D_{max}	Max distance travel by EV in single charge.
E^h_{ev}	Aggregated hourly charging demand of EVs.
R^i	Energy consumed per kilometre by i^{th} EV.
Δ_g	Reduction in PLO tariff in percentage.
E^i	Energy required to fully charge the i^{th} EV.
$L^{i,h}_{EV}$	Hourly charging load of i^{th} EV.
η_{chrg}	Efficiency of the EV charger.
soc^h_B	Instantaneous SOC of the battery.
η_{cvtr}	Efficiency of the converter.
E^h_b	Energy supply/absorb from the battery.
B^h_{deg}	Degradation of battery.
BC_{req}	Required battery capacity.
P^h_{spv}	Output power of single PV panel.
G_{std}	Standard coefficient for solar irradiance.
T_{std}	Standard coefficient for temperature.
T^h_c	Hourly internal cell temperature of PV.
α_t	Temperature coefficient.
η_{inv}	Efficiency of inverter.
P_{peak}	Peak power of a PV panel.
G^h	Hourly solar irradiance.
$NOCT$	Normal operating cell temperature.
V_{FOR}	Decision variable for FOR.
V_{cld}	Decision variable for cloud effect.
r	Random number $\in (0,1]$.
E^h_{pv}	Hourly solar PV system output
N_{PV}	Number of installed PV panels.
S_A	Total available area in PL for PV installation.
α_{PL}	Percentage of shaded area in the PL.
S_{pv}	Area occupied by single PV panel.
E_{error}	Error between EV load and energy resources.
E^h_g	Hourly energy consumed/ supply to grid.
E_{max}	Maximum BESS capacity needed for PL.
BC_{up}	Updated battery capacity.
X_{min}	Minimum boundary of the solution.
X_{max}	Maximum boundary of the solution.
k	Decision variable for calculating BC_{up}.
$C^h_{b,deg}$	Cost of battery degradation.
C^h_{grid}	Cost of energy purchase/sell to grid.
$C^h_{b,capital}$	Capital Cost of optimal battery capacity.
$C^h_{ev,chg}$	Revenue for charging electric vehicles.
α_{cp}	Hourly value of capital cost of battery.
$capb$	Battery degradation cost per cycle.
E^h_{dis}	Instantaneous discharging power of battery.
$\vartheta(\rho_{(c/d)})$	Battery degradation factor.
γ^h	Absolute value of the BESS power.
N_{life}	Life of the battery.
λ	Charger rating (charging/discharging limit).
C^h_P	Time of use tariff.
C^h_S	Tariff for EVs charging offered by PLO.
U_{cost}	Unit cost of the BESS.
δ	Grid power constrained.

E_{chg}^{h} Instantaneous charging power of BESS.
N_c Total number of cars visited per day.

Abbreviation

BESS	Battery Energy Storage System
EV	Electric Vehicle
FOR	Force Outage Rate
HTSD	Household Travel Survey Data
PLO	Parking Lot Operator
SCPL	Shopping Centre Parking Lot
SOC	State of Charge

I. INTRODUCTION

The greenhouse gas emission is a great challenge for the environment and human life. Many countries are electrifying their transportation to reduce co_2 emissions [1]–[3]. Eco-friendly nature of electric vehicles makes it a viable source of commuting [4]. People spend most of their time at the workplace, shopping centre and homes [5]. It is expected that the rapid increase in the market participation of EVs will change the parking lots (PLs) into a charging station. Instead of going to the dedicated EV charging stations, it will be more convenient for EV owners to charge their vehicles in the PLs associated with workplaces, shopping centres, and homes.

EVs are mobile loads and difficult to estimate. The arrival and departure times of the EVs as well as the occupancy patterns depend on where they are parked. For example, workplace or home parking lots usually have periodic and well-defined arrival and departure times. Typically, people spend an extended amount of time at their workplaces and homes [5]. Conversely, in shopping centre parking lot (SCPL), the arrivals and departures of vehicles are scattered throughout the day, and vehicles stay for a very short period. Moreover, EV charging behaviour entirely depends on its random usage, EV owner's behaviour and travel needs. To convert PLs into an EV charging station, it is essential to accurately estimate the charging behaviour of EVs. Significant research efforts have been made focusing workplace and home EV parking lots [6]–[8]. However, to the best of authors' knowledge, the estimation of EV charging patterns in SCPLs have not been investigated yet.

Economic scheduling of EV charging at SCPL is challenging due to shorter occupancy time of vehicles. Moreover, on arrival, EV gets connected into the charger and start charging at their maximum charging rate. This opportunistic/cluster charging of EVs in SCPL contributes to increasing the peak demand of the electrical system [9]. The increase in load adversely impacts systems' reliability. A constrained power grid is a feasible solution to maintain the reliability of the power system [10]. In a constrained grid, the system operator specifies the power limit, so, in any given time, the grid cannot supply more than specified power to the load. So, the parking lot operator (PLO) must flatten their charging demand according to the power constraint enforced by the grid. However, PLO is interested in fulfilling the charging requirement of each vehicle, without reducing their energy consumption. In this context, a stationary BESS can be used to provide energy when needed and recharge itself in off-peak hours. Even though the advancement to improve the efficiency and lifetime of BESS make it a feasible solution for peak shaving. However, high capital cost for implementing the BESS still a primary concern for PLO [11]. Moreover, there is a high degree of unpredictability around how car parks are used. It is challenging for PLO to decide what BESS is required to meet the intermittent charging demand of EVs. Over-sizing of BESS may not achieve cost-benefit ratio, and under-sizing will create reliability issues. Therefore, the correct size of BESS is the essential aspect in designing of SCPL containing charging infrastructure for EVs.

Several studies have been conducted to estimate the optimal capacity of BESS in the grid-connected system. For example, the authors in [12], [13] presented a probabilistic optimisation approaches for BESS to charge EVs in the fast-charging station. In [11], [14]–[17], an economical and reliable combination of photovoltaic, wind and energy storage system has been conducted. However, these studies did not consider the intermittency of renewable energy sources. The authors in [18], [19] develops a stochastic method to evaluate battery sizing by taking demand shift capability into account. However, it overlooked the uncertainty in the household load profile. The authors in [14] aim to find the optimal combination of PV, WT and BESS. However, their convergence criteria resulted the BESS to discharge below 95% depth of discharge (DOD). A comprehensive battery sizing model considering battery degradation is proposed in [15]. A BESS capacity is computed in the fast-charging station by formulating a relationship between waiting time of EV users and size of BESS [20]. In [21], [22], the authors developed a techno-economical sizing method for DC-micro grid by considering EV mobility on different charging stations but neglecting EV's driving pattern whiles estimating BESS sizing. To determine the charging behaviour of EVs, many authors considered deterministic model whereas EV charging load is entirely dependent on its variable usage. Authors in [23]–[25] neglected the effect of driving style on energy consumption per kilometre of EVs and EV's battery degradation in estimating EVs behaviour in PLs. Detailed EV modelling is still an issue in determining vehicle availability and EV's charging demand in the PLs

To conclude, many studies overlooked critical factors, for example the intermittency of renewable resources and EV load [3], [9], [17], some considered utility grid as an infinite bus [11], [13], many assumed fixed values of random parameters while estimating EV charging demand [4], [23], [25]. Moreover, methods presented in [12], [19], [26], [27] are computationally inefficient and taking long time to converge. As per authors' knowledge, an efficient sizing method for BESS to fulfil the intermittent EV charging demand in a constrained power grid at SCPL has not previously been reported.

This paper proposes an on-site grid-connected BESS sizing method for SCPL equipped with charging infrastructure of EVs in a constrained grid. The proposed method depends on the intermittent EV charging demand, photovoltaic (PV) output and grid power constraints. On the contrary to the literature that neglecting the uncertain behaviour of the above-mentioned factors. At first, a stochastic model is proposed to construct the EVs charging demand at SCPL and PV output. Then a region reduction method is introduced to reduce the search space for the optimisation problem. Based on the computed EV charging demand and PV output, an optimisation problem is formulated to calculate the optimal size of the stationary BESS, such that the capital cost and operational cost of the SCPL are minimised. In addition, the optimal tariff offered by PLO is computed. Detailed analyses and simulation results are presented with real data of household travel survey of Sydney region, weather data and parking lot occupancy data.

To conclude, the key contributions of this work are summarised as follows:

- Proposing a stochastic model to estimate the EVs charging behaviour in the SCPL by mapping each EV's parameter in an appropriate distribution with quantified uncertainty.
- Proposing an optimisation based sizing method combined with region reduction method to estimate the size of BESS and the optimal tariff for PLO.
- Study the impact of EV charging and grid power constraints on BESS sizing.

Different case studies are conducted to validate the efficacy and applicability of the proposed BESS sizing method.

The remainder of the paper is organised as follows: Section II describes the system overview, whilst section III presents the modelling of the available energy resources. The BESS sizing method is discussed in Section IV, Section V presents the results of the proposed method, and Section VI concludes the paper.

II. SYSTEM OVERVIEW

A. Parking Lot Architecture

The conceptual architecture of a PL is shown in Fig.1. The PL is equipped with charging/discharging infrastructure of EVs coupled with on-site BESS and PV systems. EVs are connected to a DC bus through control switches and DC-DC converters. The control switches allow PLO to schedule the charging and discharging of EVs. The main bi-directional power converter connects parking lots with the AC bus. Communication and control signal in-between BESS, EVs and utility grid help the PLO to manage the EV charging demand.

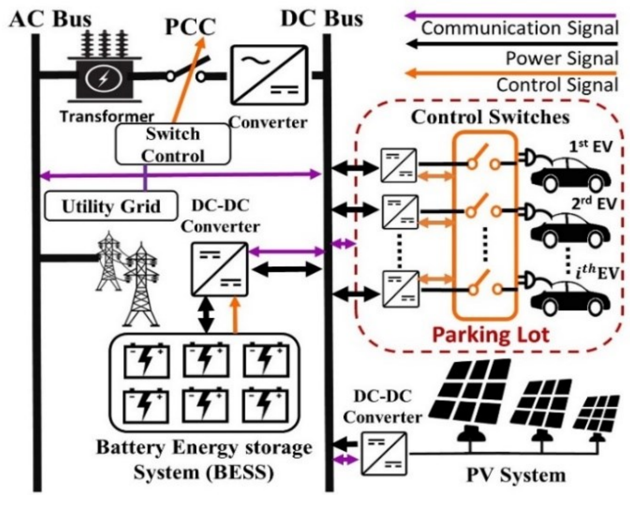

Fig. 1. Parking Lot architecture

B. Overview of the proposed BESS sizing method

The overview of the proposed BESS sizing method is illustrated in Fig. 2. The yearly power output from the PV system is calculated by using real weather data of the Sydney region. The arrival/departure pattern, charging behaviour and travel needs are emulated with probability distribution functions with quantified uncertainties. Then EV charging demand is calculated by using the proposed stochastic model. The search space for the optimisation problem is reduced by region reduction method. Then the BESS capacity to balance the EV load in a constrained grid condition is calculated by formulating an optimisation problem. The objective of the optimisation problem is to minimise the capital and operational cost of the system. Finally, economic analysis is conducted to estimate the economical and reliable BESS capacity for SCPL.

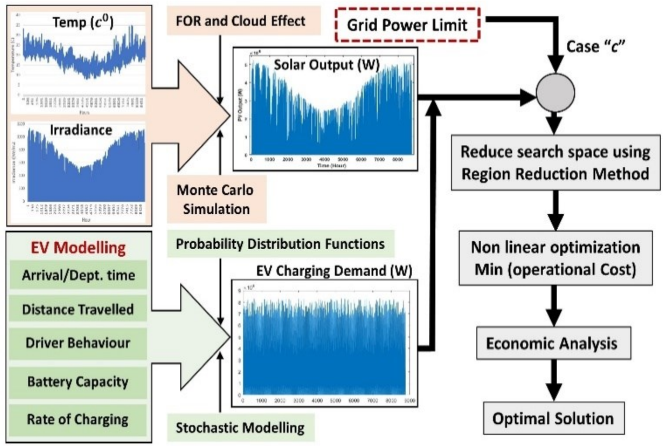

Fig. 2. Overview of the proposed BESS sizing method

III. SYSTEM MODELLING

A. EV Load Modelling

EVs are movable load, and its charging/discharging pattern depends on its random usage, travel need and driver's behaviour. In this work, EVs are characterised by five parameters (i.e. $A^i, D^i, BC^i, R^i, KM^i$). Refer to nomenclature for details on symbols used.

The aggregated occupancy time and arrival/departure pattern of vehicles in SCPL was modelled using hourly data collected from a nearby suburban shopping centre (the Macquarie Shopping Centre) and household travel survey data (HTSD). The HTSD is obtained from 25,443 people in 9,715 households across the state of new south wales (NSW) over a period of three years [5]. We analysed that on average, 17000 vehicles visited the SCPL per day (N_c). Out of 17000, more than 23% of vehicles were parked for less than 30 minutes, and almost 92% of vehicles departed within 3 hours. (Note: a parking fee applied for stays longer than 3 hours). The considered SCPL has a parking space for 4500 vehicles.

The arrival time A^i departure time D^i of EVs in the SCPL was best fitted with a log-normal distribution having means μ_p and standard deviation σ_p.

$$A^i = lognormal(\mu_p, \sigma_p) \quad \forall\, i \tag{1}$$
$$D^i = lognormal(\mu_p, \sigma_p) \quad \forall\, i \tag{2}$$

The values of mean μ_p and standard deviation σ_p for A^i and D^i are shown in Table 1.

Table 1: Statistical Parameters

Parking Lots	Arrival Time		Dept. Time	
	μ_p	σ_p	μ_p	σ_p
SCPL	11.5368	0.293	16.89	2.414

In this work, Nissan leaf 2018 is considered. The energy consumption per kilometer of EV (R^i) and battery capacity (BC^i) is significantly affected by EV usage and calendar aging. It is stated in [28], [29] that R^i varies up to 33% of its rated value and, BC^i degraded up to 12.1% of its rated capacity. The R^i, and BC^i were best fitted with truncated gumbel-min and normal distributions, respectively. The upper and lower limits of R^i and BC^i are listed in Table 2. In (3), $\mu_R = R_{min}$ and $\sigma_R = 7.034$ whereas, in (4) $\mu_B = BC_{max}$ and $\sigma_B = 0.4512$.

$$R^i = gumbel\ min(\mu_R, \sigma_R)_{(R_{min} \le R^i \le R_{max})} \tag{3}$$

$$BC^i = normal(\mu_B, \sigma_B)_{(BC_{min} \le BC^i \le BC_{max})} \tag{4}$$

Table 2. Electric vehicle specifications

EV Parameters	Nissan Leaf
R_{min}(kWh/km)	0.164
R_{max}(kWh/km)	0.219
BC_{min}(kWh)	36
BC_{max}(kWh)	40
D_{max} (km)	243
η_{chrg}	0.94

The daily travel pattern of the Sydney region is derived from HTSD [5]. We analysed that vehicles in NSW travel approximately 11650 kilometres per annum and about 88% of those vehicles drive less than 30 km per day, and approximately 95% of vehicles travel less than 45 km per day. These results are comparable to the travel patterns identified in other works [30]. The distance travelled KM_c^i by each vehicle was best fitted by a Weibull distribution with shape parameter ς_{MD} = 36 and scale parameter ν_{MD}= 4.9.

$$KM^i = Weibull(\varsigma_{MD}, \nu_{MD}); \quad \forall i \tag{5}$$

To calculate the charging load of EVs, we assumed that the travel patterns of EVs are the same as in the HTSD [5]. The energy consumed/required to charge the i^{th} EV while parked in the SCPL can be computed as

$$E^i = \begin{cases} BC^i & if\ KM^i = D_{max} \\ R^i * (KM^i / D_{max}), & otherwise \end{cases}, \forall i \tag{6}$$

A Level 2 EV charger (i.e. V = 240 V and A= 15 ampere) is used to charged EVs. With the help of (1)-(6) we are now able to estimate the EV charging demand ($L_{EV}^{i,h}$) in the SCPL.

$$L_{EV}^{i,h} = \sum_{A^i}^{\min(T^i_{charge}, D^i)} P^i_{charge}(h) * \eta_{chrg} \tag{7}$$

Here $T^i_{charge} = E^i / (P^i_{charge} * \eta_{chrg})$, and η_{chrg} is the efficiency of the charger and P_{charge}= 3.6 kW is the rate of charging of EVs. Equation (8) is used to aggregate the hourly charging demand of EVs.

$$E_{ev}^h = \sum_{i=1}^{N_c} \begin{bmatrix} L_{EV}^{1,1} & L_{EV}^{1,2} & \cdots & L_{EV}^{1,h} \\ \vdots & & \vdots & \vdots \\ L_{EV}^{i,1} & L_{EV}^{i,2} & \cdots & L_{EV}^{i,h} \end{bmatrix}_{(N_c \times h)} \tag{8}$$

Equations (1-8) are used to estimate the charge consumed by EV in the SCPL.

The SOC levels of EVs at arrival and departure time from the SCPL is shown in Fig. 3. Fig. 4 shows the estimated aggregated EV's charging demand in the SCPL. In Fig 3 each cross represents the arrival of EV, and each circle indicates the departure of EV. The dense cluster in between 1000 to 1800 hrs show the higher number of vehicle availability in the SCPL. It can be observed in Fig 3 that the SOC level of EVs at the departure time is higher than arrival SOC. However, due to shorter occupancy time, approximately 1.28% of the vehicles (visited per day) are charged up to 100%.

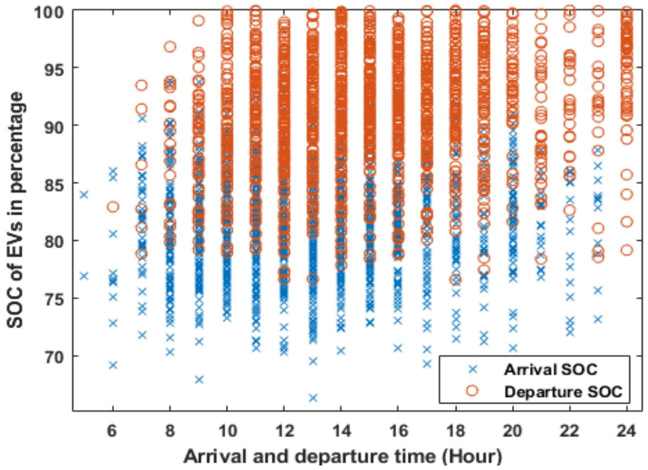

Fig. 3. Arrival and departure SOC of EVs at SCPL

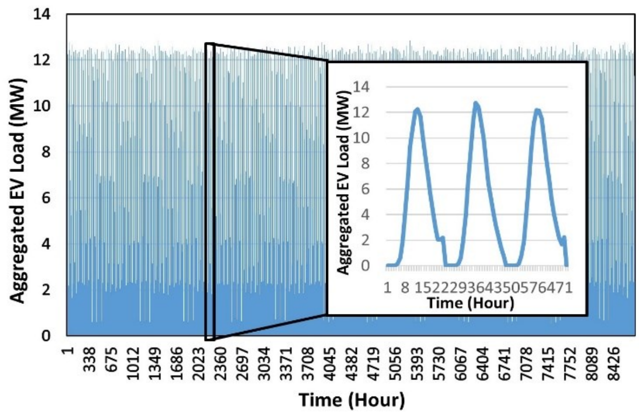

Fig. 4. Aggregated EVs charging demand at SCPL

B. Battery Energy Storage System Modelling

Application of BESS in the car parks is considered a way to mitigate the impacts of EVs on the power grid and provide operational flexibility. BESS is used to store energy in the off-peak hour and supply energy back when needed. The degradation of BESS has a considerable effect in sizing BESS so it should be reflected in the calculation. The SOC of the BESS at any instant can be computed as

$$soc_B^h = soc_B^{h-1} + {\eta_{cvtr}\left(E_b^h + B_{deg}^h\right)}/{BC_{req}} \quad \forall h \qquad (9)$$

Subject to

$$soc_{min} \le soc_B^h \le soc_{max}$$

Where soc_B^h is the SOC of the battery. η_{cvtr} is the efficiency of the DC-DC converter. The battery degradation B_{deg}^h is calculated by using (10) – (12).

$$B_{deg}^h = \vartheta\left(\rho_{(c/d)}\right) * \gamma^h \qquad (10)$$

$$\gamma^h = \left|E_b^h\right|/\beta \qquad (11)$$

Where $$E_b^h = E_{chg}^h - E_{dis}^h \qquad (12)$$

Where the battery degradation factor $\vartheta\left(\rho_{(c/d)}\right)$ is model as a function of charging/discharging power [31].

$$\vartheta\left(\rho_{(c/d)}\right) = (\beta_1 V + \beta_3 V^2 + \beta_5 V^3 + \beta_7 V^4) + (\beta_2 + \beta_6 V) . \left|\rho_{(c/d)}\right| + \frac{\beta_4}{V} . \left|\rho_{(c/d)}\right|^2 \qquad (13)$$

C. Photovoltaic system (PV system) Modeling

Power generation through PV system depends on the atmospheric temperature, weather conditions and solar irradiance. The relationship between the output power of the PV system with temperature and solar irradiance is shown in (14) [32].

$$P_{spv}^h = \left[P_{peak}\left(\frac{G^h}{G_{std}}\right) - \alpha_t\left[T_c^h - T_{std}\right]\right]\eta_{inv} \quad \forall h \qquad (14)$$

Where $$T_c^h = \left(\frac{NOCT-20}{800}\right)G^h + T_{std} \quad \forall h \qquad (15)$$

The values of α_t, P_{peak} and $NOCT$ are obtained from the PV manufacture datasheet and shown in Table 3 [33].

Table 3 Photovoltaic System Specification

Parameter	Value
NOCT	44
α_t	-4%
η_{inv}	0.95
T_{std} (C^o)	25
P_{peak} (W)	260
S_A (m^2)	44000
α_{PL}	10%
$S_{pv}(m^2)$	2.01

The hourly data of solar irradiance G^h and the ambient temperature of Sydney are taken from [34]. Many factors (like weather, cloud, dust) significantly affect the output of the PV system. Due to clouds shadow, the output power of the PV system decreases up to 12% from its nominal value [32], [35]–[37]. The effect of cloud and forced outage rate (FOR) on the output of the PV system is computed in (16) - (17).

$$V_{FOR} = Zero_{(r > FOR_{PV})}, 1_{(otherwise)} \qquad (16)$$

$$V_{cld} = 0.88_{(FOR_{PV} < r < P_{cld})}, 1_{(otherwise)} \qquad (17)$$

Here r is the random numbers, and it is compared with FOR_{PV} and P_{cld} to set the value of the decision variables (i.e. V_{FOR} and V_{cld}). Equation (18) calculates the hourly output power/energy of the installed PV system.

$$E_{pv}^h = P_{spv}^h * N_{PV} * V_{FOR} * V_{cld} \quad \forall h \qquad (18)$$

Subject to $$N_{pv}^{min} \le N_{PV} \le N_{pv}^{max} \qquad (19)$$

Where $N_{pv}^{max} \le (1 - \alpha_{PL}) * \left[\frac{S_A}{S_{pv}}\right]$ & $N_{pv}^{min} \ge 1$

N_{pv}^{min} and N_{pv}^{max} are integer numbers and their values are based on the availability of the area for PV installation. The values of S_A and S_{pv} are shown in Table 3. The estimated yearly PV output power in the SCPL is depicted in Fig 5.

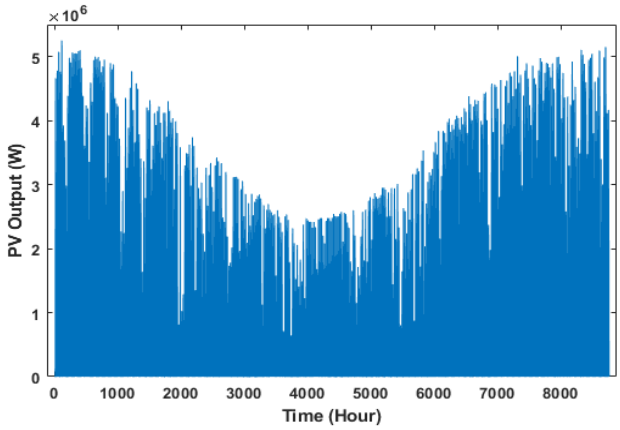

Fig. 5. Estimated PV output power in SCPL

IV. BESS SIZING METHOD

A 2-step method to compute the optimal size of the BESS is proposed while taking grid power-constrained and intermittent EV charging demand into account. In the first step, region reduction method is used to reduce the search space for the optimisation problem. Then an objective function is formulated to minimise the operational and capital cost of the system.

A. Region reduction method

The error between the EV charging load and power supplied by the grid is calculated as

$$E_{error}^h = E_{ev}^h - \left(E_g^h + E_{pv}^h\right) \qquad \forall h \qquad (20)$$

Where E_g^h is the power-constrained enforced by the grid and E_{ev}^h is the hourly charging demand of EVs. The negative values of the error are the surplus charging demand. The maximum battery capacity (E_{max}) required to meet the additional charging load is calculated by taking the sum of all the negative values of the error, as shown in (21).

$$E_{max} = \sum_{h=1}^{n} \begin{cases} E_{error}^h & E_{error}^h > 0 \\ 0 & otherwise \end{cases} \qquad \forall h > 0 \qquad (21)$$

E_{max} is a reliable BESS capacity but it's not the optimal capacity. The required BESS can be less than or equal to E_{max}. A modified region reduction method is introduced to reduce the search space. The required battery capacity BC_{req} for SCPL is calculated as

$$BC_{req} = \begin{cases} E_{max} & \alpha < \min(soc_B^h) < \beta \\ BC_{up} & otherwise \end{cases} \qquad (22)$$

Here $\alpha = 0.1 * BC_{req}$ and $\beta = 0.15 * BC_{req}$. The proposed method is not allowed the battery to discharge less than 10% of its rated capacity and not to hold a charge of more than 90% of its rated capacity. Updated battery capacity BC_{up} is calculated if $BC_{req} \neq E_{max}$. Before calculating BC_{up}, decision variable "k" is selected depending on the SOC of the battery. K equals zero, if at any instance, the battery discharge less than 10% of its maximum capacity. This condition is referred as under-sizing. Conversely, k equals to 1, if at any instance, the minimum SOC of the battery remains above 15% of its maximum capacity. This condition implies that the battery is oversized.

$$k = \begin{cases} 0 & \min(soc_B^h) \leq \alpha \\ 1 & \min(soc_B^h) \geq \beta \end{cases} \qquad (23)$$

BC_{up} is the updated BESS capacity and it is calculated by using (24) – (26).

$$BC_{up}(u) = \left(X_{min}(u) + X_{max}(u)\right)/2 \qquad (24)$$

Here u is the iteration number. $X_{min}(u)$ and $X_{max}(u)$ are the minimum and maximum bounds of the solution. Initially, the values of $X_{min}(u)$ and $X_{max}(u)$ are set to be zero and E_{max} respectively.

$$X_{min}(u+1) = \begin{cases} X_{min}(u) & k = 1 \\ BC_{up}(u) & k = 0 \end{cases} \qquad (25)$$

$$X_{max}(u+1) = \begin{cases} BC_{up}(u) & k = 1 \\ X_{max}(u) & k = 0 \end{cases} \qquad (26)$$

$X_{min}(u)$ and $X_{max}(u)$ are updated in each iteration based on decision variable "k". The algorithm continues until the solution reaches to its acceptable convergence (i.e. $\alpha < \min(soc_B^h) < \beta$). BC_{req} is the reliable solution but it's not the economical or optimal battery capacity. The region reduction method considers all possible combinations to ensures the maximum utilisation of the BESS. This method gives a range of reliable solutions. However, these solutions are not optimal. To find optimal solution for BESS an objective function is formulated to minimise the operational and capital cost of the system.

B. Optimisation Problem Formulation

The PLO owns/installed the PV system and the BESS and work as a mediator between EV users and the grid. The PLO is interested in fulfilling the EVs charging requirement without violating the grid constrained. Fig.6 shows the energy flow in the PL. In Fig. 6 it can be seen that the EVs are only consuming energy. It is because the shopping centre is not the final destination of an EV owner in a day. Moreover, vehicles mostly stay for a very short period of time. So, there is very little room for scheduling.

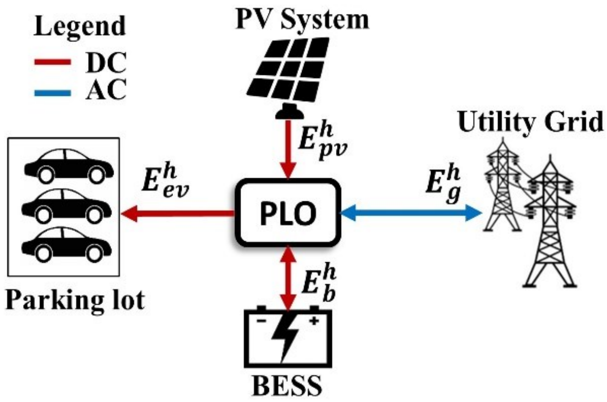

Fig. 6. Energy flow in the SCPL

The energy flow in the SCPL can be mathematically expressed as.

$$E_g^h + E_{pv}^h = E_b^h + E_{ev}^h \qquad \forall h \qquad (27)$$

Here E_b^h, E_g^h and E_{ev}^h are free variables and E_{ev}^h is a positive variable. The optimisation is based on hourly data, so power and energy rating are the same. As displayed in Fig. 6, the PLO has to manage its available resources (i.e. grid, BESS and PV) to meet the charging demand of EVs.

One of the most important factors which have a significant impact on BESS capacity is the electricity tariff. At any time instant, the PLO offered (1-Δ_g) times less price than grid tariff. So, EV user preferred to charge their vehicle while parked in SCPL. Equation (28) ensure that the tariff offered by PLO to charged EV in the SCPL should always be less than the grid tariff.

$$C_s^h \leq C_p^h * (1 - \Delta_g) \qquad (28)$$

Equation (29) ensure the power-constrained enforced by the grid. It means that the power supplied by the grid cannot exceed the sanctioned load.

$$E_g^h \leq \delta \qquad (29)$$

Equations (30)-(31) show the upper and lower bound of instantaneous energy drawn from the BESS (E_b^h) and the required battery capacity BC_{req} respectively. Here "λ" is the charger rating (C-rate). C-rate is the instantaneous charging and discharging power limit of BESS charger. The computed values of λ are tabulated in Table 5.

$$-\lambda \leq E_b^h \leq \lambda \tag{30}$$
$$X_{min} \leq BC_{req} \leq X_{max} \tag{31}$$

BESS is a key energy resource in the PLs that provide operational flexibility. An optimal cost model for the PL in an operational cycle is formulated as

$$Min\ Cost = \sum_{h=1}^{n} C_{b,deg}^h + C_{grid}^h + C_{b,capital}^h - C_{ev,chg}^h$$

Here

$$C_{b,capital}^h = \alpha_{cp} * BC_{req} \tag{32}$$
$$C_{b,deg}^h = B_{deg}^h * capb \tag{33}$$
$$C_{grid}^h = E_g^h * C_P^h \tag{34}$$
$$C_{ev,chg}^h = E_{ev}^h * C_s^h \tag{35}$$

Subjected to (27) - (31). Where α_{cp} is the life loss cost of the BESS in a cycle, $\alpha_{cp} = U_{cost} * BC_{req}/N_{life}$." U_{cost}" is the unit BESS cost and N_{life} is the total life cycle time. The objective of the optimisation function is to minimise the yearly operational cost and the capital cost for PLO. The flow chart of the proposed method is shown in Fig. 7.

The initial investment cost and yearly maintenance cost of BESS are taken into consideration. The initial investment cost is calculated by adding cost of the battery (i.e. $C_{bt} = U_{cost} * BC_{req}$ and power electronic devices (C_{inv}). The power electronic equipment cost (C_{inv}) and unit cost of the battery (U_{cost}) are shown in Table 4. Other costs are neglected in this work.

Table 4 Optimization Parameters

Parameter	Value
N_{life}	10 years
U_{cost} \$/KWh	560
Δ_g	0.05
$capb$ \$/KWh	0.44
C_{inv} \$/KW	175

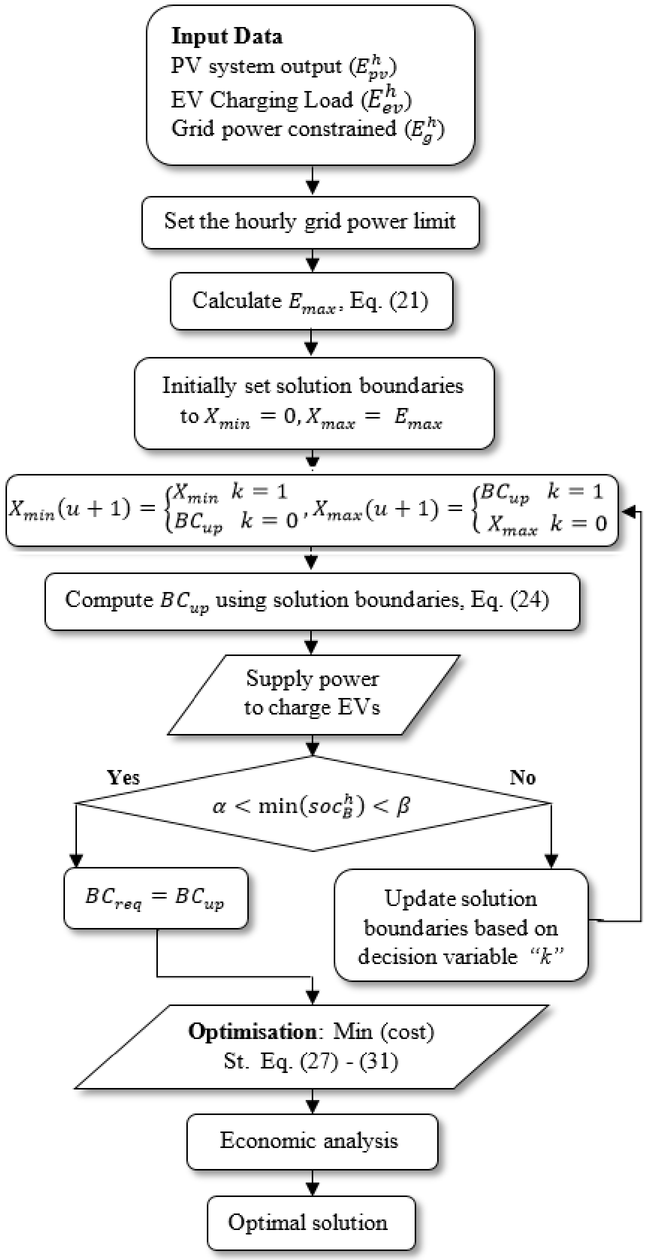

Fig. 7. Flow chart of the proposed sizing method

V. Results And Discussion

Simulation is carried out in MATLAB/GAMS environment, and the results are presented as follows. Firstly, this section demonstrates the impact of grid power-constrained on the BESS capacity. Then the optimum energy flow in the SCPL and PLO tariff for EV owners are calculated by solving optimisation formulation. Finally, economical analysis is conducted to select BESS. The simulation is done for one year (i.e. n =8760). However, two consecutive days (48 hours) are randomly selected to visualise the obtained results.

The proposed sizing method is tested in six different cases. Each case represents the different power limit enforced by the utility grid. Fig. 8. shows the power limit for each case together with the computed optimal battery capacity. It can be observed that the size of BESS is inversely proportional to the grid constraints. Even a small reduction (i.e. 1MW) in grid constrained, exponentially increases the capacity of the BESS. Moreover, if the grid committed less than 58% of the peak EV demand than the optimal BESS capacity will be approximately eight times more than the grid limit.

In this work, it is assumed that in SCPL EVs need to charged their batteries or retained some adequate SOC for its next travel. Therefore, the scheduling margin is very less. By using (28), we enforced that in any given time, the PLO offered at-least 5% less price to EV owners then the grid tariff. So, instead of taking energy from the grid, it is beneficial for

EV owners to charge its vehicle at SCPL. However, PLO also wants to maximise its revenue. So, the optimisation simulation is conducted to compute an optimal tariff that is beneficial for both EV owners and the PLO. The resulted tariffs (i.e. PLO tariff) together with the grid tariff are shown in Fig. 9.

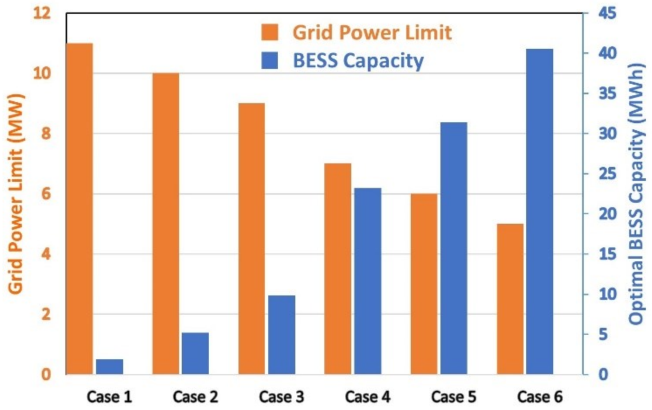

Fig. 8. Grid limits and computed BESS capacity

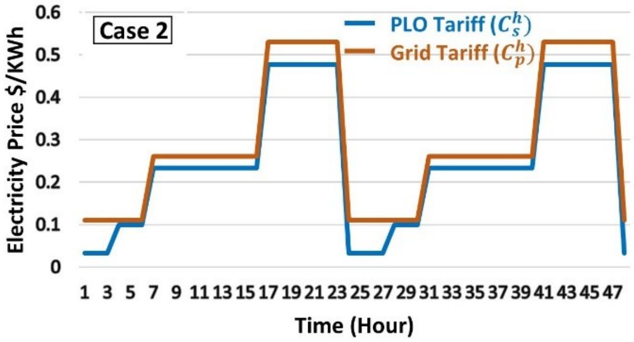

Fig. 9. Grid tariff and computed PLO tariff

Fig. 10 shows the instantaneous energy flow between the utility grid and the BESS. It can be seen in Fig. 10 that in the evening, BESS is supplying power to the load and recharge itself in the early morning or late at night. To maintain the reliability of the power system, the PL should operate within the specified grid limits. As seen in Fig. 10 that at any instant the energy drawn from the grid (E_g^h) is not exceeding its specified limit (i.e. 10 MW for case # 2). So, the computed BESS maintains the system reliability. It can be observed that during the day, E_g^h and E_{pv}^h are supplying power to the load whereas the BESS retains its SOC. Thus, the proposed method

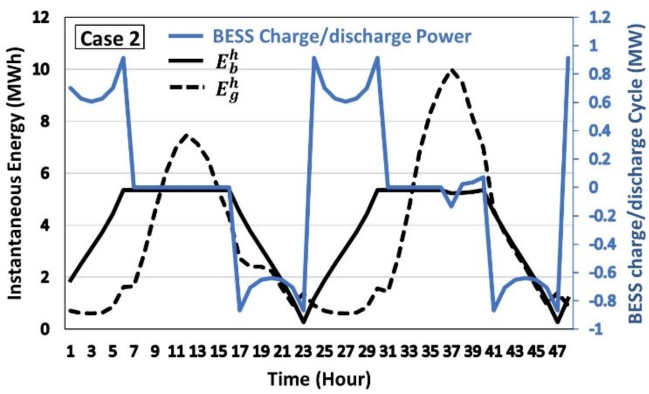

Fig.10. Optimal energy flow in the SCPL

ensures the maximum utilisation of the PV system. Consequently, the computed BESS capacity is able to manage the EV charging demand in the SCPLs with limited grid supply.

A. Discussion

This section demonstrates the economic analysis of the proposed sizing method. Moreover, a comparison is made in Table 6 to show the efficacy of the proposed method.

The economic analysis was performed, and the results are tabulated in Table 5. Tesla powerwall2 battery having a unit cost of U_{cost} = 560 $/KWh is considered [38]. In this work, both instantaneous charging/discharging power (i.e. C-rate) and energy capacity of BESS are considered while calculating the capital cost of the system. It can be seen in Table 5 that the C-rate is small as compared to the energy capacity of the BESS. However, the estimated C-rate for each case is enough to supply the peak demand. High power capacity BESS is commercially available, but those BESS are very costly. Secondly, cycling BESS at high charging/discharge rate (i.e. C-rate) reduces the life of the battery. It can be observed in Table 5 that the capital cost of the system increased significantly when the grid committed less than 58% of the peak demand. It is recommended that the network operator should supply more than 58% of peak charging load to the PLs. However, in each case, the break-even point for PLO reaches in approximately 3 years, whereas the BESS life is 10 years. It is profitable for PLO to upgrade its PL to charging station.

Table.5 Economical Analysis

Cases	BC_{req} (MWh)	Charger Rating (λ) (MW)	Capital Cost $C_{inv} + C_{bt}$ (1000 X $)	Annual Revenue (1000 X $)
1	1.9	0.75	1234	1602
2	5.3	1.78	3252	1820
3	9.8	2.85	5022	2370
4	23.2	3.74	13865	3320
5	31.4	5.85	18624	3725
6	40.6	7.74	23933	11578

The comparison of the proposed BESS sizing method with the literature is tabulated in Table 6. It can be observed in Table 6 that most of the published works on EV behaviour modelling [23]–[25] neglected the effect of driving style on energy consumption per kilometre of EVs and EV's battery degradation in calculating the charging demand of EVs. Work on BESS sizing methods [12], [14], [15], [17] have not incorporated battery degradation and BESS charging and discharging rate in their analysis. Moreover, some methods are computationally expensive. On the contrary, the proposed sizing method incorporated the uncertain EV behaviour of the above-mentioned factors and effectively calculated the optimal size of BESS in a constrained grid. Fig. 11. depicted the characteristic of the BESS computed by using the proposed sizing method. The red, blue and green hexagons

Table 6: Comparison with the literature.

Stochastic Modelling for EV Behaviour						BESS Sizing			
Papers	Distance Travel (KM^i)	Arrival & Dept. time	Battery Capacity (BC^i)	Driving style (R^i)	SCPL	Papers	BESS Degradation	Computational time	C-rate (MW)
[23]	✓	✓	×	×	✓	[14]	×	Low	High
[4]	✓	✓	Fixed	×	×	[15]	✓	High	Low
[24]	✓	✓	✓	×	×	[17]	×	High	High
[25]	✓	✓	Fixed	×	×	[12]	×	High	Low
This paper	Eq. 5	Eq.1&2	Eq. 4	Eq. 3	✓		Eq. 10	Low	Low

Legends: ✓ = Considered as stochastic parameter, **Fixed** = Considered as rated/fixed parameter, × = Not considered

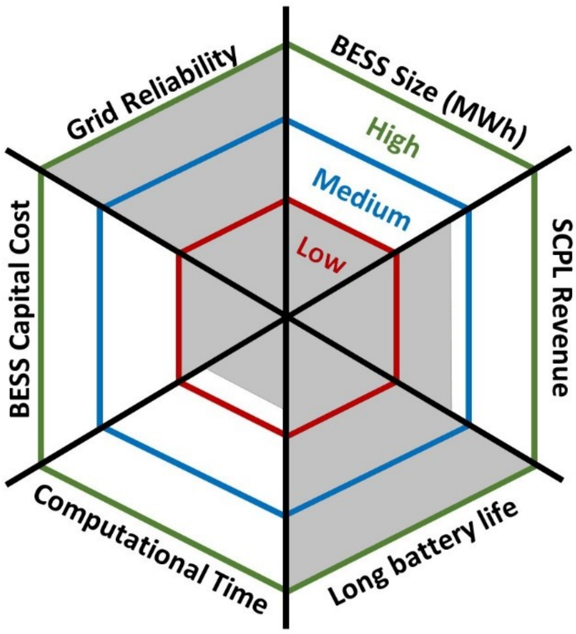

Fig. 11. Characteristics of the computed BESS

show the low, medium and high level of the attributes of the resulted solution respectively. The shaded grey region defines the ratio of each attribute of the computed BESS.

In this work, simulations ran with and without region reduction method. Without region reduction method, the state space was from 0 to E_{max} whereas the simulation time to process the optimal solution was 60.5hrs. With region reduction method, the state space was refined, and the simulation time to process the optimal solution was 0.75hrs. However, for both the simulation runs the optimal solution were 5.3 MWh (i.e. for case 2), as depicted in Fig. 8. The optimal solutions for other cases with and without region reduction method was same.

The prominent features of the sizing method are to compute an economical and minimal energy capacity of BESS. However, the computed BESS is reliable and effectively manages the EV charging in a limited grid power supply. The proposed method allows the BESS to charge and discharge only in its nominal range (10% - 90% SOC). Moreover, the estimated C-rate (λ) is enough to meet the charging demand of EVs in peak hours, as depicted in Fig. 10. Cycling BESS at low C-rate reduces the battery degradation due to thermal issue, thus prolong the life of the BESS. The computed PLO tariff is always less than the grid tariff so it encourages EV owners to take services from PLO, on the other hand, helps PLO in maximising their profit. It can be observed that the computed BESS is supporting the grid in peak hours by sharing the EV charging load. Thus, increases the reliability of the electrical grid.

VI. Conclusion

A novel method is presented in this paper to estimate the size of the BESS for SCPLs having a charging infrastructure for EVs. The proposed sizing method considers the EV charging demand at SCPL, intermittent PV output and grid power constraints. At first, the stochastic method is proposed to compute the intermittent EV charging demand at SCPL. Then, PV output is calculated by using the Monte Carlo Simulation. At last, non-linear optimisation combined with region reduction method is proposed to estimate the optimal BESS capacity for SCPL. Simulations were conducted with the real data of HTSD, Sydney weather data and vehicle occupancy pattern data at SCPL. The results show that the computed BESS can not only reduce the impact of EV charging on the grid but also allows PLO to manage the EVs charging demand in a constrained grid, such that the operational cost is minimised. Introducing region reduction method in the proposed sizing method significantly reduces the computational time. It was analysed that despite the capital cost of BESS being significantly higher in some cases, the installation of BESS in SCPL is profitable for the PLO. The proposed method can be applied to other parking lots of different capacity and sizes. This work didn't incorporate vehicle-to-grid (V2G) while calculating the optimal size of BESS. Efforts must be made in exploring the impact of V2G behaviour of EV owners on estimating the capacity of BESS.

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