Novel Method for Sizing of Battery Energy Storage System for Parking Lot in a Constrained Grid

U.B. Irshad [1], S. Rafique[1], M.J. Hossain[2], S.C. Mukhopadhyay[1]
[1] School of Engineering, Macquarie University, Australia
[2] School of Electrical and Data Engineering,UTS, Australia
*usama.bin.irshad@gmail.com

Abstract—**Charging of electric vehicles (EVs) significantly impact the reliability of the power system. A constrained power grid is a feasible solution to maintain the reliability of the power system. However, in a constrained power grid, it is challenging for the system operator to balance the additional load. Fast and high-power density of batteries makes them a conceivable option for this task, if properly sized. Charging profile of EVs is constructed by considering travel pattern, charging need and driver's behaviour of EVs. Moreover, a sizing algorithm is proposed to compute the battery capacity for parking lots equipped with EV chargers in a constrained grid. The proposed sizing algorithm ensures 1) balance the EV load, 2) avoid over/under-sizing of the system. The accuracy of the proposed battery sizing algorithm is shown by simulation results, characterised by using real data of household travel survey and parking occupancy data.**

Keywords—Battery sizing, Electric vehicle, Constrained grid, Parking lots.

Indices

i	Sampled electric vehicle
c	Case index
h	Hour
n	Total number hours
u	Iteration number

Variables and parameters

BC^i	Battery capacity of i^{th} EV.
KM^i	Distance travel by i^{th} EV.
a^i & d^i	Arrival & Depart. time of i^{th} EV.
X^c_{min}& X^c_{max}	Min/Max boundaries of the solution
N_{ev}	Total number of EVs.
E^i	Energy required to charge i^{th} EV.
$L^{i,h}_{EV}$	Hourly load of i^{th} EV.
P_B	Instantons SOC of the battery
P^c_{error}	Error between EV load and grid power.
BC^c_{req}	Required battery capacity for case "c".
R^i	Energy consumed per kilometre of i^{th} EV.
P^c_G	Utility grid power limit
E^c_{max}	Maximum battery required in case "c".
$BC^c_{updated}$	Updated battery capacity
$D_{c,max}$	Maximum travel distance

Abbreviation

BESS	Battery Energy Storage System
EV	Electric Vehicle
OPL	Office Parking Lot
PLO	Parking Lot Operator
PL	Parking Lot

I. INTRODUCTION

Greenhouse gas emissions are a great challenge for the environment and human life. Eco-friendly nature of electric vehicle makes it a viable source of commuting. Many countries are electrifying their transportation in order to reduce the level of CO_2 emission [1]–[3]. The rapid increase in market participation of EVs will change the parking lots (PLs) to a charging stations. PLs associated with workplace/shopping centre/ homes will be the most convenient spots for EV owners to charge their vehicles. The increase in load demand due to the charging of EVs destabilises the power system. To reduce the impact of EV charging on the power system, the constrained grid is a feasible option [3]. 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. In a constrained grid, 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 EV charging requirement of every vehicle, without reducing their energy consumption. In this context, battery energy storage systems (BESS) can be used to provide energy when needed and recharge itself in off-peak hours. Therefore, the correct power/energy size of BESS system is the most important aspect in designing and planning of PLs containing charging and discharging infrastructure for EVs.

Several studies aim to evaluate the capacity optimisation of BESS has been conducted [4]–[7]. The economical and reliable combination of photovoltaic, wind and energy storage system has been presented in [8]. However, the author did not consider the force outage rates of renewable energy sources like wind and solar system. The author in [9] develops a stochastic method to evaluate battery sizing by taking demand shift capability into account. However, he overlooked the uncertainty in the household load profile. In [5], the author aims to find the optimal combination of PV, WT and BESS. However, their convergence criteria for battery sizing resulted the selected battery to discharge below 90% depth of discharge (DOD). A comprehensive battery sizing model considering battery degradation is proposed in [6]. In [10], the author developed a techno-economical sizing method for DC-micro grid by considering EV mobility on different charging station but neglecting EV's driving pattern. To conclude, many authors overlooked critical factors (like the volatility of renewable sources and load, depth of discharge, forced outage rate of renewables, consider grid as an infinite bus etc.) Secondly, no one had considered the sporadic nature of EV charging in a constrained grid conditions.

A. Contribution

This work develops a model to construct charging profile for EVs in parking lots. Moreover, proposes an algorithm to precisely compute the size of battery energy storage capacity for parking lots in a constrained grid. The proposed method considers all possible combinations to avoid over/under-sizing of the system. It also ensures the maximum utilisation of the BESS. The proposed method is developed using real data of household travel survey of Sydney region and parking lot occupancy data of OPL.

II. SYSTEM MODELLING

A. EV Load Modelling

It is essential to develop a realistic model to estimate the availability of EVs in PLs. In the proposed model, EV usage is characterized by five parameters (i.e. $a^i, d^i, BC^i, R^i, KM^i$). All are random variables with their probability distribution functions derived from real data. In this work, an OPL with space for 1000 vehicles is considered.

The aggregated occupancy of a OPL and daily distance travelled was derived from vehicle travel survey data obtained from 25,443 people in 9,715 households across the State of NSW (Australia) over a period of three years [11]. The data contains 9,822 office/workplace trips and showed that about 70% of commuting vehicles arrived at their workplace (office) between 0600 and 0800, and almost the same percentage departed between 1500 and 1800. The arrival time a^i departure time d^i of OPL was best fitted with a log-normal distribution having means μ_p and standard deviation σ_p. The values of μ_p and σ_p for a^i are 2.17 and 0.32 respectively. For d^i the values of μ_p and σ_p are 16.99 and 3.47 respectively.

$$a^i = lognormal(\mu_p, \sigma_p) \qquad \forall\, i, p \qquad (1)$$
$$d^i = lognormal(\mu_p, \sigma_p) \qquad \forall\, i, p \qquad (2)$$

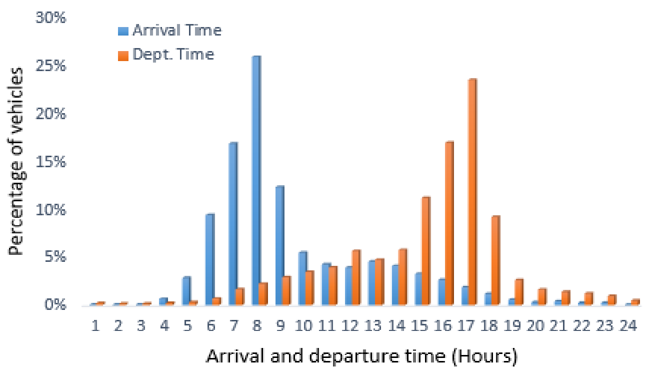

Figure 1: Arrival and departure pattern in OPL

In Fig. 1, the arrival and departure pattern of EVs in OPL is synthetically generated by using (1)-(2). About 65% of commuting vehicles arrived at their workplace (office) between 0600 and 0900, and almost the same percentage departed between 1500 and 1800. The average dwell time of individual EV in the OPL is around 5 hours.

Nissan leaf is considered in this work. Battery capacity BC^i and energy consumption R^i of Nissan leaf 2018 is 40 KWh and 0.164 KW/km respectively. Travel pattern of Sydney region is also analysed from the HTS survey data [11]. On average, vehicles in NSW travel approximately 11650 kilometres per annum. It was reported in [12] that about 88% of those vehicles drive less than 30 km per day, and approximately 95% of vehicles travel less than 45 km per day. The distance travelled KM^i by vehicles was best fitted by a Weibull distribution with shape parameter ς_{MD} = 36 and scale parameter ν_{MD}= 4.9.

$$KM^i = Weibull(\varsigma_{MD}, \nu_{MD}); \quad \forall i \qquad (3)$$

To calculate the load, we assume that all vehicles are electric, and their travel patterns are the same as in the Household Travel Survey [11].

The energy required to charge the i^{th} EV while parked in the PL is given by

$$E_c^i = \begin{cases} BC_c^i & if\ KM_c^i = D_{c,max} \\ R^i * \left(KM_c^i / D_{c,max}\right), & otherwise \end{cases}, \forall i, c \qquad (4)$$

Here $D_{c,max}$ is the maximum distance travelled, KM_c^i is the daily distance travelled, and BC_c^i is the battery capacity of the EV. Level 2 charger having a rate of charging P_{charge}= 3.6 kW and an efficiency η_{chrg} = 0.94 is considered to charge EVs in workplace car parks. With the help of arrival/departure time energy consumed per kilometre driven, battery capacity of EV, we are now able to calculate how much charge is needed to charge the battery.

$$L_{EV}^{i,h} = \sum_{a_c^i}^{\min(T_{\text{charge}}^i, d_c^i)} P_{charge}^i(h) * \eta_{chrg} \qquad (5)$$

$$P_{Load}(h) = \sum_{i=1}^{N_c} \begin{bmatrix} L_{EV}^{1,1} & L_{EV}^{1,2} & \cdots & L_{EV}^{1,h} \\ \vdots & & \vdots & \vdots \\ L_{EV}^{i,1} & L_{EV}^{i,2} & \cdots & L_{EV}^{i,h} \end{bmatrix} \qquad (6)$$

Here $L_{EV}^{i,h}$ is the hourly load demand of i^{th} EV, $T_{L_{charge}}^i$ is the time required to charge the battery, P_{Load} is the hourly aggregated load demand of EVs in OPL and N_c is the total

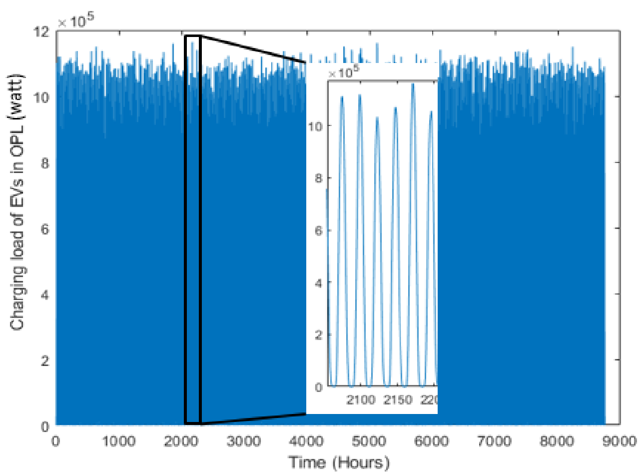

Figure 2: Hourly EV charging load profile throughout the year

number of vehicles visited OPL in one day.

The aggregated load of EVs in OPL is calculated by assumed 100% penetration of EVs. Equations (1-6) are used to calculate the aggregated annual EV load in the OPL. Fig 2. shows the estimated hourly aggregated load demand in OPL throughout the year. The daily peak demand is not constant because of using the stochastic model for estimating EV load in OPL.

B. Modelling of Battery Energy Storage System:

The SOC of the battery at any instant can be computed as

$$P_B(h) = P_B(h-1) + \left(\eta_b * P_{abs}(h) - {}^{P_{sply}(h)}/_{\eta_b}\right) \quad (7)$$

Subject to

$$P_B^{min} \leq P_B(h) \leq P_B^{max} \quad (8)$$

Where P_B is the instantons power of the battery and η_b is the charging/discharging efficiency of the battery. P_{abs} and P_{sply} are the power absorbed and supply by the BESS

III. BATTERY SIZING ALGORITHM

In this section, step by step battery sizing algorithm to flatten the energy consumption of EV charging in the PL are presented. The battery capacity is computed by taking grid power constraints into account. Different cases were considered in this work, and each case has different power constraint.

A. Battery sizing method

The method to compute the BESS to meet the intermittent load demand of EVs is computed as follows. The error between the EV charging load and power supply by the utility grid for each case "*c*" is calculated as

$$P_{error}^c(h) = P_{Load}(h) - P_G^c(h) \quad \forall c, h > 0 \quad (9)$$

Where P_G^c is the power constraint by the grid in case "*c*". and P_{Load} is the hourly load demand of the EVs. The negative values of the error are the additional load that the grid cannot supply. The maximum battery capacity (E_{max}^c) required to meet the extra load demand is calculated by taking the sum of all the negative values of the error. The E_{max}^c can be computed as

$$E_{max}^c = \sum_{h=1}^{n} \begin{cases} P_{error}^c(h) & P_{error}^c(h) > 0 \\ 0 & otherwise \end{cases} \quad \forall c, h > 0 \quad (10)$$

Where E_{max}^c is the maximum battery capacity that can be employed to support the load of EVs in the parking lot. E_{max}^c is reliable but it's not the optimal capacity of BESS. The required BESS can be less than or equal to E_{max}^c. A modified region reduction method is used to find the required battery capacity BC_{req}^c for each case and it is calculated as

$$BC_{req}^c = \begin{cases} E_{max}^c & \alpha < \min(P_B^c) < \beta \\ BC_{updated}^c & otherwise \end{cases} \quad (11)$$

Here P_B^c is the instantaneous energy of the selected battery, $\alpha = 0.1 * P_B^c(1)$ and $\beta = 0.15 * P_B^c(1)$. The battery is not allowed to discharge less than 10% of its rated capacity and not to hold a charge of more than 90% of its rated capacity. If the $\min(P_B^c)$ is in-between 10% to 15% of its rated battery capacity than the solution is optimal otherwise $BC_{updated}^c$ is needed.

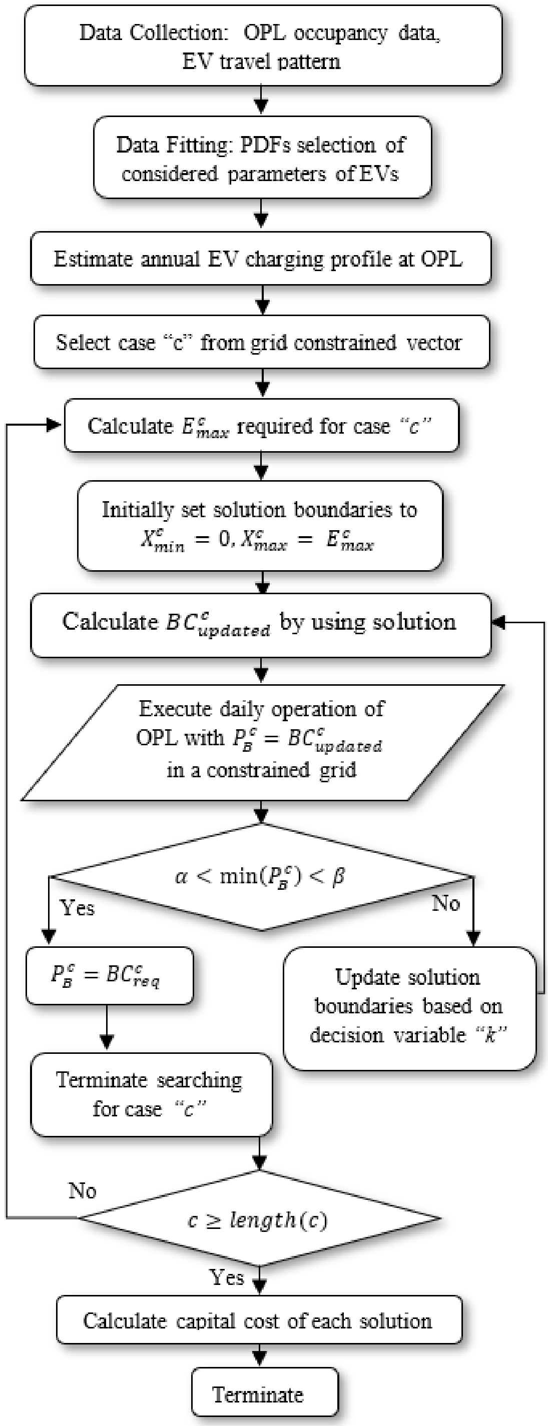

Figure 3: Flow chart of the proposed method

Before calculating $BC_{updated}^c$, decision variable "*k*" is selected depending on the SOC of the battery. *K* equals zero, if at any instance of time, the battery discharge less than 10% of its maximum capacity. This condition is referred as under-sizing. Conversely, *k* equals to 1 if the minimum SOC of the battery remains above 15% of its maximum capacity. This condition implies that the battery is oversized.

$$k = \begin{cases} 0 & \min(P_B^c) \le \alpha \\ 1 & \min(P_B^c) \ge \beta \end{cases} \tag{12}$$

Updated battery capacity $BC_{updated}^c$ is calculated by using the following relations.

$$BC_{updated}^c(u) = (X_{min}^c(u) + X_{max}^c(u))/2 \tag{13}$$

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

$$X_{min}^c(u+1) = \begin{cases} X_{min}^c(u) & k = 1 \\ BC_{updated}^c(u) & k = 0 \end{cases} \tag{14}$$

$$X_{max}^c(u+1) = \begin{cases} BC_{updated}^c(u) & k = 1 \\ X_{max}^c(u) & k = 0 \end{cases} \tag{15}$$

$X_{min}^c(u)$ and $X_{max}^c(u)$ are updated in each iteration based on decision variable "k". The algorithm continues until the solution reaches to its acceptable convergence (i.e. $\alpha < \min(P_B^c) < \beta$).

IV. Results and Discussion:

The results of the proposed method to obtain the required battery capacity in the OPL is presented in this section. Table 1 shows five cases of constrained grid. Each case represents the maximum power limit supplied by the grid. Optimal sizing of the BESS in the PLs is entirely dependent on the EV charging load and the grid power constraints.

We randomly selected a load profile of three consecutive days (i.e. 72 hours) to clearly visualise the results, as shown in Fig 4. The dotted line represents the power constraint applied by the utility grid. So, the grid can only supply a maximum of 1.0 MW of power. The shaded region in Fig. 4 is the additional load that need to be fulfilled by PLO.

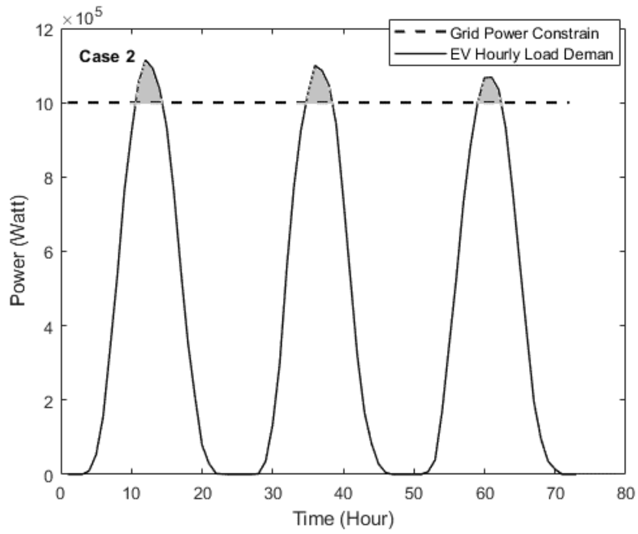

Figure 4: EV charging load demand for 3 random days

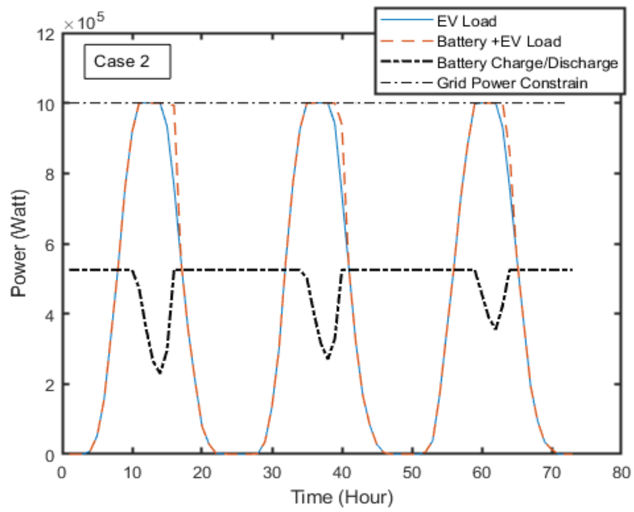

Figure 5: Instantaneous power flow and load demand of EVs

Fig. 5 shows the instantaneous power flow between EV load, utility grid and the selected BESS of case 2. Fig. 5 shows 1) the load profile of EVs (blue line), 2) power supply by the grid (orange line) and 3) charging/discharging of BESS (black dotted line) of case 2. In this work, fixed tariff is considered throughout the day. In the peak hours, BESS is supplying power to charge EVs and recharge itself in off peak hours. In Fig. 5, the orange line represents the sum of the EV load and the charging load of the BESS. The load profile is flattened, and at any instance of time the battery is not discharge below 10% of its rated battery capacity. Consequently, the computed battery capacity can meet the load in peak hours and hence manage the EV load under a constrained grid.

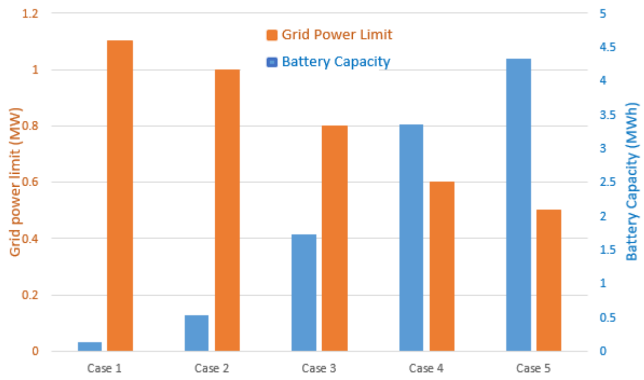

Figure 6 Required battery capacity for each case

Fig 6 represents the required battery capacity (BC_{req}^c) together with the grid power limits. It can be observed that the required battery size is inversely proportional to the grid constraints. Moreover, the size of the battery increases exponentially when grid committed less than 60% of the peak load of OPL. A simple cost analysis was performed and the results are tabulated in Table 1.

In this work, Tesla powerwall2 battery having a cost of 571.4 \$/KWh is considered [13] for cost analysis. The BESS is not economically feasible if the grid commits less than 60% power of the daily peak demand. Conversely, if the grid is supplying more than 60% of the average peak demand than

Table.1 Required battery capacity and grid constraints

Cases	Grid Power limits (MW)	BC^{c}_{req} (MWh)	Battery Capital Cost ($)
Case 1	1.1	0.13	74285.7
Case 2	1	0.53	302857.1
Case 3	0.8	1.73	988571.4
Case 4	0.6	3.35	1914285.7
Case 5	0.5	4.32	2468571.4

less battery capacity is needed to meet the charging demand in constrained grid.

V. Acknowledgement

The authors acknowledge the support of Macquarie University through the International Research Training Program.

VI. Conclusion

This work proposed the battery sizing algorithm for parking lots incorporating charging infrastructure of EVs. The proposed sizing algorithm is developed by using real data of household travel survey and parking occupancy data of office parking lot. The resulted battery energy storage system 1) effectively balance the intermittent EV load, 2) flatter the EV charging demand, 2) maintain the reliability of the grid and 3) ensures the maximum utilisation of the BESS. Moreover, the battery installation would not be economically viable, if the grid commits less than 60% of the peak charging demand. The proposed generic sizing method applies to other situations as well.

References

[1] J. Hofmann, D. Guan, K. Chalvatzis, and H. Huo, "Assessment of electrical vehicles as a successful driver for reducing CO2 emissions in China," *Appl. Energy*, vol. 184, pp. 995–1003, Dec. 2016.

[2] R. Atia and N. Yamada, "Sizing and Analysis of Renewable Energy and Battery Systems in Resident[1] R. Atia and N. Yamada, 'Sizing and Analysis of Renewable Energy and Battery Systems in Residential Microgrids,' IEEE Trans. Smart Grid, vol. 7, no. 3, pp. 1204–1213, May 2016.ial M," *IEEE Trans. Smart Grid*, vol. 7, no. 3, pp. 1204–1213, May 2016.

[3] O. Sundstrom and C. Binding, "Planning electric-drive vehicle charging under constrained grid conditions," in *2010 International Conference on Power System Technology*, 2010, pp. 1–6.

[4] Y. Luo, L. Shi, and G. Tu, "Optimal sizing and control strategy of isolated grid with wind power and energy storage system," *Energy Convers. Manag.*, vol. 80, pp. 407–415, Apr. 2014.

[5] U. Akram, M. Khalid, and S. Shafiq, "Optimal sizing of a wind/solar/battery hybrid grid-connected microgrid system," *IET Renew. Power Gener.*, vol. 12, no. 1, pp. 72–80, Jan. 2018.

[6] I. Alsaidan, A. Khodaei, and W. Gao, "A Comprehensive Battery Energy Storage Optimal Sizing Model for Microgrid Applications," *IEEE Trans. Power Syst.*, vol. 33, no. 4, pp. 3968–3980, Jul. 2018.

[7] M. C. Pham, T. Q. Tran, S. Bacha, A. Hably, and L. N. An, "Optimal Sizing of Battery Energy Storage System for an Islaned Microgrid," in *IECON 2018 - 44th Annual Conference of the IEEE Industrial Electronics Society*, 2018, pp. 1899–1903.

[8] Lin Xu, Xinbo Ruan, Chengxiong Mao, Buhan Zhang, and Yi Luo, "An Improved Optimal Sizing Method for Wind-Solar-Battery Hybrid Power System," *IEEE Trans. Sustain. Energy*, vol. 4, no. 3, pp. 774–785, Jul. 2013.

[9] C. W. Tan, T. C. Green, and C. A. Hernandez-Aramburo, "A stochastic method for battery sizing with uninterruptible-power and demand shift capabilities in PV (photovoltaic) systems," *Energy*, vol. 35, no. 12, pp. 5082–5092, Dec. 2010.

[10] B. Aluisio, M. Dicorato, I. Ferrini, G. Forte, R. Sbrizzai, and M. Trovato, "Optimal Sizing Procedure for Electric Vehicle Supply Infrastructure Based on DC Microgrid with Station Commitment," *Energies*, vol. 12, no. 10, p. 1901, May 2019.

[11] "Household Travel Survey (HTS) | Transport for NSW." .

[12] S. Rafique and G. Town, "Aggregated impacts of electric vehicles on electricity distribution in New South Wales, Australia," *Aust. J. Electr. Electron. Eng.*, vol. 14, no. 3–4, pp. 71–87, Oct. 2017.

[13] "Powerwall | The Tesla Home Battery," *2019*. [Online]. Available: https://www.tesla.com/en_AU/powerwall.