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ORIGINAL RESEARCH

Optimal sizing of grid-connected rooftop photovoltaic and battery energy storage for houses with electric vehicle

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Abstract

A practical optimal sizing model is developed for grid-connected rooftop solar photovoltaic (PV) and battery energy storage (BES) of homes with electric vehicle (EV) to minimise the net present cost of electricity. Two system configurations, (1) PV-EV and (2) PV-BES-EV, are investigated for optimal sizing of PV and BES by creating new rule-based home energy management systems. The uncertainties of EV availability (arrival and departure times) and its initial state of charge, when arrives home, are incorporated using stochastic functions. The effect of popular EV models in the market is investigated on the optimal sizing and electricity cost of the customers. Several sensitivity analyses are adopted based on variations in the grid constrains, retail price and feed in tariff. Uncertainty analysis is provided based on the variations of insolation, temperature, and load to approve the optimal results of the developed model. A practical guideline is presented for residential customers in a typical grid-connected household to select the optimal capacity of PV or PV-BES system considering the model of EV. While the proposed optimization model is general and can be used for various case studies, real annual data of solar insolation, temperature, household's load, electricity prices, as well as PV and BES market data are used for an Australian case study. The developed optimal sizing model is also applied to residential households in different Australian States.

KEYWORDS

battery storage plants, building management systems, electric vehicle charging, optimisation, particle swarm optimisation, power system planning, rooftop solar photovoltaic

1 | INTRODUCTION

1.1 | Background and motivation

The report by the International Energy Agency stated that without adoption of any appropriate measures, the electricity demand and carbon emission would increase by 65% and 70%, respectively, over the next 2 decades [1]. Around 40% of the electricity demand is for the residential and commercial buildings [2]. To reduce electricity demand and carbon emission, integration of renewable energy is a vital task for environmentalists and policy makers. Among the renewable energy sources, photovoltaic (PV) systems have been broadly used for residential buildings [3]. Installation of PV systems on the rooftop of residential buildings not only decreases the emission but also reduces the electricity cost [4].

In Australia, more than 3 million homes have had a rooftop PV system as of January 2022, accounting for over 30% of homes in the country [5]. Over the past 7 years, there was a significant increase in the number of Australian homes investing in home energy storage. In 2021, there were 30,246 home energy storage systems installed at a total capacity of 333 MWh. Since 2015, a total of 133,000 battery storage installations have been installed. This suggests that 2 in 13, or 15%, of Australian households with a solar PV also have battery energy storage (BES) [6]. Figure 1 demonstrates the trend of uptake of BES from 2015 to 2022 in Australia. With such a large uptake of rooftop solar PV systems and an increasing trend of including battery, it is important to consider not only optimising the PV system for households but also BES.

Another important factor that should be considered for PV and BES system designs is electric vehicle (EV) in the premises of the grid-connected household. Figure 2 indicates the trend of uptake of EVs' sales from 2015 to 2022 in Australia. There was an increase in sales of EV as the number of sold EVs in 2021 was three times of the sold EVs in 2020 in Australia [7]. There was also a survey which revealed that 32% of respondents would be interested in using a PV and BES system to charge their EV at home [7]. With this trend likely to continue, the importance of considering the EV for household PV and BES systems is especially important. Hence, it is important to develop new models for optimal planning of EV owner homes with PV and BES.

1.2 | Literature review

Capacity optimization of solar PV and BES is previously investigated in several studies. In [8], the rate of return of PV–battery system investment was investigated for residential customers in Thailand under decreasing battery prices. In [9], it was found that a 9-kW PV system achieves optimal results for a South Australian household, giving up to a 40% decrease in the cost of electricity (COE). A BES was not recommended as it was not an economical option over the 20-year lifespan of the project [9]. These guidelines considered energy consumption, rooftop space, annual load consumption, solar insolation, and ambient temperature. However, this study did not consider the implementation of an EV in the household system.

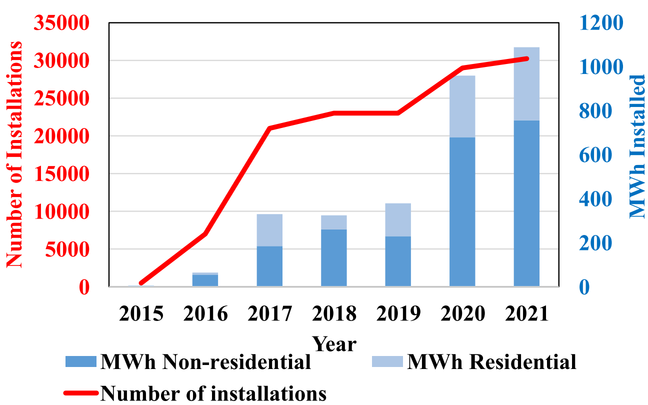

FIGURE 1 BES Installation trend from 2015 to 2022 in Australia [6]

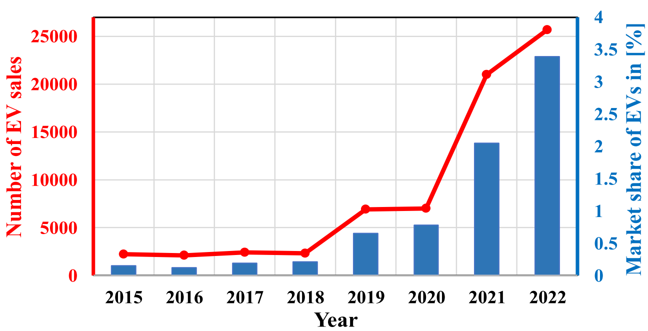

FIGURE 2 EVs' sales and their market share from 2015 to 2022 in Australia [7]

Reference [10] considered grid constraints and created an energy management system under different pricing mechanisms for a household in China based on short-term (some days of the year) data. The effect of battery degradation on capacity optimization of BES was investigated in [11]. In [12], a multi-objective capacity optimization of PV-BES system was compared for two grid-connected homes in the USA and the Netherlands. A techno-economic analysis of solar PV and BES for Finland grid-connected residential customers was adopted in [13]. In [14], optimal sizing of only battery storage was considered in a residential house with demand-side management. The environmental and economic outcomes of installing solar PV systems for residential customers were investigated in [15]. In [16], optimal sizing of PV and wind turbine was investigated in the residential sector by considering BES and EV for capturing the variations of renewable generation. Optimal sizing of renewable-battery system was conducted for a household in [17] by considering battery degradation. It was shown that degradation could significantly affect the sizing problem. In [18], the solar PV and BES were optimally sized for a grid-connected home with and without considering variations of PV generation, respectively. However, several issues to achieve a practical optimal sizing-like grid constraint, efficient home energy management system (HEMS), effect of EVs in the premises of the household, and clear guidelines for customers were not comprehensively considered in the existing studies.

Table 1 summarises the limitations of the existing studies. As indicated, practical guidelines for customers are not provided by the existing studies. No energy management system is developed in the optimal sizing model to guide the customers about the power flow when they have EV, PV, and BES. The existing studies have not investigated the optimal sizing model for a grid-connected household with EV, which significantly change the optimization results. There are several neglected realistic parameters in the existing studies, which can affect the results notably.

1.3 | Contribution

This paper investigates a timely topic of practicing engineering problem for a real case study from a practical point of view. The main novelty and contribution of this paper as compared to the previously mentioned studies are summarised as follows:

- As the major innovation, a practical and comprehensive optimal sizing model is developed for grid-connected PV and BES in homes with EV. It is notable that previous studies have not investigated optimal capacity of PV and BES for EV owner grid-connected homes when the consumers use flat electricity tariffs. Hence, this study can act as a guideline for EV owner homes to purchase the best capacity of PV and BES.
- Two novel HEMSs are developed for two system configurations, PV-EV and PV-BES-EV, to enable the most accurate utilisation of the system by the user to reduce the

TABLE 1 Summary of existing studies limitations on photovoltaic (PV) and battery energy storage (BES) optimisation

Reference	HEMS	EV	Uncertainty analysis	Practical guideline	Neglected practical parameters
[8]	✗	✗	✗	✗	Grid constraint
[9]	✓	✗	✓	✓	BES degradation
[10]	✓	✗	✗	✗	Long term data
[11]	✓	✗	✓	✗	Grid constraint and real input data
[12]	✗	✗	✗	✓	Grid constraint
[13]	✗	✗	✗	✓	Grid constraint
[14]	✓	✗	✗	✗	Real input data
[15]	✓	✗	✗	✗	BES degradation
[16]	✓	✓	✓	✗	Real input data
[17]	✗	✗	✗	✗	Grid constraint
[18]	✗	✗	✗	✓	BES degradation
This study	✓	✓	✓	✓	-

electricity cost. The developed HEMSs take into consideration practical factors, such as grid constraints, electricity prices, as well as real annual load and weather data.
- Uncertainties of arrival and departure times, and initial state of charge (SOC), as well as other specifications for an EV are incorporated to make an accurate and practical model of the system. The impact of uncertainties associated with insolation, ambient temperature, and load is assessed on the optimal sizing results.
- The proposed optimisation model, developed HEMS, and uncertainties of parameters for realistic scenarios are implemented for a typical Australian household as a case study to show its feasibility.

A practical guideline is presented for residential customers for selecting the optimal capacity of PV and BES, given the presence of an EV in the system. An analysis is provided to investigate the effects of the popular 2020 EV models in the market on the optimal sizing and electricity cost of the customers. Several sensitivity analyses are provided based on variations in the grid constrains, retail price, and feed in tariff. While the proposed optimization model is general and can be used for various case studies, realistic data of solar insolation, ambient temperature, household electricity consumption, electricity prices and limits, as well as PV and BES market data are used for an Australian case study. The developed optimal sizing model is also applied to residential households in different Australian States.

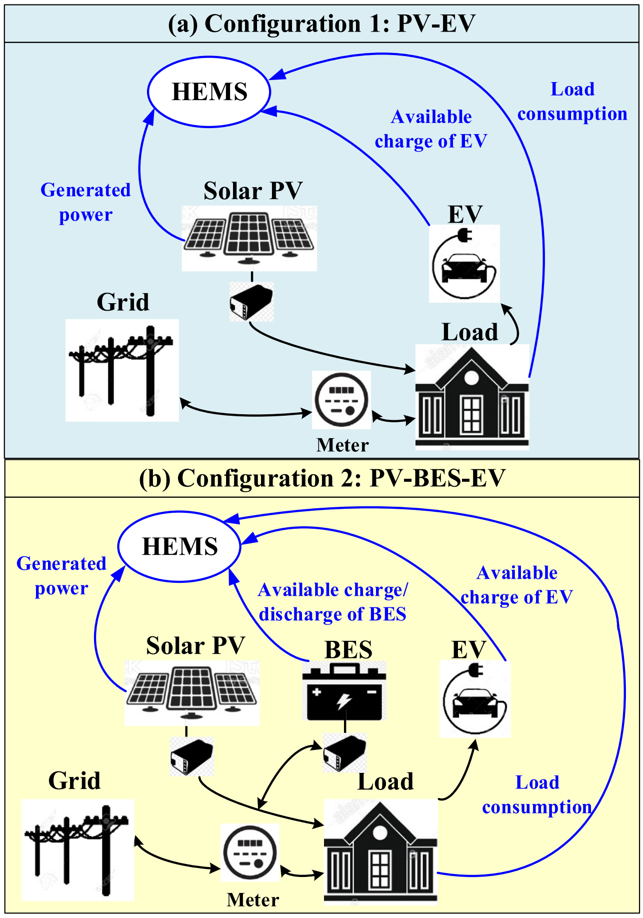

FIGURE 3 Two different configurations for a grid-connected household with home energy management system (HEMS): (a) PV-EV and (b) PV-BES-EV

2 | HOME ENERGY MANAGEMENT SYSTEM

Two different system configurations for grid-connected households are considered. These configurations are PV-BES-EV and PV-EV as shown in Figure 3. In the cases that include a PV and BES, these components are coupled in parallel. It is assumed that the EV was already purchased by the homeowner. As illustrated in Figure 3, the household can have a bidirectional power flow with the grid either purchasing or selling electricity. All the information of generated power by solar PV, load consumption of house, available charge/discharge of BES, and available charge of EV are collected in home energy management system (HEMS) to manage the power flow between the components, load, and grid. It is assumed that the EV is charged once it arrives home. The main feature of rule-based HEMS is to work in real-time systems (by considering t). The rules are designed based on inputs, for example, electricity demand (power usage) and PV generation. The rule-based EMS decides for the power dumping, charge/discharge of BES, EV charging, and purchase/sell power from/to the grid as the outputs.

The rule-based HEMS of PV-EV configuration is demonstrated in Figure 4. It depicts the rules used in the HEMS in a simplistic way and can be easily updated for any future changes. The HEMS first checks if the EV is at home or not. When the EV is not available, if the generated power of PV (P_{pv}) is higher than the household's load (P_l), then the extra power is sold to the main grid considering the maximum export power limit (P_e^{max}).

$$P_e(t) = \min\left(P_e^{max}, P_{pv}(t) - P_l(t)\right) \tag{1}$$

$$P_{pv}(t) = N_{pv}.P_{pv}^{rated}(t) \tag{2}$$

If the export power exceeds the constraint, the extra power is dumped using the inverter of solar PV system. The dumped power (P_d) can be given by

$$P_d(t) = P_{pv}(t) - P_l(t) - P_e^{max} \tag{3}$$

If P_{pv} is less than the load, then the deficit power is purchased from the main grid.

$$P_i(t) = P_l(t) - P_{pv}(t) \tag{4}$$

When the EV is parked at home, the generated power of PV is compared with household's load and the available input power of EV. If it is higher, then the extra power is sold as follows:

$$P_e(t) = \min\left(P_e^{max}, P_{pv}(t) - P_l(t) - P_{ev}^{cha}(t)\right) \tag{5}$$

The extra power of PV, after exporting the maximum power to the grid, is dumped.

$$P_d(t) = P_{pv}(t) - P_l(t) - P_{ev}^{cha}(t) - P_e^{max} \tag{6}$$

The deficit power, when the generated power of PV is lower than the load and EV, is imported from the main grid.

$$P_i(t) = P_l(t) + P_{ev}^{cha}(t) - P_{pv}(t) \tag{7}$$

The available input power limit of EV and its state-of-charge level at each time interval are calculated as follows:

$$EV_{in}(t) = min\left(P_{ev}, E_{ev}/\Delta t.\left(SOC_{ev}^{max} - SOC_{ev}(t)\right)\right) \tag{8}$$

$$SOC_{ev}(t + \Delta t) = SOC_{ev}(t) + \frac{P_{ev}^{cha}(t).\eta_{ev}^{cha}}{E_{ev}/\Delta t} \tag{9}$$

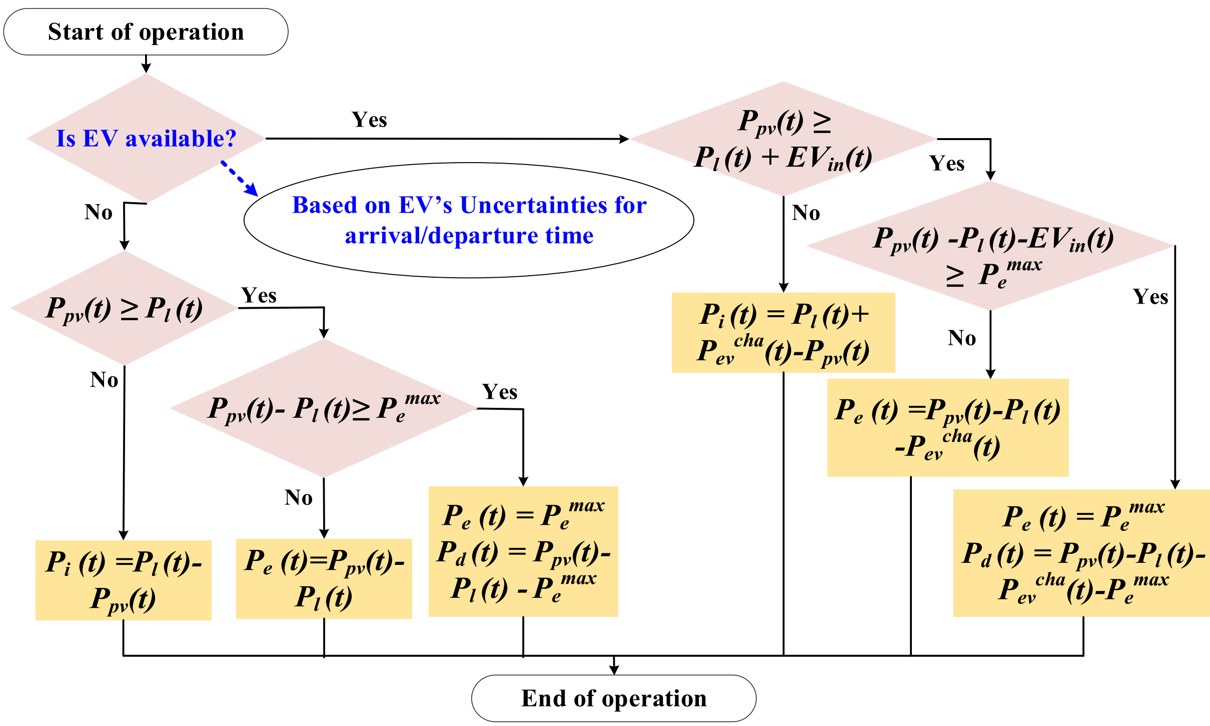

FIGURE 4 Rules-based home energy management system (HEMS) for the PV-EV system configuration

The rule-based HEMS of the PV-BES-EV configuration is shown in Figure 5. Like configuration 1, it depicts the rules used in the HEMS that can be updated for any future changes.

In the PV-BES-EV configuration, there is a battery coupled in parallel with the PV. The extra demand of the EV is added to the load and its battery's SOC is considered. Like configuration 1, the first factor in configuration two is the arrival and departure times of the EV. If the EV is not available, when the PV power does not exceed the household demand and the battery does not have adequate available power, the remaining power must be taken from the grid.

$$P_i(t) = P_l(t) - P_{pv}(t) - P_b^{dis}(t) \tag{10}$$

If the BES does have available charge, then it is discharged to supply the necessary amount of power.

$$P_b^{dis}(t) = P_l(t) - P_{pv}(t) \tag{11}$$

However, when the solar PV generates adequate power for the load, if the remaining power of PV is more than that of the input power of the battery, and the grid limit is less than PV power the load and the battery input power, then any excess power is sold or exported to the grid:

$$P_e(t) = P_{pv}(t) - P_l(t) - P_b^{cha}(t) \tag{12}$$

If the grid limit condition is met, then the maximum possible power is exported, and the remaining power dumped:

$$P_e(t) = P_e^{max} \tag{13}$$

$$P_d(t) = P_{pv}(t) - P_l(t) - P_b^{cha}(t) - P_e^{max} \tag{14}$$

If the earlier condition is not met and the remaining load is not more than that of the input power of the battery, then the battery is charged with any remaining power from the PV:

$$P_b^{cha}(t) = P_{pv}(t) - P_l(t) \tag{15}$$

Outside of the previously mentioned hour conditions, when EV is available, if the PV cannot supply the load and the EV, then power is first sourced from the battery.

$$P_b^{dis}(t) = P_l(t) + P_{ev}^{cha}(t) - P_{pv}(t) \tag{16}$$

Alternatively, if this is not possible, the grid supplies the remaining load and EV power.

$$P_i(t) = P_l(t) + P_{ev}^{cha}(t) - P_{pv}(t) - P_b^{dis}(t) \tag{17}$$

When the PV can supply the load and EV, and the batteries available input is checked, and it is not less than the PV power minus the load and the EV, then:

$$P_b^{cha}(t) = P_{pv}(t) + P_{ev}^{cha}(t) - P_l(t) \tag{18}$$

If it is more, then, it is checked whether the power may be exported to the grid, if it does not exceed the grid limit then:

$$P_e(t) = P_{pv}(t) + P_{ev}^{cha}(t) - P_l(t) - P_b^{cha}(t) \tag{19}$$

Otherwise, the maximum amount of power is first exported to the grid and the remaining power is dumped:

$$P_d(t) = P_{pv}(t) - P_{ev}^{cha}(t) - P_l(t) - P_b^{cha}(t) - P_e^{max}(t) \tag{20}$$

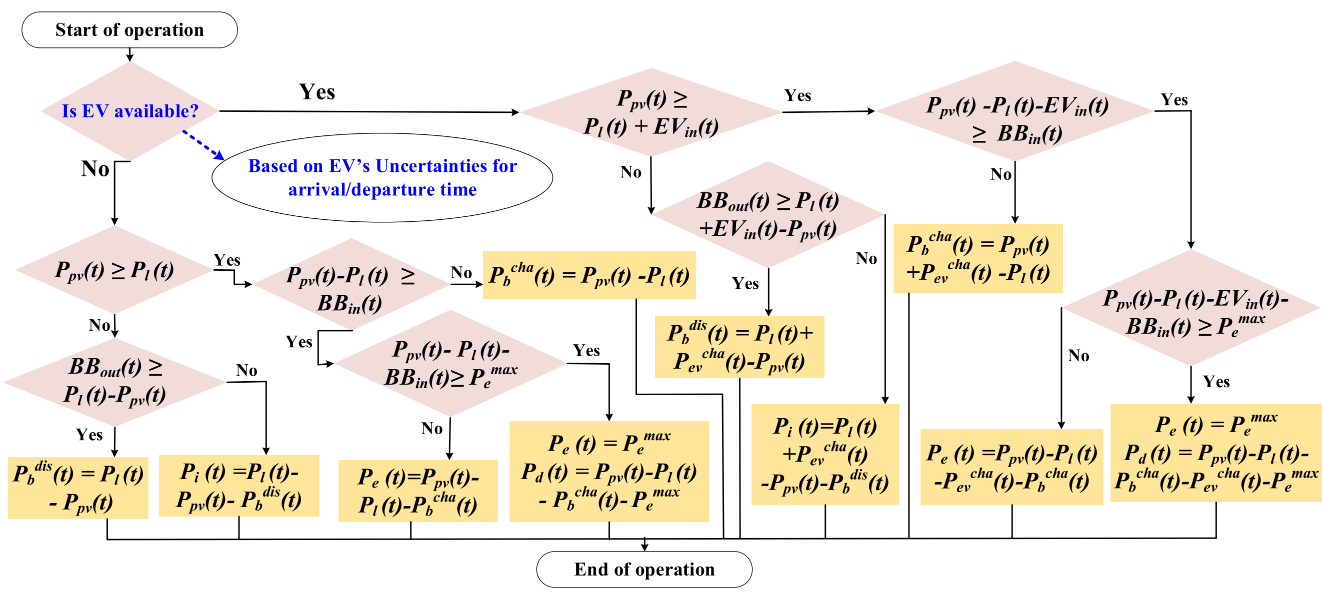

FIGURE 5 Rules-based home energy management system (HEMS) for the PV-BES-EV system configuration

The available input and output power limits of battery and its SOC level at each time interval are calculated as follows:

$$P_b^{inp}(t) = \min\left(P_b^{max}, (E_b/\Delta t).\left(SOC_b^{max} - SOC_b(t)\right)\right) \quad (21)$$

$$P_b^{out}(t) = \min\left(P_b^{max}, (E_b/\Delta t).\left(SOC_b(t) - SOC_b^{min}\right)\right) \quad (22)$$

$$SOC_b(t+\Delta t) = SOC_b(t) + \frac{P_b^{cha}(t).\eta_b^{cha} - P_b^{dis}(t)/\eta_b^{dis}}{E_b^{max}/\Delta t} \quad (23)$$

$$P_b^{max} = N_b P_b^{rated}, \quad E_b^{max} = N_b E_b^{rated} \quad (24)$$

3 | OPTIMIZATION MODEL

The conducted optimization model for sizing of PV and BES is described in this section. This contains the objective function, design constraints, and optimization algorithm.

3.1 | Objective function

The objective function of this optimization problem is total net present cost (NPC) over the 20-year lifespan of the project. The components of the PV and BES net present cost (NPC_c) as well as the electricity net present cost (NPC_g) are used to calculate the total NPC [19].

$$f = \min_{N_i}(NPC_t) = NPC_c + NPC_g \quad (25)$$

The net present cost of components includes the capital present cost (PC_i^c), maintenance present cost (PC_i^m), replacement present cost (PC_i^r), and salvation present cost (PC_i^s).

$$NPC_c = \sum_{i=1} N_i \bullet \left(PC_i^c + PC_i^m + PC_i^r - PC_i^s\right) \quad (26)$$

The annual maintenance cost over the lifetime at an interest rate x is given by [9]

$$PC_i^m = C_i^y.\frac{(1+x)^n - 1}{x(1+x)^n} \quad (27)$$

The components are replaced every Y year of the lifetime of the system:

$$PC_i^r = C_i^z.\sum_{t=1}^{tY<L_i} \frac{1}{(1+x)^{tY}} \quad (28)$$

The salvation present cost is the value of components at the end of project lifetime.

$$PC_i^s = N_i.PC_i^c.\frac{R_i}{L_i}.\frac{1}{(1+x)^n} \quad (29)$$

The lifetime of BES is reached when its capacity decreased to 80% of its initial value. The battery lifetime should be hence estimated by operation capacity degradation (CD) of battery. The CD of battery is calculated based on the number of cycles and the depth of discharge (DOD) of each cycle. Therefore, after the annual operation of the grid-connected household, the SOC data of battery is collected. After that, the DOD of battery is calculated by

$$DOD_b(t) = 1 - SOC_b(t) \quad (30)$$

In this paper, Rainflow Algorithm is used to extract the cycle data from the collected DOD. The battery CD is then calculated for lithium-ion technology in each full cycle (ψ) by [20]

$$D_b(\psi) = \frac{20}{33000.e^{-0.06576.DOD_b(\psi)} + 3277} \quad (31)$$

It is notable that half of D_b is used for the half cycles. The total battery CD in the yearly operation is calculated by

$$AD_b = \sum_{\psi} D_b(\psi) \quad (32)$$

It is generally accepted that a BES lifetime will be reached when 20% of the battery capacity has degraded and hence assumed in this study.

The net present cost of electricity is usually escalated by a rate of v above x; therefore, the real interest rate for electricity cost is:

$$z = \frac{x - v}{1 + v} \quad (33)$$

Given the real intertest rate, the net present cost of electricity is given as

$$NPC_g = AE_g.\frac{(1+z)^n - 1}{z(1+z)^n} \quad (34)$$

The C_e is the annual electricity cost of trade with the grid, which can be calculated as follows:

$$AE_g = \sum_{t=1}^{8760} rp(t).P_i(t).\Delta t - \sum_{t=1}^{8760} fit(t).P_e(t).\Delta t + \overbrace{D_y.S_c}^{ASC} \quad (35)$$

where annual supply of charge is the annual supply of charge, which is calculated based on daily supply of charge (S_c).

3.2 | Design constraints

The design constraints of the optimization problem are represented by the following equations:

$$0 \le P_{pv}(t) \le P_{pv}^{max} \tag{36}$$

$$0 \le P_b^{cha}(t), P_b^{dis}(t) \le P_b^{max} \tag{37}$$

$$0 \le P_{ev}^{cha}(t) \le P_{ev}^{max} \tag{38}$$

$$SOC_b^{min} \le SOC_b(t) \le SOC_b^{max} \tag{39}$$

$$SOC_{ev}^{min} \le SOC_{ev}(t) \le SOC_{ev}^{max} \tag{40}$$

$$P_{pv}(t) + P_b(t) + P_i(t) - P_e(t) \ge P_d(t) + P_{ev}(t) \tag{41}$$

$$0 \le P_e(t) \le P_e^{max} \tag{42}$$

Equations (36–38) are the power constraints of the PV, BES, and EV, respectively. It is notable that the load of the house, except the charging of EV, is not controllable. So, the load restriction is only considered on EV load which is showed by Equation (38). The SOC constraints of the battery and electric vehicle are given by Equations (39) and (40), respectively. Equation (41) is the power balance constraint, and Equation (42) is the export power constraint from the solar PV of the house to the main grid. The constraints should be valid for the total 't' which is 8760 h.

3.3 | Cost of electricity

Cost of electricity is usually used to evaluate the cost of various electrical systems [21]. It is notable that for flat electricity price, the COE of the system, in the absence of BES and PV, is the same as the retail price. The COE is calculated based on the ratio of net annual payment to the annual load demand of the household. This can be formulated by

$$COE = \frac{NPC_c.\, crf_c + NPC_g.\, crf_g}{E_l} \tag{43}$$

$$crf_c = \frac{u(1+u)^n}{(1+u)^n - 1} \tag{44}$$

$$crf_g = \frac{w(1+w)^n}{(1+w)^n - 1} \tag{45}$$

$$E_l = \sum_{t=1}^{8760} P_l(t).\, \Delta t \tag{46}$$

where crf_g and crf_c are the capital recovery factor of electricity and components NPCs, respectively.

3.4 | Optimization procedure

The optimal sizing problem in this study is a mixed integer problem. However, the developed optimization model by (25)–(42) shows that the objective function cannot be computed in a closed form. This is because the degradation of BES and its lifetime cannot be calculated at the beginning of the optimization process. In other words, the Rainflow Algorithm needs the future data of DOD level to obtain the BES lifetime. This makes it impossible to connect the objective function and decision variables in a closed form. Therefore, the classic approaches are unable to solve the problem and metaheuristic methods are suitable candidates.

It is notable that several software are available that can be used for optimization of energy systems. However, there are some deficiencies with the software for optimal sizing. The first deficiency is regarding the battery degradation issue that the software do not usually contain any model for degradation. The second deficiency is about the salvation value of PV and BES, which is usually not considered in the economic analysis of the software. The other and most important deficiency is about the energy management system. In most of the software, the energy management cannot be changed and there is no possibility to design rule-based energy management systems.

In this paper, particle swarm optimisation (PSO) is used as the optimisation algorithm since the PSO has been successfully used for optimal sizing problem of power systems [9, 22–24]. The PSO is a simple method, which gives suitable convergence with little dependency on the initial conditions [25]. The PSO algorithm works by, at each iteration, evaluating its current position compared to any other so far and then storing the new, better position. This position becomes the new previous best and can again be compared to a new position in later iterations [25]. The aim is to eventually find the best position through the interaction of individual particles. Algorithm 1 shows the PSO optimal sizing procedure for the EV owner grid-connected household with PV and BES. The algorithm commences by receiving the input data and initialisation of the PSO. In this stage, PSO randomly selects the sizes of PV and BES to start the energy management. Then, based on the selected sizes, the HEMS is evaluated for 1 year since it is impossible to run the simulation for 20 years (project lifetime) mostly because of unavailability of data (e.g., solar insolation and load) and computational time of the solution. It is notable that the linkage between the decision variables and the optimization problem is shown in Equation (2), for the PV capacity, and Equations (21–24) for the BES capacity. After evaluating the HEMS for 1 year, if the design constraints are satisfied for all time intervals, the obtained results are extended for 20 years based on the engineering economic concepts by considering interest and escalation rates as shown in Equations (27–29) and (34), and the NPC is calculated. This process is repeated for all number of populations and generations to find the optimal sizes of PV and BES. To guarantee the globality of the results by the PSO, 200 populations are considered along with 200 iterations, and the whole process by PSO is repeated for 10 runs. At the end, the results of the run with the minimum NPC will be presented as the optimal results. It is worth mentioning that the comparison of the PSO results with the other optimization methods is out of scope of this study.

Algorithm 1 Optimization algorithm to achieve optimal capacity of PV and BES

```
Input data of the system (load, weather,
  and components data)
Initialisation of the PSO algorithm
Choose the capacity of PV and BES (200
  population)
for t = 1: 8760 do
   Run the system HEMS
   if the system constraints satisfied,
   then
       Calculate the objective function
       and save it.
       else
       Ignore the solution
   end if
end for
Calculate NPC_t
while generation is less than the
  maximum do
   Repeat steps Equations (3-12)
end while
while run is less than the maximum runs do
   Repeat steps Equations (3-15)
end while
Obtain the minimum objective function
  and show the optimal results
```

4 | CASE STUDY

The case study, which is used for the development of a HEMS and optimal sizing, is of a typical grid-connected household in South Australia (SA). The optimisation model created for this case assumes that the household has previously purchased or intends to purchase an EV.

Table 2 presents the actual parameters of the system for the considered case study. The length of project lifespan is 20 years in which the interest and escalation rates are considered as 8% and 2% per year, respectively [9]. The electricity supply charge is 79 ¢/day. The single-phase customers like grid-connected houses are prohibited to export more than 5 kW to the main grid at any time. The current feed-in tariff (FIT) value (17 ¢/kWh) is almost one third of the retail price (RP) value (48 ¢/kWh) [9]. In this study, a flat electricity tariff is assumed since most of the residential households in SA are under the flat tariff structure.

Table 3 presents the economic and lifetime data of solar PV and battery. Solar PV's lifetime is 25 years with an inverter replacement in 10 years. Battery's lifetime is to be decided based on the charging/discharging operation in the system. In SA, the government encourages customers to purchase BES with a high subsidy [26]. So, the current market price of battery is \$350/kWh. Minimum and maximum constraints are considered for battery SOC as 20% and 100%, respectively. Battery's efficiency for charging/discharging is assumed as 92.5%. The maximum capacity of PV for the optimization problem is considered as 10 kW, which is obtained based on the assumption that in a typical grid-connected household, the available rooftop cannot be more than 50 m^2 [9].

Real annual data of insolation, electricity consumption, and air temperature is hourly collected for the case study. Figure 6 illustrates the actual data. While the energy management uses hourly data for 1 year, the annual and weekly data are shown to give more details about the variations of the data. The electricity consumption is collected for a typical household in SA. The average of load is 0.65 kW where the household consumes a daily energy of 15.6 kWh [9]. The temperature and insolation are real-measured data for 2018 taken from Australian Bureau of Meteorology for a location in Adelaide city of SA [27]. The air temperature changes between minimum 2.2°C and maximum 41.8°C for the urban area [27]. The maximum solar insolation through the year is 0.89 kWh/m^2 [27].

The type of EV is considered as Renault Zoe (2020 R135) with 54-kWh battery and 5-kW single-phase charging power [28]. The arrival/departure time to/from home as well as the SOC of EV when arrives home are considered as uncertainties. These uncertainties of the EV are modelled by truncated Gaussian distribution method as it is common for such studies [29]. For this aim, these uncertainty parameters are formulated based on a lognormal probability distribution function (PDF_{ev}) expressed by

$$PDF_{ev}(\mathcal{Q};\lambda,\vartheta) = \frac{1}{\mathcal{Q}.\vartheta.\sqrt{2\pi}}.e^{-(ln\ \mathcal{Q}-\lambda)^2/2\vartheta^2} \quad (47)$$

where $\mathcal{Q}$ shows the uncertainty parameter of the EV to be generated by the probability function. ϑ and λ represent the standard and mean deviation parameters, respectively. Table 4 presents the parameters of the probability distributions for the uncertainties of EV.

TABLE 2 Actual parameters of the system for the considered case study

Parameter	Value	Parameter	Value
Project lifetime (year)	20	Retail price (¢/kWh)	48
Escalation rate (%)	2	Feed-in-tariff (¢/kWh)	17
Interest/Discount rate (%)	8	Electricity supply charge (¢/day)	79
Grid export limit (kW)	5		

TABLE 3 Economic and lifetime data of solar photovoltaic (PV) and battery

Component	Size unit	Capital cost	Replacement cost	Maintenance cost	Lifetime
PV	1 kW	$ 1500	$ 300 (for inverter in 10th year)	$ 50/year	25 years
BES	1 kWh/0.5 kW	$ 350	$ 200	NA	TBD after annual operation

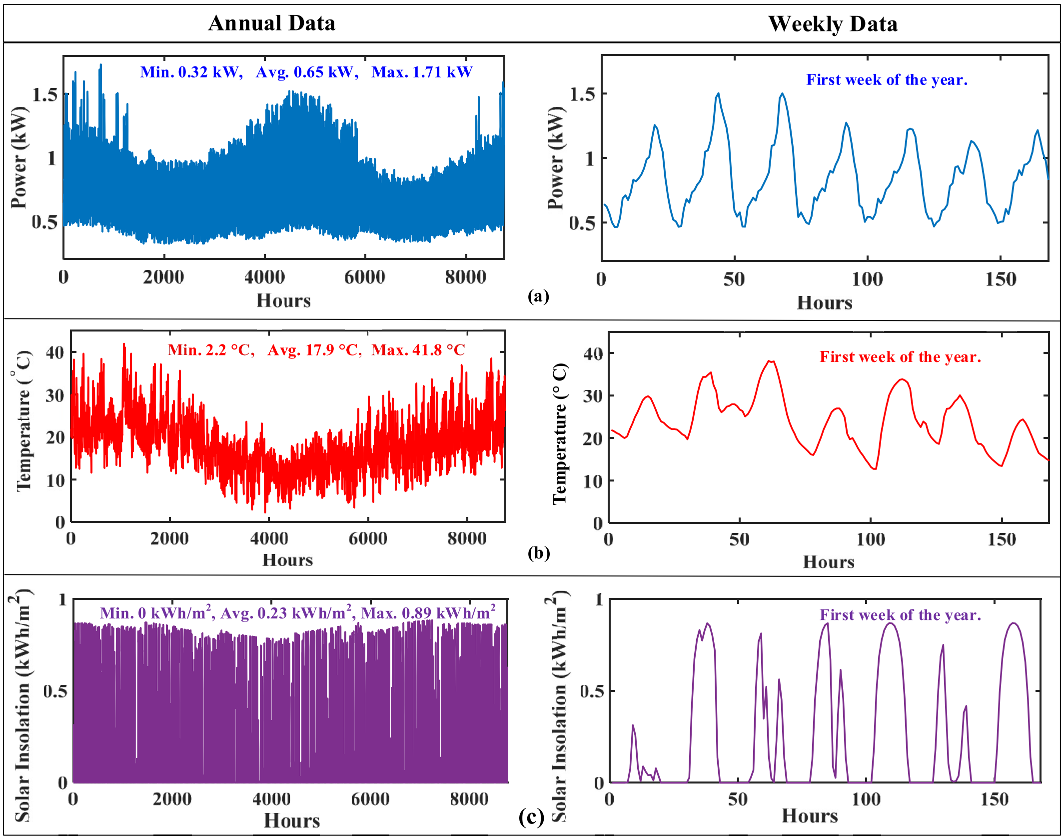

FIGURE 6 Annual and weekly data of (a) electricity consumption, (b) air temperature, and (3) solar insolation of the case study

TABLE 4 Probability parameters to produce electric vehicle's (EV's) uncertainties

Parameter	Mean	S.D.	Min.	Max.
Initial SOC at arrival (%)	50	30	20	85
Arrival time (hr)	18	3	15	21
Departure time (hr)	8	3	5	10

5 | RESULTS AND DISCUSSIONS

In this section, the optimization results for two system configurations are presented at first. Then, an economic analysis is provided based on different available EVs in the market. Sensitivity analyses are presented to study the effects of grid constraint, RP, and FIT on the optimisation results. The operation of the grid-connected household with PV, BES, and EV is investigated in a 48-h basis. A practical guideline is provided, and the optimisation results are adopted for different Australian States.

5.1 | Technical and economic results

Table 5 lists the optimisation results, including the capacity of PV and BES, NPC, and COE. The results of the grid-connected household with EV and without PV and BES were also presented for the sake of comparison. It was discovered that the optimal capacity of PV is 10 kW for both system configurations. The optimal battery capacity was found as 1 kWh for the second configuration. Although the NPC of PV-BES-EV is slightly lower than that of PV-EV, the COE of both configurations is almost the same. Adding the solar PV system has decreased the NPC of electricity by more than $ 15,000 for the grid-connected household. The COE has also decreased by about 7 ¢/kWh. As shown in the table, the incorporation of 1 kWh BES is not that much effective in cost reduction. But it should be noted that it can be a valuable point and guideline for houses with EV to not buy BES with the current market price.

Figure 7 demonstrates the annual energy exported to the grid (AEEG), annual energy imported from the grid and the annual dumped energy (ADE) of the systems. By adding BES, the AIEG and AEEG are decreased slightly. The ADE is also the same for both system configurations. Dumped energy is the extra energy of solar PV after supplying the household demand, charging the battery, and exporting to the grid. It is assumed that this extra power is dumped using the controller of the inverter of the PV. So, there is not any physical dump load in the system.

Figure 8 demonstrates the convergence rate of the PSO algorithm for optimal sizing of the household with PV-BES-EV. It is notable that in 8 runs (of 10 runs), the minimum NPC was obtained and only in 2 runs, the NPC was different from a higher value. Figure 8 shows the convergence rate of one of those 8 runs with the minimum obtained NPC. As shown, the NPC is converged to the minimum value at around 90 iterations.

TABLE 5 Optimal capacity of components, net present cost (NPC), and cost of electricity (COE) for the system configurations

Configuration	PV (kW)	BES (kWh)	NPC ($)	COE (¢/kWh)
Household with only EV	-	-	75,202	48.0
Household with PV-EV	10	0	58,633	41.6
Household with PV-BES-EV	10	1	58,586	41.6

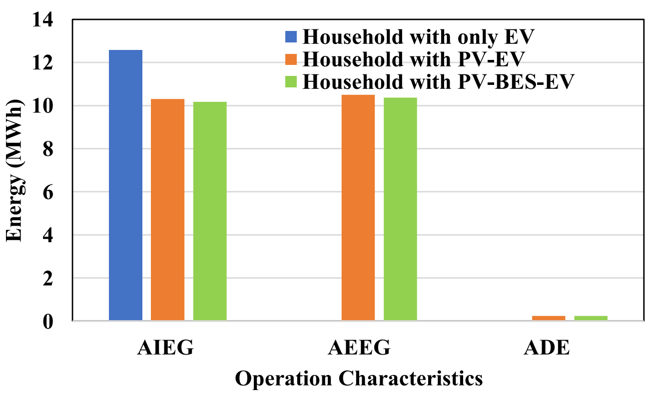

FIGURE 7 Operation characteristics of the system configurations

FIGURE 8 Convergence rate of the particle swarm optimisation (PSO) algorithm for optimal sizing of the household with PV-BES-EV

Comparing the profitability of having an EV in a renewable household system rather than an internal combustion engine vehicle (ICEV) is important for making recommendations. Considering the average Australian passenger vehicle as of 2020 uses approximately 10.8 L of fuel per 100 km based on the average distance travelled of 12,648 km per year [30], it can be calculated that 1366 L of fuel is consumed per vehicle per year. With the average price of fuel in Australia as of 2019 being $1.42 [31], the average vehicle consumes around $1939.72 worth of fuel a year.

At a COE of 48 ¢/kWh, investigating the Renault Zoe, which has the consumption rate of 13.67kWh/100 km [28], it costs the average user $829.70 per year to run, assuming that they travel the average distance previously mentioned of 12,648 km. A comparative car, the Renault Clio 1.2 L turbo petrol, has an estimated real-world consumption of 9.5 L/100 km, which would make its fuel consumption cost $1706.21/year.

The COE drops from approximately 48 to 41.6 ¢/kWh when a PV-BES system is in place and running an EV on electricity. This is more economical than running an ICEV on petrol. Hence, it is viable to own an EV rather than an ICEV and implement a PV-BES-EV system.

5.2 | Analysis of two electric vehicles in the household

In many states including SA, it is common for a household to have two EVs. Therefore, it is important to consider how this may affect the electricity cost of a household if two EVs are available. For this purpose, it is assumed that a household has two Renault ZOE EVs. The results show that for SA customers with two EVs and without PV and BES, there would be approximately a 49% increase in the NPC of electricity over 20 years ($111,217). However, it is found that when the customer purchases PV and BES, the NPC would decrease to $ 94,264. The capacities of PV and BES are obtained as 10 kW and 1 kWh, respectively. These results indicate that two EVs in a system would remain economical for an SA grid-connected residential customer when they purchase PV and BES.

5.3 | Analysis of electric vehicles in the market

The Renault Zoe is a popular model of EV in Australia used for the purpose of this study. Other popular models are also considered so the consumer may make an informed decision. The popular 2020 model EVs on the Australian market are BMW i3 (42 kWh), Tesla Model 3 (54 kWh), Hyundai IONIQ (38.3 kWh), Nissan Leaf (62 kWh), and Tesla Model X (100 kWh), where the number in the parentheses shows the battery capacity of each EV model. The charging power of all these EVs (when parked at home) is limited to 5 kW at any time.

These vehicles are then compared by simulation. The simulation conducted is of a PV-BES-EV system, swapping out the EV data each time. Table 6 presents the results of these EVs. It is evident that the most desirable car for a consumer to own over the 20-year study period is a Hyundai IONIQ as it obtains the lowest NPC. Although over this period, it can be said that each car performed similarly other than the tesla model X, which gives a very high NPC of $90,000. This is mainly because of its high capacity of battery.

5.4 | Sensitivity analysis

The results of a sensitivity analysis for the export power limit are presented in Figure 9. As Australia employs a limit to the export power from residential houses, the effect of this limit is investigated in relation to the COE and the PV and BES capacities in PV-EV and PV-BES-EV systems. The system optimal capacities for each component and COE can be seen against the export power limit in each figure. When the configuration is PV-EV and no power exportation is allowed, the optimal capacity for a solar PV is 2-kW. For each configuration, while the power export limit increases, so too does the optimal capacity of the PV. With this increase in PV capacity, the COE decreases as the export power limit decreases. For the PV-BES-EV system as shown in Figure 9, little changes from the PV-EV only configuration because the BES remains at 1-kWh throughout the analysis as it never becomes viable to have a larger capacity BES.

A similar analysis is conducted for the retail price of electricity as this is a variable, which differs in each state and is not constant. The results of the sensitivity analysis on retail price can be observed in Figure 10. This figure shows that as the retail price increases, predictably, the cost of energy increases at a directly proportional rate. As the cost increases, the BES capacity eventually increases from 0 to 2kWh, which results in a slight but negligible decrease in the cost of energy in this case. Ultimately, it can be observed that changes to the retail price of electricity do not have a significant effect on the optimal capacity of PV.

The feed-in tariff is another variable, which should be considered for sensitivity analysis. Just as the export power limit can be limited, the tariff may also be adjusted. The

TABLE 6 Electric vehicle simulation results

Vehicle	NPC ($)	COE (¢/kWh)	AIEG (MWh)	AEEG (MWh)
BMW i3	49,797	40.73	8.59	10.36
Tesla model 3	58,587	41.62	10.17	10.36
Hyundai IONIQ	47,076	40.41	8.10	10.37
Nissan leaf	64,437	42.10	11.22	10.36
Tesla model X	90,000	43.41	15.78	10.25

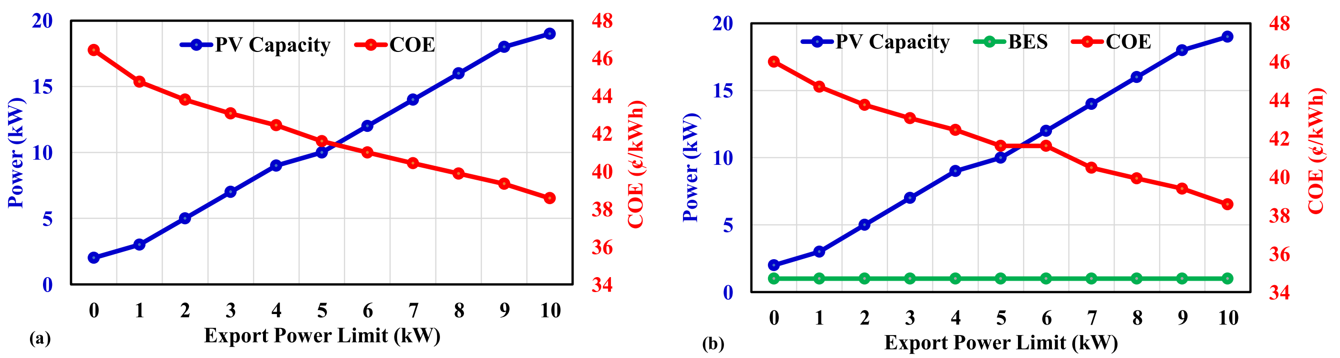

FIGURE 9 Sensitivity analysis of export power limit for (a) PV-EV and (b) PV-BES-EV configurations

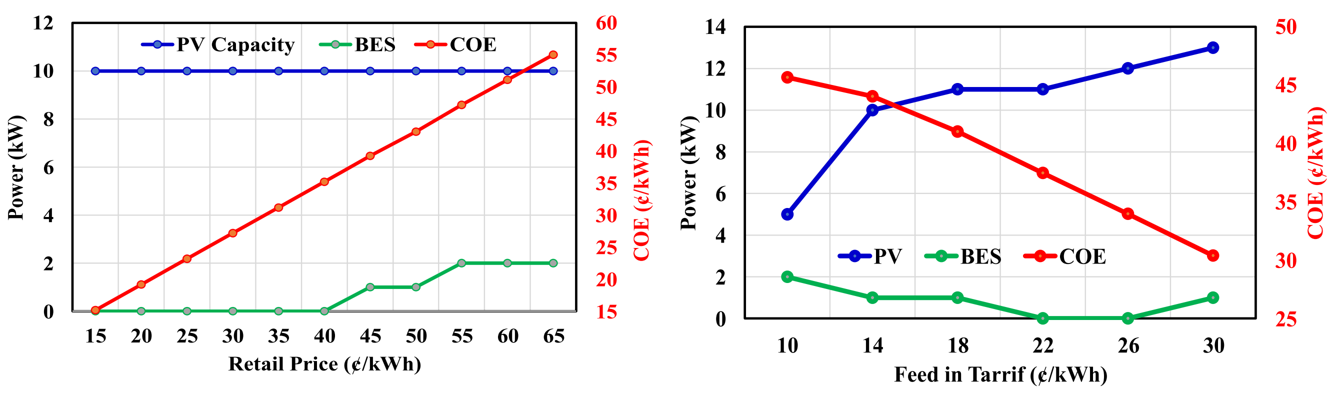

FIGURE 10 Sensitivity analysis of retail price and feed-in-tariff for PV-BES-EV configuration

results of the sensitivity analysis can be observed in Figure 10. As the feed-in tariff increases from 10 to 30 ¢/kWh, having a larger PV capacity increase in viability. The capacity increases from 5kW to 13kw, bringing the COE down from 45 to 30 ¢/kWh.

5.5 | Daily load analysis

The daily power flow for a PV-BES-EV is investigated to analyse the operation of the system. This is completed for both summer and winter over 48-h periods as seen in Figure 11. In summer, overnight, all the loads are supplied by the grid. During the day between approximately 7 and 10am, the BES partially supplies the load minimising the imported power to zero at the BESs peak output. During the sunny part of the day, from approximately 8am, the PV begins to generate power to supply the load, which also begins to increase in the morning. The remaining power is exported to the grid during the hours that the PV is generating until approximately 8pm, when the sun begins to set in SA's summer. As the EV returns at the end of the day and begins to charge around 7pm, all the power demand for this must be imported from the grid. When the car ceases to charge at 2am the next morning, the imported power matches that of the household load, which is minimal during the night. This pattern then repeats similarly for the next 24-h period as in Figure 11.

During winter, this pattern is similar with some deviations. The overall seasonal capacity for PV generation is reduced; however, the PV generation is still able to supply the load with surplus during sunlight hours and import power from the grid during the night to supply the load and EV.

5.6 | Uncertainty analysis

To approve the optimal capacity of PV and BES for the EV owner grid-connected house, an uncertainty analysis is provided based on 10 scenarios of hourly variations of insolation, temperature, and electricity consumption. For the scenarios, the data of solar insolation and temperature are selected based on real data from 2011 to 2020 in Adelaide [27]. The plug-in electric vehicle's uncertainties for the availability (departure and arrival times) and level of SOC at arrival time are separately generated by equation (33) for each scenario. The electricity consumptions of the above 10 scenarios (or years) are obtained by adding parameters of uncertainty to the available actual data as follows:

$$P_l^s(t) = P_l(t) + P_l(t).\gamma.\mathscr{g}(t) \tag{48}$$

where P_l^s is the randomly generated electricity consumption for sth scenario, γ represents a factor of deviation in the range of 10%–50%, and $\mathscr{g}(t)$ is a function that generates random number between −1 and +1. The value of γ is selected different for each scenario and $\mathscr{g}(t)$ generates random number for each time interval in each scenario.

Figure 12 demonstrates the average daily load of the house, average annual temperature, and daily insolation for the uncertainty scenarios. As shown, the average daily load of the hourly uncertainty scenarios changes between 15.2 kWh and 16.8 kWh.

Figure 13 illustrates the optimization results of uncertainty scenarios for optimal sizing of the PV-BES-EV system. The optimal capacity of solar PV has obtained as 10 kW for seven scenarios of the uncertainty analysis. The results show that the optimal capacity of BES is 1 kWh for eight scenarios. Hence, it can be inferred that the obtained optimal capacities by the developed method of this study are valid against the variations of solar insolation, temperature, and electricity consumption. As indicated in the figure, the COE of the system

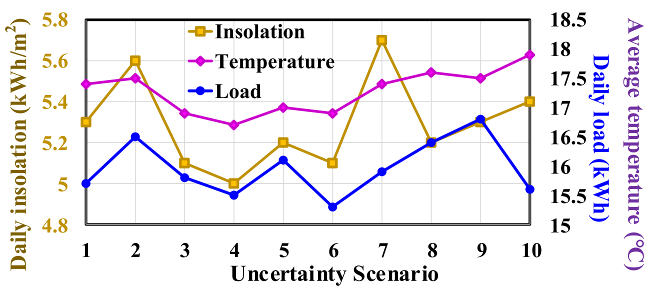

FIGURE 12 Average daily load, average annual temperature, and daily insolation for the uncertainty scenarios

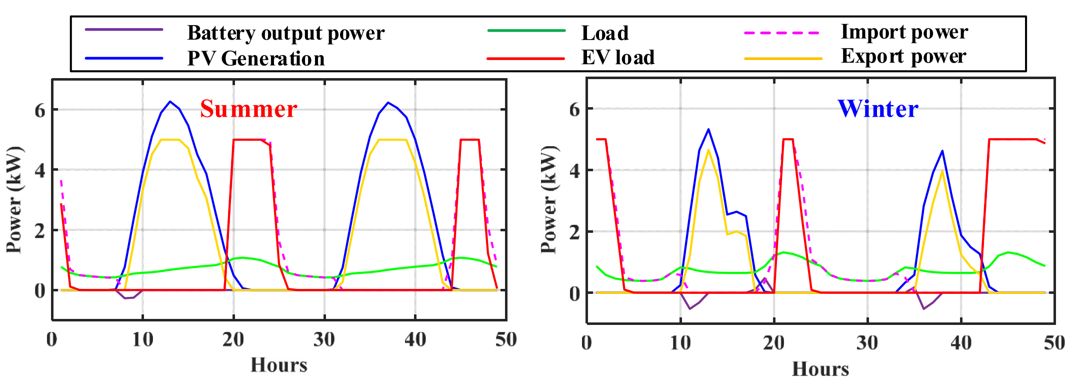

FIGURE 11 Daily power flow of load power, photovoltaic (PV) power and export power for PV-BES-EV over two 48-h periods in summer and winter

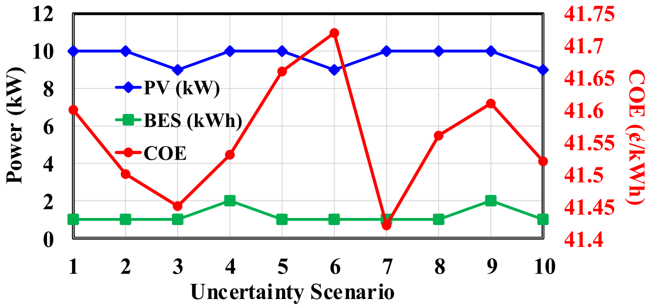

FIGURE 13 Results of uncertainty scenarios for optimal sizing of the PV-BES-EV system

changes in a range from 41.4 ¢/kWh to 41.72 ¢/kWh. Hence, the COE does not change significantly by uncertainties of the data.

5.7 | Guideline for consumers

This study facilitates a practical guideline for South Australian residential customers to purchase the optimal capacity PV-BES system to accommodate the load of an EV. The guidelines are for the customers with an EV and without a PV or PV-BES system who wish to purchase the optimal PV or PV-BES configuration.

For customers who already own an EV, the capacity of the system can be optimised to the size of the vehicle. For those who do not and are considering buying one at the same time as the PV system, further recommendations can be made. The electricity rates and metrological averages for the state of residence should also be considered. For a South Australian customer looking for the optimal capacity of PV and BES, not considering roof size, it is advised from the results that they instal a 10-kW PV with a 1-kWh BES. This was found using the average daily load assuming a Renault Zoe or similar EV in the premises of the household. For customers with a larger capacity EV, the recommendation for system capacity does not change. For those who have not yet purchased an EV, a smaller capacity car is recommended over a larger as the NPC is significantly lower. For example, a Hyundai IONIQ would be more economical than a Tesla model X.

5.8 | State-by-state optimisation

The developed optimal sizing model of PV and BES is examined for grid-connected households in other Australian States (NSW: New South Wales, QLD: Queensland, TAS: Tasmania, VIC: Victoria, WA: Western Australia). For this purpose, the real electricity rates and weather data of each State are used [9]. For states other than SA, the recommended capacities can be seen in Table 7. The lowest PV capacity can be seen to be recommended for TAS and WA with no BES. This is due to TAS and WA's low retail prices and feed in tariffs, making it less beneficial to have a PV system. TAS also has the lowest daily

TABLE 7 Electricity rates for Australian states with simulation results

State	RP (¢/kWh)	FIT (¢/kWh)	PV (kW)	BES (kWh)	COE (¢/kWh)
TAS	25	9	2	0	24.24
VIC	26	12	9	0	24.69
WA	26	7	2	0	25.21
QLD	31	13	10	0	28.40
NSW	33	16	9	0	27.98
SA	48	17	10	1	41.6

average solar insolation of 4.6 kWh/m^2, just after VIC's 4.7 kWh/m^2 [9], further decreasing its desirability for PV. SA benefits the most from a PV-BES-EV system as it has the highest initial retail price and FIT as well as insolation at 5.4 kWh/m^2 giving the highest COE reduction from 48 to 41.6 ¢/kWh.

6 | CONCLUSION AND FUTURE WORKS

This study developed a practical optimal sizing of solar PV and battery for grid-connected households with EV. Two new energy management systems were developed for two different configurations, PV-EV and PV-BES-EV. Real annual dataset for load consumption, solar insolation, and ambient temperature for SA was used along with a stochastic model for arrival/departure time and initial SOC of EV. It was found that for a typical household with a common EV model (Renault ZOE), the optimal capacity of the system is 10-kW for PV and 1-kWh for BES, bringing the COE from 48 to 41.6 ¢/kWh. An optimisation comparison for new market available EVs showed that the most COE reduction can be obtained for Hyundai IONIQ from 48 to 40.41 ¢/kWh. Optimum capacities for a PV-BES-EV system were also considered for Australian states other than SA. It was found that in states, such as WA and TAS, where the FIT and RP of energy are both much lower than the rest of Australia, it is not desirable to have more than a 2-kW PV capacity with no BES. With TAS's low solar insolation, the state is least desirable location for installation of solar PV. The uncertainty analysis approved the optimal capacities of PV and BES based on the variations of load, insolation, and temperature.

For future works, the conducted optimal sizing problem can be further developed in twofold. First, the scalability of the method can be investigated for bigger systems such as apartment buildings with several EVs. Second, the system model can be extended to consider dynamic electricity tariff structures. For this purpose, the optimal sizing model would remain similar, but the annual electricity bill should be calculated through (35) using the new tariff rate. However, the rules in the energy management systems should be updated based on the electricity rate in the tariff structure, and hence, new optimal results and guidelines can be conducted.

NOMENCLATURE

Symbol **Description**

ECONOMIC TERMS

AE_g Annual bill of electricity (AU$).
coe Cost of electricity.
crf_c Capital recovery factor of components.
crf_g Capital recovery factor of electricity.
C_i^y Annual maintenance cost of component i (AU$).
C_i^z Replacement cost of component i (AU$).
PC_i^c Capital present value of components (AU$).
PC_i^m Maintenance present value of components (AU$).
PC_i^r Replacement present value of components (AU$).
PC_i^s Salvation present value of components (AU$).
S_c Daily supply charge (AU$).
rp Retail price ($/kWh).
fit Feed-in-tariff ($/kWh).
n Project lifespan (yr).
NPC_c Net present cost of components (AU$).
NPC_g Net present cost of electricity trade with grid (AU$).
NPC_t Total net present cost (AU$).
z, w Electricity interest/discount rates (%).
x, u Project interest/discount rate (%).
v Escalation rate (%).

SYSTEM TERMS

AD_b Annual degradation of battery (%).
BB_{in} Available input power of battery (kW).
BB_{out} Available output power of battery (kW).
D_b Degradation of battery (%).
D_y Number of days of operation.
DOD_b Depth of discharge of battery (%).
E_b Nominal energy of battery (kWh).
E_b^{rated} Rated energy of battery (kWh).
E_l Annual electricity demand of home (MWh).
E_{ev} Nominal energy of electric vehicle (kWh).
EV_{in} Available input power of electric vehicle (kW).
L_i Lifetime of component i (year).
N_i Number of components.
N_b/N_{pv} Number of battery and solar photovoltaic.
P_b Battery's power (kW).
P_b^{rated} Rated power of battery (kW).
P_b^{cha} Charging power of battery (kW).
P_b^{dis} Discharging power of battery (kW).
P_d Dumped power (kW)
P_e Exported power to the grid (kW).
P_e^{max} Maximum export power limit (kW).
P_{ev} Electric vehicle's power (kW).
P_b^{cha} Charging power of electric vehicle (kW).
P_i Imported power from the grid (kW).
P_l Power consumption of the household (kW).
P_{pv} Solar PV's output power (kW).
P_{pv}^{rated} Rated power of solar photovoltaic (kW).
R_i Remaining lifetime of component i (year).
SOC_b State-of-charge of battery (%).
SOC_{ev} State-of-charge of electric vehicle (%).
t Time (hr).
η_b^{cha} Charging efficiency of battery (%).
η_b^{dis} Discharging efficiency of battery (%).
η_{ev}^{cha} Charging efficiency of electric vehicle (%).
ψ Battery cycle.
Δt Time interval (hr).

AUTHOR CONTRIBUTION

Sarah Merrington: Conceptualisation; Data curation; Formal analysis; Methodology; Resources; Software; Writing – original draft. **Rahmat Khezri**: Conceptualisation; Formal analysis; Methodology; Software; Supervision; Writing – review and editing. **Amin Mahmoudi**: Formal analysis; Project administration; Supervision; Writing – review and editing.

CONFLICT OF INTEREST

The author declares that there is no conflict of interest that could be perceived as prejudicing the impartiality of the research reported.

DATA AVAILABILITY STATEMENT

Data sharing is not applicable to this article as no new data were created or analysed in this study.

PERMISSION TO REPRODUCE MATERIALS FROM OTHER SOURCES

None.

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