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Optimum battery depth of discharge for off-grid solar PV/battery system

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ABSTRACT

In this paper, we propose a multi-objective optimization model that considers the loss of load probability (LLP) and the cost of energy (COE) together with the battery life loss cost and the costs of operation, replacement, and maintenance. These factors form the projected operating framework of the off-grid system for which we utilize the non-dominated sorting genetic algorithm (NSGA-II) method. The proposed model includes the depth of discharge (DOD) of the battery, which is determined based on the battery life loss cost. In addition, in the optimal model, the amount of energy flow from the battery bank during the charging and discharging cycles must satisfy the load demand at the lowest cost and with the highest reliability. The results show that the optimal DOD value for a battery in the solar PV system being investigated is 70%, with LLP = 0% and COE = 0.20594 USD/kWh.

1. Introduction

The standalone solar PV/battery (SSPVB) system is becoming a popular option for providing electrical power to isolated areas. Battery energy storage (BES) is an essential part of the SSPVB system as it maintains the continuity of the electrical energy produced. Many types of battery technologies are appropriate for use in standalone solar PV applications such as lead–acid, nickel cadmium, sodium (sulfur), lithium-ion, and sodium (nickel chloride) batteries. In general, lead–acid and lithium batteries are recognized as having the most mature technologies because of their low cost, maintenance-free operation, and high efficiency. However, the drawback of these batteries is their short cycle life, which results in comparatively higher cost. Hence, there is a need to perform optimization to ensure battery longevity. BES technologies can support a high degree of intermittence by the PV source.

Optimization tools play a vital role in determining the size and utilization of BES for a given load demand. Various optimization techniques have been reported for sizing SSPVB system components, including numerical [1–3], analytical [4,5], and intuitive [6,7] methods. However, these techniques require massive calculations and long-term methodological data. Artificial intelligence methods such as genetic algorithms (GAs), fuzzy logic, and neural networks [8–11] can also be employed in the SSPVB system. GAs have high accuracy and reliability as well as the ability to program different parameters [12].

Researchers have proposed many ways to improve the BES in standalone PV systems, including ways to help to assess their reliability and feasibility and to help the designer to correctly size the system components. The authors of [1] simulated two standalone hybrid PV systems with different types of lead–acid batteries and compared their aging patterns. To do so, they took into account all the components of a PV system, i.e., the battery bank, inverter, and charge controller, to simulate the system's behavior. The authors of [13] presented a socio-technical approach to increase the lead–acid battery lifetime in an off-grid hybrid PV and diesel generator system, using HOMER and MATLAB models to minimize the net present cost. They proposed a strategy for influencing the end-user behavior and boosting the PV size to decrease the annual capacity shortage and improve the lifecycle of the battery. In [14], the authors investigated the economic viability of residential battery storage systems with respect to grid-connected solar PV and battery optimization. Three different cases were examined in the UK, Italy, and Switzerland. The actual cost of electric energy associated with two types of batteries, i.e., lead–acid and lithium-ion, were considered. However, in that research, the evaluation of economic viability did not consider the additional benefits realized by BES.

Numerous models that predict the expected lifespan of a battery depend on the operating conditions and the charge and discharge cycles. A computation of the expected battery lifespan is necessary as it impacts the total system cost. In our literature review, we found there to

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be two main approaches used for estimating the lifespan of a battery [15]. The first approach is based on the lifespan of a battery that goes through cycles to failure, with the lifespan depending on the depth of discharge (DOD) in the discharge cycles. By employing this approach, there is the possibility of determining the equivalent full cycles as the number of cycles to failure multiplied by the DOD. The other method considers the number of cycles based on Downing‘s algorithm, which is known as Rainflow [16]. This method is more complex and precise in that it counts the cycles that correspond to each range of the DOD for a year. The DOD is typically determined as the capacity in ampere-hours that is discharged from a fully charged battery divided by nominal battery capacity. In general, DOD is presented as a percent (%). If the DOD of a battery is 0%, this means that it is 100% charged; if the DOD is 100%, the battery is flat. Another interpretation is that deep discharge indicates a battery that draws more capacity than the nominal capacity of the battery.

Even with optimization, the operational cost of batteries remains high because the characteristics and limits of the batteries are not considered. Therefore, research is needed to improve the sizing of renewable energy sources and thereby extend battery life. An optimized DOD is imperative for increasing the lifetime of batteries and minimizing the cost of energy (COE).

To address the above concerns, in this paper, we propose an optimization model that considers the battery life loss cost as well as the costs of operation, replacement, and maintenance. We also determine the most optimal battery DOD for a given case study. We use the non-dominated sorting genetic algorithm (NSGA-II) to solve the optimization problems of this system. The paper is organized in six sections. In Section 2, we present the techniques used in the sizing and modeling of the PV/battery components. We discuss our proposed optimization method in Section 3 and present our results and a discussion in Section 4. In Section 5, we validate the performance of the proposed method. We present our conclusions in Section 6.

2. Sizing and modeling of PV/battery components

In a hybrid renewable energy system, the energy sources must be designed to meet the load demand. The power generated from SSPVBs is characterized by severe fluctuations due to regularly changing weather conditions. To solve this problem, a battery bank can be installed in the hybrid system. However, a major issue in the SSPVB is its high cost and short lifetime. Thus, it is essential to optimize the PV size and the battery while taking into consideration the behavior of the battery. By doing so, we can reduce the COE and increase the likelihood of investment in renewable energy plants. An optimization model that considers the battery life loss cost and its depth of charge will contribute to the future economic viability of such plants. Fig. 1 shows the AC-bus architecture of a typical integration of PV modules and battery with a DC/AC conversion interface.

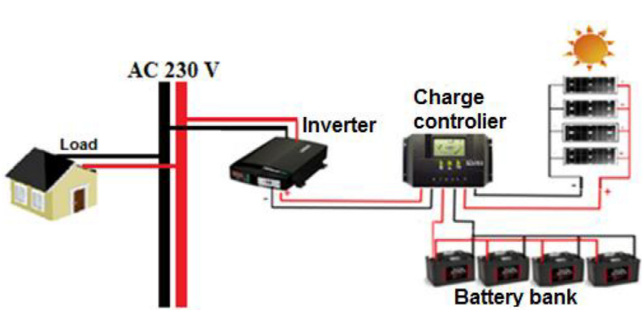

Fig. 1. AC-bus architecture of SSPVB.

2.1. Solar PV model

The solar PV output is dependent on two main factors, the solar radiation and the ambient temperature. Fluctuation in the solar radiation affects the generated power output. Normal solar radiation on a fine day is approximately 1000 W/m^2, which is referred to as peak sun. High solar radiation increases the solar PV output current, while the ambient temperature inversely affects the open circuit voltage of a solar PV [17]. The power output of a solar PV (P_{PV}) can be expressed as follows:

$$P_{PV}(t) = PV_{STC}*\left(\frac{G}{G_{ref}}\right) + (\gamma*(T_C - T_{ref}))*\eta_{wire}*\mu_{Inv} \quad (1)$$

$$T_C = Ta + (NOCT - 20)*(G/800), \quad (2)$$

where G is the solar radiation (W/m^2), G_{ref} represents standard test conditions at STC (1000/m^2), γ is the PV temperature coefficient, T_C is the temperature of the PV cell, T_{ref} = 25 °C, η_{wire} is the inverter wire, which equals 1, and μ_{Inv} is the inverter efficiency, which equals 0.95. T_a is the ambient temperature and *NOCT* is the nominal operation cell temperature tested according to a solar radiation value of 800 W/m^2 and 20 °C ambient temperature [18,19]. If the energy generated from the solar PV array, which depends on hourly climatic conditions, is equal to the power output produced by the PPV, then the net energy of the SSPVB can be expressed by the following equations:

$$\Delta_{E_{net}}(t) = E_{PV}(t) - E_L(t) \quad (3)$$

$$E_{PV}(t) = N_{PV}* P_{PV}(t), \quad (4)$$

where ΔE_{net} is the net energy, N_{PV} is the number of PV panels, E_{PV} is the energy generated from the solar PV panels, E_L (*t*) is the load demand for the corresponding period, and *t* is the time duration, which equals one hour.

2.2. Battery model

To reduce the costs of energy systems, currently, an important research topic in the energy industry is the development of energy storage technologies that can reduce the costs associated with energy systems. SSPVBs in particular have gained global acceptance due to their ability to make electricity accessible to isolated regions at less expense than is possible by network extension. The integration of BES in hybrid energy systems can serve to address the fluctuation in power supply due to changes in weather. Both lead–acid and lithium-ion batteries are used in standalone hybrid systems. Table 1 summarizes the differences between these two batteries.

For the reasons listed in the above table, due to its low cost, the lead–acid battery is generally applied as an alternative storage medium in small- to large-scale BES storage projects [20]. The capacity of this battery is measured in energy units, which indicate the total energy supplied through the battery from full charge to the cut-off voltage. This measure is related to the capacity expressed in watt-hours using Eq. (5):

$$C_B = Ah*V_B, \quad (5)$$

where *Ah* is the capacity of the battery, which can provide current for some amount of time, usually an hour, and V_B is the battery voltage. In the SSPVB, the maximum DOD is limited to prevent over-charge–discharge, therefore ensuring its extended life. In this study, we set the maximum DOD to 80%.

There are many ways to model a battery, depending primarily on the required accuracy and the parameters that must be considered. In the SSPVB system, it is important that the utilized model include the battery's state of charge (SOC). The SOC of the battery displays the battery's state at any point of its lifespan and enables accurate system control, thereby increasing the system's reliability. The SOC of the

Table 1
Difference between lead–acid and Li-ion batteries.

Battery	Advantages	Disadvantages
Lead–acid	• Low cost • Mature, reliable and well-understood technology • Low rate of self-discharge: the self-discharge rate is among the lowest in rechargeable battery systems. • Safer, especially in low-temperature locations	• Low energy density • Environmentally unfriendly • Short cycle life
lithium-ion (Li-ion)	• High energy density • Low maintenance cost • Longer cycle life • Fast charging rate • High efficiency	• High cost • Requires protection circuit to limit voltage and current.

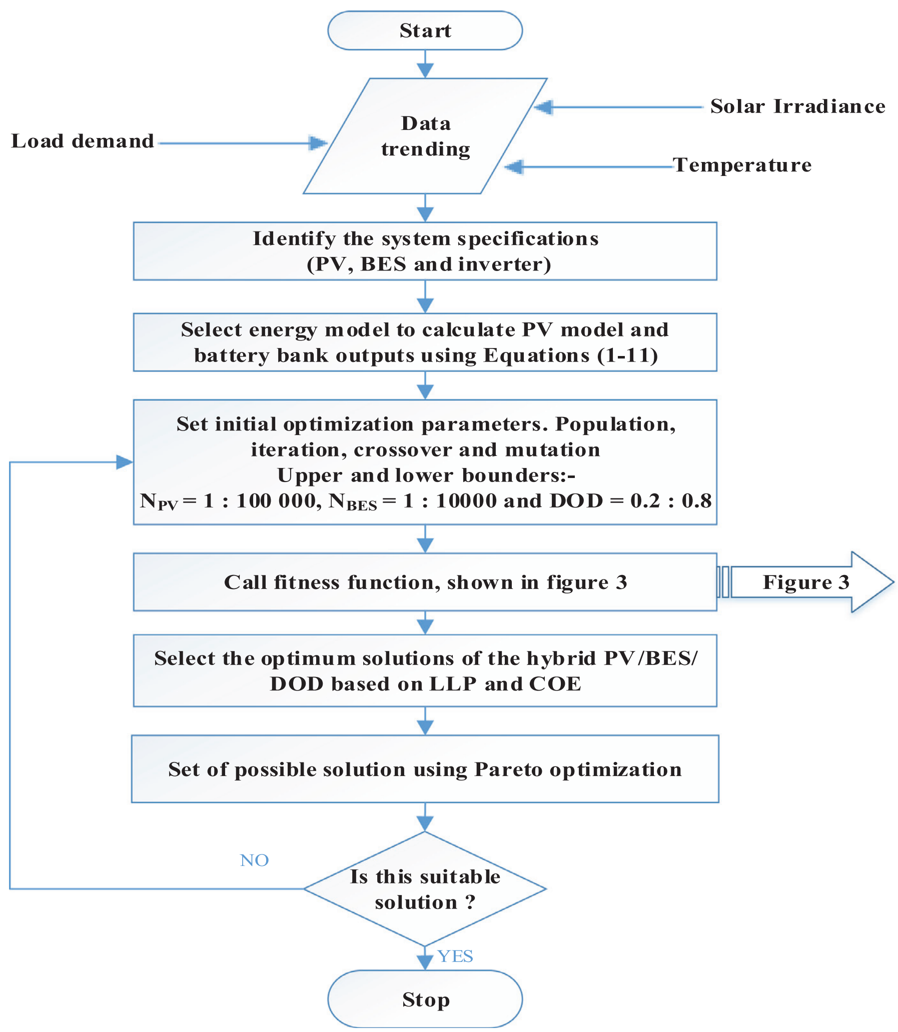

Fig. 2. Flowchart of the NSGA-II model for SSPVB system.

battery in terms of Watt-hours can be obtained with respect to three cases, charging, discharging, and standby.

- In the charging case, the *SOC* can be calculated whenever the energy generated from the PV source surpasses the load demand, that is $E_{PV}(t) > E_L(t)$, with the excess energy used to charge the battery bank. Therefore, if the PPV is greater than the required load power, the SOC should be checked. If the battery is fully charged, surplus energy should be offloaded. However, if the battery is not fully charged, then the surplus energy can be utilized to charge the battery. This is expressed mathematically in Eq. (6) below:

$$SOC(t+1) = SOC(t) + \Delta_{Enet}(t+1) \times \mu_{Bat\_C}. \tag{6}$$

- In the discharging case, when $E_{PV}(t)$ is $< E_L(t)$, the discharge of the BES is sufficient to meet the connected load demand. Thus, the discharge quantity of the BES at hour (t) can be calculated using Eq. (7):

$$SOC(t) = \frac{SOC(t+1) + \Delta_{Enet\,(t)}}{\mu_{Bat\_disc} * \mu cc * \mu_{wire} * \mu_{inv}}.. \tag{7}$$

- In the standby case, when $E_{PV}(t) = E_L(t)$, that is, $\Delta_{Enet}(t+1) = 0$, then the battery capacity remains unchanged. In this condition, the

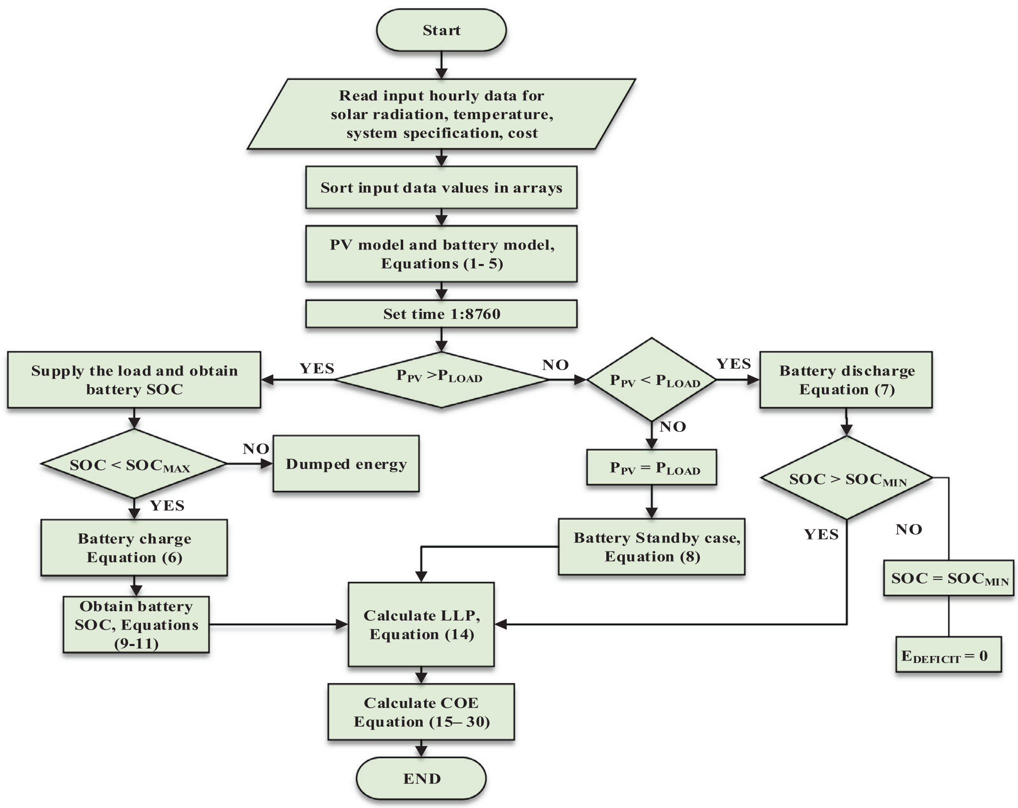

Fig. 3. Flowchart of optimization method using energy flow models.

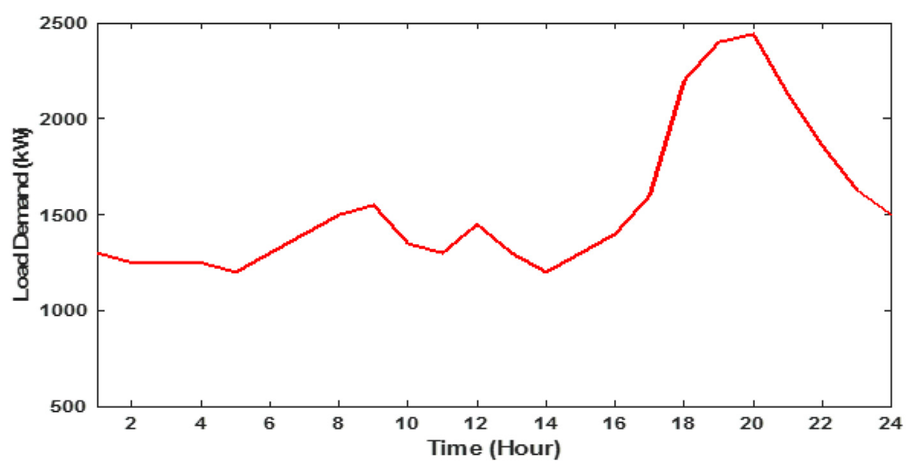

Fig. 4. Hourly load demand for an island in Malaysia.

SOC of the battery can be calculated by Eq. (8):

$$SOC\ (t+1) = SOC\ (t), \tag{8}$$

where μ_{Bat_c} and μ_{Bat_disc} are the charging and discharging efficiencies of the battery ($\mu_{Bat\_c} = \mu_{Bat\_disc} = 0.8$), respectively. μ_{CC} is the charge controller efficiency and equals 0.95 [17]. The *SOC* constraints are presented in the following equations:

$$SOC\_{MAX} \geq SOC\ (t) \geq SOC\_{MIN} \tag{9}$$

$$SOC_{MIN} = (1 - DOD(\%))^{*}Cn \tag{10}$$

$$Cn\ (Wh) = N_B{}^{*}C_B, \tag{11}$$

where SOC_{MAX} is the maximum battery charge and SOC_{MIN} is the minimum battery charge. DOD (%) is the maximum depth of discharge. Cn is the battery bank capacity and N_B is the number of batteries.

2.3. Inverter sizing

The inverter is a device that converts electrical power from DC to AC power. Accordingly, the inverter power ($P_{INVERTER}$) should meet the maximum AC load demand. In this case, the size of the inverter is calculated using Eq. (12), and the number of inverters (N_{INV}) in the system can be calculated using Eq. (13).

$$P_{INVERTER} = P_L \times 1.25 \tag{12}$$

$$N_{INV} = \frac{P_L}{P_{INVERTER}} \tag{13}$$

where P_L is the total load demand and 1.25 is the estimated oversize

Table 2
Parameters of solar PV and battery.

Solar PV	
Rated power (W)	340
Open circuit voltage (V)	46.4
Short circuit current (A)	9.56
Operating temperature (°C)	−40 to +85
PV module efficiency (%)	17.74
Lifetime (Year)	25
Initial cost ($)	306
Battery	
Battery model	12 V Flooded
Battery voltage (V)	12
Rated capacity (Ah)	1990
Lifetime (Year)	10
Dimensions (inch)	40 × 27 × 28
Efficiency (%)	80
Initial cost ($)	6275
Inverter	
Rated Power (W)	1000
Initial cost ($)	300
Efficiency (%)	90
Lifetime (Year)	10

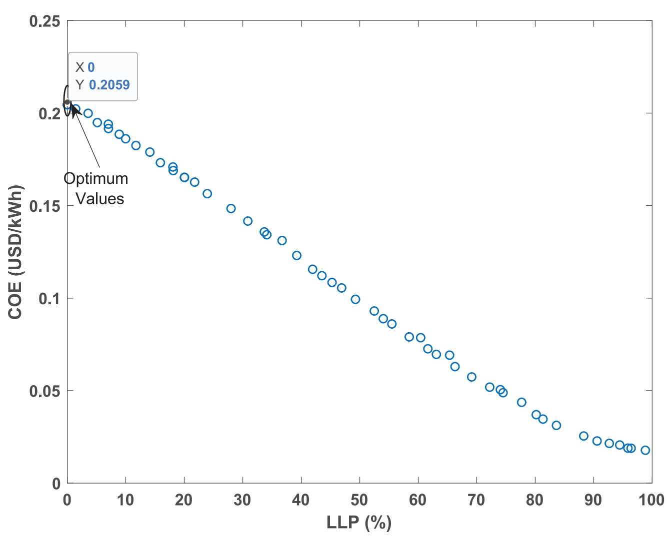

Fig. 5. Optimized system.

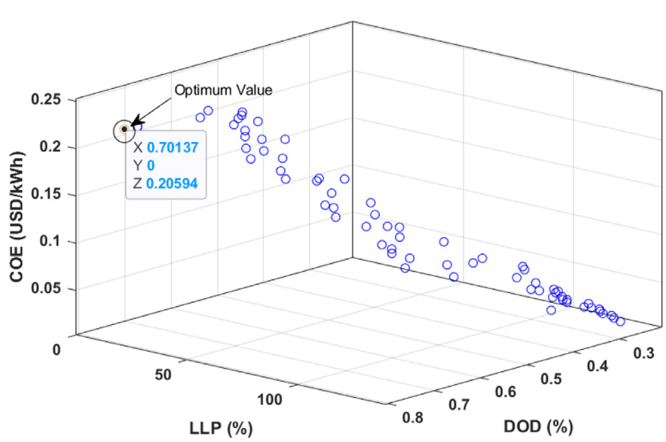

Fig. 6. Relation between COE and LLP based on DOD.

factor [17].

3. Objective function

In selecting the optimal configuration of the PV/BES system to satisfy the sizing constraints, the SSPVB system must be assessed with respect to both economic and technical aspects. Hence, the process of optimal sizing should be performed using a multi-objective optimization technique that has been formulated based on optimum global values of cost and reliability. In this study, the integration of PV and BES is designed to generate the best compromise between the COE and the loss of load probability (LLP), based on the sizing of the PV, BES, and optimum DOD value. Therefore, the multi-objective optimization must minimize the two objectives identified by Eqs. (14) and (30), i.e., the LLP and COE. These objectives are formulated as described in the following.

3.1. Reliability analysis

3.1.1. LLP

The LLP is employed to investigate the system reliability. The availability of the hybrid PV/BES system is used as a measure of its reliability, whereby if LLP = 0 or has 100% availability, this means that the load demand can always be met without interruption throughout the year. However, 0% availability or if LLP = 1 in a hybrid PV/BES system, this means that it cannot meet the load demand throughout the year. Hybrid PV/BES systems with high reliability incur a high initial cost, so it may not be desirable to design hybrid systems with high rates of availability. The availability of a hybrid PV/BES system is expressed as a statistical LLP value. The LLP of a designed hybrid system must be less than 0.01 [21]. The LLP is calculated as the ratio of the annual energy shortage to the total annual load demand, which can be expressed as shown in Eq. (14):

$$\text{LLP} = \frac{\sum_t^T E_{Deficits\,(t)}}{\sum_t^T E_L(t)} \tag{14}$$

where $E_{Deficits}$ is the energy deficit of a hybrid system in one year.

3.2. Economic analysis

In this paper, we calculate the annualized total cost (ATC) of the SSPVB system to obtain the best potential of economic profitability. ATC takes into consideration the annual capital cost (ACC), annual replacement cost (ARC), and annual operation and maintenance cost (AO&MC). The optimum design cost for an SSPVB can be determined using the following equations:

$$\text{ATC} = \text{Sum}(\text{ACC}+\text{ARC} + \text{AO\&MC}) \tag{15}$$

$$\text{ACC} = \text{Sum}(\text{ICC}^*\,\text{CRF}), \tag{16}$$

where *ICC* ($) is the initial capital cost of the whole SSPVB system, as shown in Eq. (17). *CRF* is the capital recovery factor, which determines the present value of the system components based on an interest rate (*ir*) of 2.54% [22].

$$\text{ICC}=(\text{N}_{\text{PV}}{}^*\text{C}_{\text{CPV}}) + (\text{N}_{\text{B}}{}^*\text{C}_{\text{CBAT}}) + (\text{N}_{\text{INV}}{}^*\text{C}_{\text{CINV}}), \tag{17}$$

where CC_{PV}, CC_{BAT}, and CC_{INV} are the capital costs for the solar PV, battery, and inverter, respectively.

$$\text{CRF (ir; T)} = \frac{\text{ir}^*(1 + \text{ir})^T}{(1 + \text{ir})^T \;\; - 1} \tag{18}$$

$$ARC = Sum\ (RC^*F^{REP} - SVC)^*SFF\,(ir;\ T), \tag{19}$$

where RC is the sum of the replacement costs of the solar PV, BES, and inverters. F^{REP} is a factor that arises from the hybrid system components based on the projected lifespan, which can be calculated using Eq. (20):

Table 3
Configuration result of the NSGA-II optimization method for SSPVB/year.

DOD (%)	N_{PV}	N_{BES}	COE ($/kWh)	ATC (USD/year)	LLP (%)
70.137	37,995 = 12.91 MW	3100 = 6169 kAh	0.2059	2.786 million	0

Table 4
Optimal result for DOD from 20% to 80%.

DOD (%)	NPV	NBES	COE ($/kWh)	LLP (%)
20	60,904	6590	0.36897	0
30	58,498	4550	0.28643	0
40	59,825	3329	0.24208	0
50	45,544	3466	0.22103	0
60	38,696	3363	0.20467	0
70	**37,697**	**3333**	**0.20456**	**0**
80	3737	3288	0.20483	0

$$F^{REP} = \frac{CRF(ir,\ T)}{CRF(ir,\ R_{REP})} \tag{20}$$

$R_{REP}$is the duration of the replacement cost, i.e., the number of years it will remain valid, which is calculated using the following equation:

$$R_{REP} = R^{LIF} * \text{integer}(T/R^{LIF}), \tag{21}$$

where R^{LIF} is the lifespan of the PV and inverter. The lifespan of the battery R_{BAT}^{LIF} can be derived using the following equations:

$$R_{BAT}^{LIF} = =1/L_{LOSS} \tag{22}$$

$$L_{LOSS} = \sum \frac{A^C}{A^T} \tag{23}$$

$$A^C = \lambda_{SOC} * A^{c'} \tag{24}$$

$$\lambda_{SOC} = -1.5 * SOC(t) + 2.05, \tag{25}$$

where L_{LOSS} is the battery life loss cost, A^C is the effective cumulative capacity in ampere-hours (Ah) that passes through the battery at a particular time, and $A^T$is the total accumulative energy Ah that crosses through a flooded lead–acid battery in one life cycle, which is equal to the number of battery cycles × Q. Q is the charge stored in a battery that delivers 2100 Q during its life cycle at 80% DOD [23]. The algorithm used with the battery manufacturer datasheet on lifespan estimates the expected Ah that the battery can produce over its lifespan at the given SOC. $A^{\text{<ct>ĉ<ot>}}$ is the total energy delivered by the battery during a specific period. The relationship between SOC and λ_{SOC} is expressed in Eq. (25), as reported in references [24–26].

SFF is the sinking fund factor of different kinds of components and is calculated as a ratio to determine the future amount of a series of equal annual cash flows, as shown in Eq. (26). A^C is the effective cumulative capacity in Ah that passes through the battery at a particular time.

$$SFF = ir * \frac{1}{(1 + ir)^{Rrep} - 1} \tag{26}$$

SVC is the salvage value of the system equipment evaluated at the final stage of the projected life expectancy, which is expressed as follows:

$$SVC = N_{PV} * RC_{PV} * (R^{REM}/R^{LIF}) + N_B * RC_{BAT} * (R^{REM}/R^{REM}_{BAT}) + N_{INV} * RC_{INV} * (R^{REM}/R^{LIF}), \tag{27}$$

where R^{REM} is the remaining life of the system components at the final stage of the projected lifespan, which is obtained by the following equation:

$$R^{REM} = R^{LIF} - -(T - -R_{REP}). \tag{28}$$

The annual operation and maintenance cost of the system (AO&MC) is the sum of the maintenance costs of each system unit, as shown in Eq. (29):

$$AO\&MC = N_{PV} * MC_{PV} + N_B * MC_{BAT} + N_{INV} * MC_{INV}, \tag{29}$$

where, MC_{PV}, $MC_{BAT,}$ and MC_{INV} are the maintenance costs of the solar PV, battery, and inverter, respectively.

Finally, the COE is the average cost per kilowatt-hour ($/kWh) of the total useful electric power generated by the hybrid energy system [27], which can be expressed by the following equation:

$$COE = \frac{ATC(dollar;\ )}{E_L(kWh)}. \tag{30}$$

3.3. Optimal design of SSPVB using NSGA-II

In recent years, the multi-objective evolutionary algorithm has been one of the most frequently used heuristic techniques for optimizing hybrid renewable energy systems [28]. By considering conflicting objectives, a set of solution compromises can be generated. The optimal design in this study simultaneously considers two objectives, LLP and

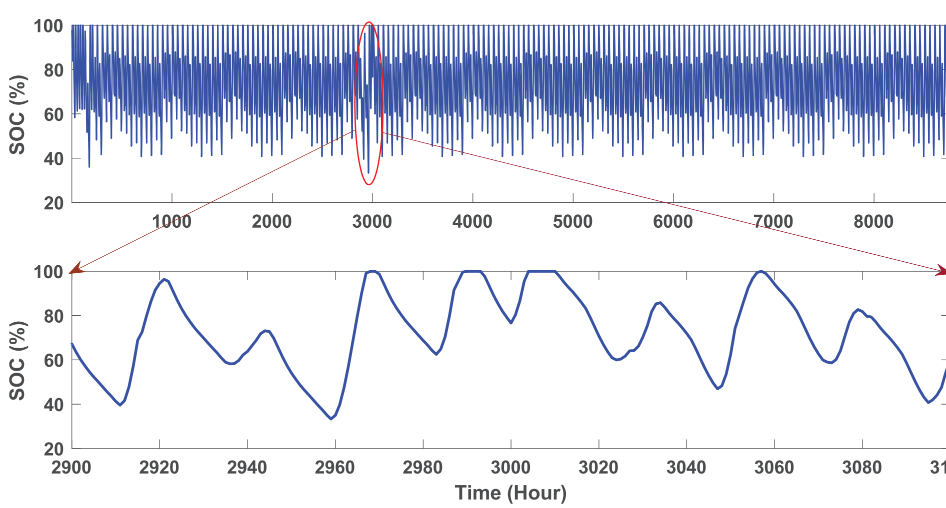

Fig. 7. Hourly battery SOC behavior for one year.

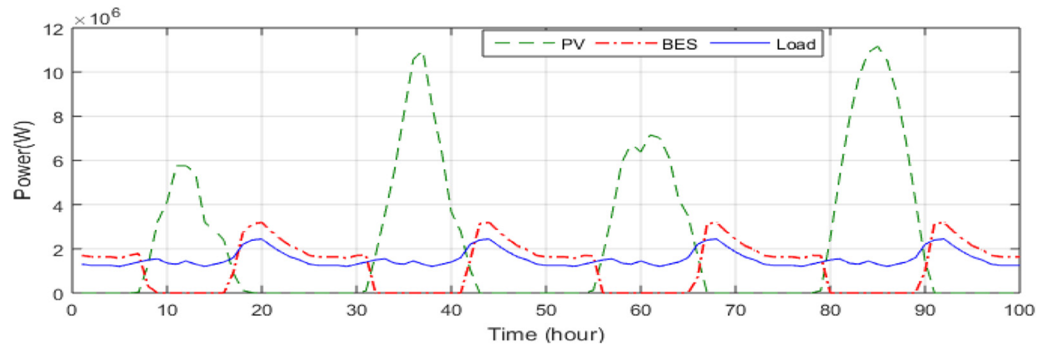

Fig. 8. Outputs of solar PV, BES, and load demand.

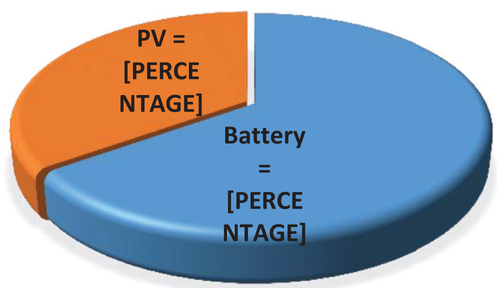

Fig. 9. Contribution of energy using solar PV and BES during one year.

Table 5
The comparison between the presented method and reference [17].

System requirements	Proposed method	Ref. [17]
LLP (%)	0	0.13
COE ($/kWh)	0.20594	0.403

COE. The design of a PV/battery system with consideration of the two abovementioned objectives poses a very complex optimization problem. The multi-objective optimization proposed here takes advantage of the GA. The NSGA-II, as proposed by Deb et al. [30], uses a computationally fast and elitist MOEA framework based on a non-dominated sorting approach. It supersedes the use of a participating function with a new crowded comparison program, which obviates the need for any user-defined parameter to maintain diversity among a population. NSGA-II is uncomplicated and easily implemented and is an excellent diversity-preserving tool with a concourse configuration near a valid set of Pareto fronts [29]. The procedure for selecting the best solution can be summarized as follows:

The population is divided into several non-domination levels and each solution is allocated a fitness equivalent to its non-domination level.

(i) A random parent population (Pi) is created with size (N). Then, using selection, mutation, and crossover operators, a population of children (Qi) is generated from the parent population. (ii) The objective functions for each individual in the Pi population (LLP and COE) are calculated. (iii) Two new populations are combined to create an (Ri) population with size 2 N. (iv) The Ri population is classified according to the Pareto front on the basis of fitness (non-dominated sorting is performed to determine the rank (front) of each population member). (v) The next population of one of the fronts is constructed based on priority by making a general comparison of the members of the Ri population. (vi) Since the Ri size is equal to 2 N, the remaining solutions can be ignored because it is impossible to place all members in the new population (Pi + 1). (vii) A non-dominated sorting resolution is obtained as the optimal size for the system.

The lifespan of a battery is directly affected by its DOD and charge/discharge state (SOC). Hence, these factors must be taken into account. Based on the above analysis, the objective function of the NSGA-II approach maximizes the system reliability (minimize LLP) and minimizes the COE, as shown in Eqs. (14) and (30).

Fig. 2 shows a flowchart of the NSGA-II model for the SSPVB system. Fig. 3 outlines the optimization method based on energy flow models for the SSPVB system. The NSGA-II is employed to determine the configuration of the solar PV and batteries that minimizes the COE and LLP. The procedure used to determine the optimal strategy is described as follows:

I The optimization operation defines the components in the system based on the requested input data, including the hourly solar radiation, temperature, load demand, and the specifications of the solar PV module, BES, and inverter.
II The upper and lower limits of the population, iterations, crossover, and mutation of the variables (PV panel, BES, and DOD) are selected. The LLP for each configuration is calculated according to the power output of the solar PV and charge state of the battery using Eqs. (1)–(5).
III Three different energy flow models then compute the LLP value in terms of the net energy, $\Delta Enet\ (t)$ = [EPV (t) > EL (t), EPV (t) < EL (t) or EPV (t) = EL (t)] using Eqs. (6)–(8).
IV Based on the model outputs for the PV, BES, and DOD, and also considering the constraints of the battery's characteristics, the LLP is calculated using Eq. (14).
V An optimal combination of solar PV/BES is identified based on the optimal DOD value that minimizes the TAC, AO&MC, and RC, including the battery life loss cost, as well as minimizing the COE, using Eqs. (15)–(30).

We examined the performance of the proposed method using MATLAB Toolbox software, based on a selected population size of 200, 0.80 crossover, and applied generations of 100. The objective of the optimization procedure was to find the optimum values of N_{PV}, N_{BES}, and DOD that minimize LLP and COE.

4. Results and discussion

To identify and improve battery operation, we applied the proposed SSPVB optimization method to environmental data obtained in Malaysia, the details of which are as follows.

In this case study, we considered the load profile of a typical island in Malaysia. The energy consumption behavior in tropical regions is relatively steady throughout the year due to the tropical weather conditions [19]. Fig. 4 shows the hourly load demand we used in this study. Table 2 lists the parameters of the solar PV and battery bank. Further details can be obtained from references [30,31]. With respect to the PV system and battery, the DOD is limited to prevent the battery from overcharging–discharging to ensure extended battery life. This is essential in the application of PV systems to guarantee good reliability at low cost, as long battery life minimizes the costs of the system.

Fig. 5 shows a set of solutions obtained by this algorithm for one year. Each solution indicates LLP and COE values that represent a multi-objective optimization set of solutions known as a Pareto optimization. From this figure, we selected one particular LLP against COE. Since any of the solutions generates an optimum, no improvement can be achieved without computing the objective function. To select the best among several solutions in the Pareto optimization, we selected the optimal point that satisfies cost and reliability. This technique selects one of the solutions and makes a decision about the LLP (%) against COE ($/kWh) based on the number of PVs (N_{PV}), BES (N_{BES}), and DOD (%). Due to requirement for high reliability, an LLP value of 0 was selected. Fig. 6 shows the relation between COE and LLP for the optimal DOD value. Table 3 shows the sizing result for the solar PV and BES based on the optimum DOD value using the NSGA-II method. A tradeoff between the cost and reliability objectives is thus achieved. The outcome obtained by the optimization method presents the lowest cost with the highest reliability.

In this paper, we utilized a global optimization approach in conditions where the optimization problem has many local minima. Because GAs provide many optimum solutions, this population-based metaheuristic strategy can successfully identify the global optimum. Hence, this technique generates outstanding outcomes for multi-objective optimization challenges. Table 4 lists the main optimization results for the SSPVB and their main variables and objectives.

To consider the applicability of a flooded lead–acid battery in an SSPVB, the characteristics of this battery must be taken into account, including the standard lifetime, capacity, and voltage of the battery, which are obtained from the datasheet. Fig. 7 shows the hourly battery SOC for one year for the given case study. From the figure, we can that the SOC of the battery bank falls to 36.79% once each year.

This means that the SOC value never reaches the minimum designed value (20% DOD), so the battery is operating in a condition that maintains its lifespan such that the battery can be expected to exceed 2100 cycles. Fig. 8 shows the response of the solar PV with BES and load demand, in which we can observe that the BES can meet the load demand without experiencing an energy deficit. The solar PV is unable to provide sufficient electrical power at night to meet the load demand. Therefore, the power required is supplied by the BES, which produces sufficient energy to satisfy the load demand during the day, while using the excess energy to charge the batteries.

For the case study, Fig. 9 shows the outputs of the PV and BES over one year period, and we can see that the total energy from solar PV is around 5.22 GWh per year. This represents 35% of the energy that can be supplied to the load through the SSPVB system. The remaining energy is provided by the BES. Thus, the battery serves as a tool to provide a smooth continuation of energy produced by the system. Moreover, an optimized DOD is needed to increase the lifespan of the battery and minimize the COE in one year.

Additionally, the stored energy of 9.75 GWh per year represents 65% of the total energy supplied to the load. As such, the results of this study show that the major share of energy comes from BES, which means that the contribution of solar energy is smaller than that of the battery bank.

5. Validation

To validate our results, we compared the performance of the proposed model with that of another model. The presented method was compared with that reported in reference [17], the authors of which used the same model we employed in our proposed method for 365 days at hourly time intervals. However, they assumed the SOC rather than optimizing the SOC. Moreover, they proposed a numerical optimization approach that is unsuitable for large-scale systems because it requires a long computation time to obtain optimal results [32], whereas the NSGA-II algorithm can generate accurate results with less computing time. Table 5 shows both sets of optimization results.

6. Conclusion

In this study, we proposed a new technique for the optimal sizing of SSPVBs for isolated areas that uses the analyses of energy flow models. Using this technique, the optimal combination of solar PV and battery bank is selected based on the maximum reliability and lowest energy cost. The proposed optimization method uses MATLAB software to consider the hourly solar irradiance, ambient temperature, and load demand in dynamic models of the solar PV array and BES system. Optimization strategies such as the energy flow model, cycle-charging dispatch, dynamic battery model, and multi-objective functions were considered for use in the proposed model. To improve the system performance and minimize the energy production cost, we use the NSGA-II algorithm to perform multi-objective optimization to find the optimal values of LLP and COE in a techno-economic analysis that considers battery behavior, life loss cost of the battery, and the costs of operation, replacement, and maintenance. The objective of this research was to achieve the most optimal battery depth of discharge based on the characteristics of a cycling battery in an SSPVB. The results indicate that the optimal DOD value for the battery in the solar PV system being investigated is 70%, with LLP = 0% and COE = 0.20594 USD/kWh. These results demonstrate that the proposed method will produce high solar PV energy levels as it considers all potential loss factors and has excellent efficiency with respect to computation and its use of hourly environmental data for one year. We validated the performance of the proposed method against that of other research work and found the proposed method to have comparatively high accuracy and performance.

Declaration of Competing Interest

None.

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