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Optimal Sizing of a Hybrid Supercapacitor-Battery Energy Storage System in Solar Application Using the Genetic Algorithms

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Abstract**—**This paper deals with an approach to optimally size a supercapacitor-battery hybrid energy storage system for solar applications using the Genetic Algorithm (GA). GA simulation shows that the cost of the proposed supercapacitor-battery renewable energy system is lower than the cost of the conventional renewable energy system, which contains only battery system as energy storage devices. This approach suggests the optimal number of components used in the renewable energy system and ensures that the 20-year round total system cost is optimized subject to the constraint that the load energy requirements are completely covered (zero load rejection) or capacity shortage of 1 % and 2 %. The implemented GA fitness function optimized the 20-year round total system cost which equals to the sum of the respective component capital (initial), operational, and maintenance cost. The concept of the proposed supercapacitor-battery hybrid energy storage system is to exploit the strength of each storage device and to compensate the weakness of each other. This means that the batteries which are known as a high energy density storage is sized at the average power for delivering the average power, whereas, supercapacitors are designed to cater the peak power. This is feasible because the supercapacitor has lower resistance which is able to shield the battery from at least a portion of the current pulses and thus extend the battery lifetime. This not only aids the reduction of the cost of replacement batteries throughout the project lifetime but it is also said to be a more environmental friendly system. The main contribution of this approach is to optimize the cost of the Supercapacitor-battery hybrid energy storage system in renewable energy system which cannot be solved in most of the commercial simulation tools, such as HOMER and HYBRIDS due to the absence of the supercapacitor components in these commercial softwares.

Keywords**—**Supercapacitor, hybrid energy storage system (HESS), Genetic Algorithm (GA), constraint optimization.

I. INTRODUCTION

AUTONOMOUS photovoltaic system has been introduced in Malaysia rural area since 1980s [1]. One of the main motivations of developing solar energy system is the strategic geographic location of the country which is situated at the equatorial region with an average solar radiation of 400-600 MJ/m^2 per month ([1], [2], [3]). In the 9th Malaysia Plan (9MP), a large allocation of funds had been dedicated for implementation of solar photovoltaic (PV) system, and in the Tenth Malaysia Plan (2011-2015), Malaysia government emphasizes greatly on improving energy efficiency, sustainability achieved through energy efficiency [2]. In addition to all the pros of having solar energy such as clean energy source, low maintenance and so on, rural electrification using photovoltaic technology has become popular and common in Malaysia. However, the conventional stand-alone solar energy system, which incorporates photovoltaic, regulator, battery-only energy storage system, and load (as shown in Figure 1), is costly for initial start-up cost and high operational and maintenance for long run. **Figure 1** shows the system layout of a typical conventional renewable energy system which is designed by using HOMER. In the Figure 1, Primary Load 1 represents the load demand with 50 % of discrepancy of the simulated load, Converter represents the DC/DC converter, PV represents the photovoltaic panels of the system, Generic 1 kW represents the wind turbines and H200 represents the batteries used. Generally, the most common energy storage technology employed is lead acid battery because of its low cost and wide availability. Photovoltaic panels are not an ideal source for battery charging; the output is heavily dependent on weather conditions, therefore an optimum charge and discharge cycle is difficult to be guaranteed. This results in a low battery state-of-charge (SOC). Low battery SOC leads to sulphation and stratification, both of which will shorten battery life ([6], [7], [8]). Hence, batteries in conventional stand-alone system are replaced typically every 3-5 years depending on the load demand curve ([6], [9], [10]). If not, an oversized battery system is suggested to cater for the peak power and also to save battery lifespan.

Generally, this is due to inconsistent battery charging by the solar energy source, as the output of the source is heavily dependent on weather condition. The output of the solar energy source fluctuates according to the intensity of the light, resulting an inconsistent battery charging and discharging cycle. Also, heavy current discharging due to a heavy load requirement will equally affect battery life ([6], [7], [8]).

The stress factor on the battery such as irregular discharging rate and extensive time at the low state-of-charge (SOC) could

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increase the rate of damage to the battery. The notable damage mechanisms are related to battery electrolyte stratification and also irreversible sulphation, which greatly shortens battery lifetime ([9], [10]).

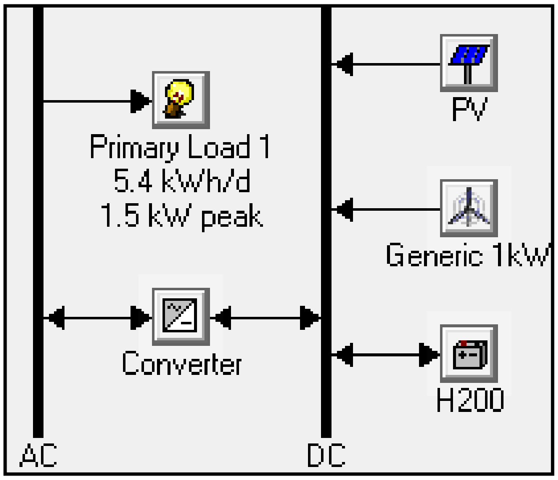

Figure 1 PV-wind-battery energy system

This proposed stand-alone solar system incorporates photovoltaic panels, charge controller, a hybrid energy storage system, and load. As mentioned previously, solar energy source is a clean and noise free source of electricity, even so, a reliable energy storage system is required as an energy buffer to bridge the mismatch between available and required energy. The proposed energy storage technology employs the integration of lead-acid batteries that acts as a main energy storage device and an auxiliary energy storage device which is the supercapacitor. The proposed hybrid energy storage system leads to system cost reduction. This is accomplished by reducing the number of batteries and also the battery replacement costs by prolonging battery lifespan. This is important, for example, in a common household load profile, where there is certain intermittent demand for high current such as when a motor starts up. This can be 6-10 times the normal operating current of the motor and thus affects battery life ([9], [10]).

In a conventional stand-alone solar system, lead-acid batteries are always used to satisfy peak current burst. Other than reducing battery life, the number of lead-acid batteries in this situation can be impracticably large in order to match the peak current requirement as mentioned previously. Non-optimal sizing of the battery for this purpose is proven to be costly and not effective as the peak current demand might only need to be met for a few seconds at a particular time. Hence the need for an optimization strategy, which minimizes the quantity of batteries while still satisfying the load requirement, is essential.

In this paper, genetic algorithm (GA) is used to optimize the system cost of the proposed supercapacitor-battery hybrid energy storage system for solar application. Additionally, the optimized cost for proposed supercapacitor-battery hybrid energy storage system for solar application is compared with the cost of the battery-only system for solar application. This paper is organized as follows: research methodology on system cost minimization is presented in Section II. Optimal sizing of the renewable energy system is discussed in section III. Results obtained from GA simulation on the conventional PV system (battery-only system) and the proposed SB-HESS for solar application is discussed and analyzed in Section IV. Lastly, conclusion for this research is presented in Section V.

II. RESEARCH METHODOLOGY

In this paper, Genetic Algorithm (GA) is used to optimize a Supercapacitor-Battery hybrid energy storage system (SB-HESS) to reduce system cost for solar energy applications. This is done to efficiently and economically utilize the hybrid energy storage devices; an appropriate optimization technique is required to accommodate all the number of parameters in this domain (supercapacitor-battery hybrid energy storage system (SB-HESS) for solar application).

Optimal sizing renewable energy system has been gaining interest from researchers. Generally, the aim of this sizing is to determine the optimal configuration of the power system and sizing of components installed which subject to constraint of the system meeting load requirements at minimum cost.

The efficient performance of the GA iterative searching methods for finding the global optimum enables the utilization of an objective function in sizing renewable energy methodology. GA avoids local minimum traps as GA operators avoid premature convergence and permutation problem [11]. Mutation is one of the GA operators, which introduces random walk in search space. This explains how GA has higher probability of getting global optimal [12]. Besides that, GA operators also prevent the population chromosomes from becoming too similar to each other thus slowing or even stopping evolution. The GA is relatively harder to code due to its complex structure; however, the advantage of being able to code large number of parameters on a chromosome makes GA suitable for sizing renewable energy system [13]. This advantage is not available in some other mostly applied approaches like Simulated Annealing, Particle Swam Optimization (PSO) ([13], [14]). It is more practical in which it consists of more than three main components such as PV module, wind turbine, battery and supercapacitor. The idea in combining more than one energy source with hybrid energy storage in the proposed renewable energy system provides a more economic environment friendly and reliable supply of electricity in all load demand conditions compared to single-use of such systems [15].

Hence, GA optimal sizing a renewable energy system is better suited to this optimization domain where the system consists of larger number of components (such as PV panels, wind turbines, batteries, supercapacitors, and etc.). This is because GA is a stochastic algorithm; randomness as an essential role in GA. Both operators in GA (selection and reproduction) require random procedures. Moreover, it also reduces the risk of trapping at the local optimal due to its nature and characteristic of GA. GAs always operate on a whole population of points (strings) i.e., GA uses population of solutions rather than a single solution for searching. This plays a major role to the robustness of GAs. It improves the chance of reaching the global optimum and also helps in avoiding local stationary point. Another operator in GA, mutation also aids in the randomness of algorithm and avoid algorithm to get trapped at the local optimal point. This increases the efficiency and accuracy of searching optimal number of components used in our SB-HESS. Two sub-sections are divided in this section, objective function for battery-only renewable energy system and supercapacitor-battery hybrid energy storage system renewable energy system.

III. OPTIMAL SIZING RENEWABLE ENERGY SYSTEM

The implemented GA fitness functions embeds with the essential information which is related to initial, maintenance and operational cost of the components used in the systems based on the market price. The conventional battery-only system and SB-HESS are designed and optimized for 20 years. Twenty years is selected based on the longest lifespan components in the system for this simulation and optimization, which is PV panel [16]. According to ([16], [17], [18]), PV panel can last approximately 20-25 years of lifespan, but the efficiency drops after 12 years installation and it is estimated from 90 % to 85-80 %. It applies in GA fitness function.

The objective function is the total net present cost (NPC) of the system which also represents the life-cycle cost. Net present cost includes the initial cost of the components, and all the future cost which consists of the maintenance and operational cost of the components throughout the total life of installation.

A hypothetical location is used for GA optimal sizing RES, which is Semenyih (Latitude: 2.9° N, longitude: 101°53 E, altitude: 39 m (approximately) above sea levels, data was extracted from Google Map). The cost optimization using GA is carried out based on the load profile shown in Figure 2. This load profile is simulated by following the pattern of a typical load profile which was found in [12]. However, the value of the power output depends on the power output of the electrical appliances that can be found in most of the household as shown in **TABLE I**.

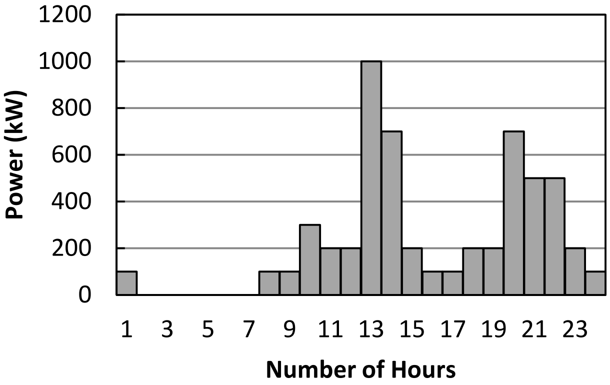

Figure 2 Simulated load profile

From **Figure 2**, the highest load peak is 1000 W. However, the load profile might fluctuate in actual case. A 50 % of discrepancy is added to the highest power peak. The calculation for constraint shown below is based on 1.5 kW as the peak power.

TABLE I Energy demands of the electrical appliances

Electrical Appliances	Power (W)
Compact fluorescent bulb	15
Refrigerator	700
Personal computers	600
Control system/electrical power point	500
Fans	150
Washing machine	300

A. Fitness Function

The objective function optimizes the following costs:

- Cost of purchasing solar panels, the batteries, the inverter, and the PV battery chargers.
- Cost of maintenance and operational of the solar panels, the batteries, the PV battery chargers, and the inverters.
- Cost of replacing the batteries, the PV battery chargers, and the inverters.

This methodology aims to minimize the 20-year round total system cost function ($Z_{(x)}$) by taking the total capital of the devices (C_c), the costs of the 20-year round maintenance (C_m). The set of variables (x) that consists of umber of PV modules (N_{PV}), batteries (N_{BAT}), supercapacitor (N_S), battery chargers (N_{CH}) and PV chargers is optimized. The focus of the objective function is the number of replacement batteries which is based on the battery lifespan, R and the number of batteries N_{BAT} that benefits from the inclusion supercapacitor N_{SCAP} in the energy storage system. The total system cost function is equal to the sum of the capital cost of the components, C_c in $ and the cost of the maintenance and operational of the components $C_{m\&o}$ in $, the function is shown below:

$$\min\left(Z_{(x)}\right) = \min\left(C_{c(x)} + C_{m\&o(x)}\right) \qquad (1)$$

where x is the vector of the decision variables mentioned.

The decision variables are the unknowns that are to be determined by the proposed GA objective function. A specific decision is made when decision variables take on specific values. The decision variables in the objective function deal with component numbers and installation settings. The GA computation information for the number of generation, population, probability of crossover and probability of mutation are shown in **TABLE II**:

TABLE II Computational information

Number of generation	500
Number of population	30
Probability of crossover	0.3
Probability of mutation	0.01

Fitness function for battery-only energy storage system in solar energy application is mentioned as follows:

$$Z_{(N_{\mathrm{PV}},N_{\mathrm{BAT}},N_{\mathrm{CH}})} = N_{\mathrm{PV}} \cdot (C_{\mathrm{PV}} + y_{\mathrm{P}} \cdot M_{\mathrm{PV}}) + N_{\mathrm{BAT}} \cdot \left(C_{\mathrm{BAT}} + \frac{y_{\mathrm{P}}}{R} \cdot C_{\mathrm{BAT}} + \left(y_{\mathrm{P}} - \frac{y_{\mathrm{P}}}{R} - 1\right) \cdot M_{\mathrm{BAT}}\right) + N_{\mathrm{CH}} \cdot C_{\mathrm{CH}} \cdot (y_{\mathrm{CH}} + 1) + N_{\mathrm{CH}} \cdot M_{\mathrm{CH}} \cdot y_{\mathrm{P}} - (y_{\mathrm{CH}} - 1) + C_{\mathrm{INV}} \cdot (y_{\mathrm{INV}} + 1) + M_{\mathrm{INV}} \cdot (y_{\mathrm{P}} - y_{\mathrm{INV}} - 1) \tag{2}$$

Fitness function for a hybrid supercapacitor-battery energy storage system in solar energy application is presented as follows:

$$Z_{(N_{\mathrm{PV}},N_{\mathrm{BAT}},N_{\mathrm{CH}},N_{\mathrm{SCAP}})} = N_{\mathrm{PV}} \cdot (C_{\mathrm{PV}} + y_{\mathrm{P}} \cdot M_{\mathrm{PV}}) + N_{\mathrm{BAT}} \cdot \left(C_{\mathrm{BAT}} + \frac{y_{\mathrm{P}}}{R} \cdot C_{\mathrm{BAT}} + \left(y_{\mathrm{P}} - \frac{y_{\mathrm{P}}}{R} - 1\right) \cdot M_{\mathrm{BAT}}\right) + N_{\mathrm{CH}} \cdot C_{\mathrm{CH}} \cdot (y_{\mathrm{CH}} + 1) + N_{\mathrm{CH}} \cdot M_{\mathrm{CH}} \cdot y_{\mathrm{P}} - (y_{\mathrm{CH}} - 1) + C_{\mathrm{INV}} \cdot (y_{\mathrm{INV}} + 1) + M_{\mathrm{INV}} \cdot (y_{\mathrm{P}} - y_{\mathrm{INV}} - 1) + N_{\mathrm{SCAP}} \cdot C_{\mathrm{SCAP}} \tag{3}$$

Subjects to the constraints:

$$15 < N_{\mathrm{PV}} < 30 \tag{4}$$

$$4 < N_{\mathrm{BAT}} < 32 \tag{5}$$

$$N_{\mathrm{CH}} < 0 \tag{6}$$

$$N_{\mathrm{INV}} < 0 \tag{7}$$

$$2 < N_{\mathrm{SCAP}} < 8 \tag{8}$$

where N_{PV} , N_{BAT} , N_{CH} , N_{INV} and N_{SCAP} are the number of the PV panel, batteries, charge controller, inverter and C_{PV}, C_{BAT}, and C_{SCAP} are the capital cost ($) of one PV module, battery, and supercapacitor respectively. C_{CH} is the capital cost of one PV battery charger ($), y_{CH} and y_{INV} are the expected numbers of PV battery charger and DC/AC inverter replacements during the 20-year system lifetime and it is equal to the lifetime (20 years) divided by the Mean Time Between Failures (MTBF) of power electronic converters. MTBF is used in the manufacturing world and even in the military as a way to measure a system's reliability. The assumption behind measuring MTBF is that a system will periodically fail and will correct itself according to its design [19]. The higher the mean time between failures, the more reliable a system is. C_{INV} is the capital cost of the DC/AC inverter, ($), R is the expected battery lifespan during the 20-years system operation ($R \leq 20$). It is calculated using (9). Expected battery lifetime depends on the battery energy each hour of the simulation by dividing the total year-to-date of charging the battery bank by the total year-to-date amount of energy put into the battery bank.

$$R = \frac{Q_{\mathrm{lifetime}}}{Q_{\mathrm{annual}}} \tag{9}$$

where

$$Q_{\mathrm{lifetime}} = N_{\mathrm{BAT}} \cdot \mathrm{DOD} \cdot C_{\mathrm{cycleDOD}} \cdot V_{\mathrm{N}} \cdot C_{\mathrm{N}} \tag{10}$$

$$Q_{\mathrm{annual}} = \eta_{\mathrm{RT}} \cdot P_{\mathrm{annual}} \tag{11}$$

N_{BAT} is the number of batteries, DOD is Depth-of-discharge of the battery (where the state-of-charge minimum SOC of the battery is set). C_{cycleDOD} is the number of charge and discharge cycle of the battery (based on data sheet of the battery), V_{N} is the nominal voltage of the battery, C_{N} is the nominal capacity of the battery, η_{RT} is the round-trip energy efficiency and P_{annual} is the total power output from renewable energy source.

It is difficult to predict battery lifetime. Real battery banks are subjected to all kinds of temperature and operational stresses that affect performance and lifetime in complex ways. Battery banks are complicated and difficult to model accurately. In this approach, battery lifetime is estimated based on the DOD set in the control strategy in the energy management system and the lifetime throughput of the battery life cycle of the battery before the battery fails to supply the amount of energy that cycled through the battery (before failure). This means the final voltage of the battery drops below the end-of-discharge voltage which is stated in the battery data sheet.

As mentioned earlier, the replacement cost of the battery shows significant impact on the total cost of the system. R represents the lifetime of the lead-acid battery. It is calculated based on the lifetime curve for a sealed lead acid battery data sheet of the battery. Q_{lifetime}, lifetime throughput is the amount of energy that cycled through the battery before failure. It can be calculated by finding the product of the number of cycles, the depth of discharge, the nominal voltage of the battery, and the aforementioned maximum capacity of the battery. Q_{annual} is the annual throughput. It represents the total amount of energy that cycles through the battery bank in one year. Assumption is made to calculate the battery lifetime. This implemented optimization models a single battery as a device capable of storing a certain amount of DC electricity at fixed round-trip energy efficiency, with limits as to how quickly it can be charged or discharged, how deeply it can be discharged without causing damage, and how much energy can cycle through it before it needs replacement.

This optimization assumes that the properties of the batteries remain constant throughout its lifetime and are not affected by external factors such as temperature. Therefore, the key physical properties of the battery are its nominal voltage, capacity curve, lifetime curve, minimum state of charge, and round-trip efficiency. It estimates the life of the battery bank simply by calculating the amount of energy cycling through it.

M_{CH} and M_{INV} are the maintenance costs per year ($/year) of one PV battery charger and DC/AC inverter respectively. In addition, the number of PV battery chargers, $N_{\mathrm{ch}}^{\mathrm{PV}}$equals with the total number of PV power generation blocks which depends on the number of PV modules, N_{PV}. The equation of calculating number of charge controller is shown below:

$$N_{\mathrm{ch}}^{\mathrm{PV}} = \frac{N_{\mathrm{PV}} \times P_{\mathrm{PV}}^{\mathrm{m}}}{P_{\mathrm{ch}}^{\mathrm{m}}} \tag{12}$$

where $P_{\mathrm{ch}}^{\mathrm{m}}$ is the power rating of the selected battery charger (W), and $P_{\mathrm{PV}}^{\mathrm{m}}$ is the maximum power of one solar panel under standard test condition (W), under the manufacturers' specification. In this case, the power rating for solar panel, is 100 W and the power rating for PV battery charger, is 300 W.

The objective function is a cost function for this domain. It changes value as a result of changes in the values of the decision variables. This cost function measure the desirability of outcome of a decision. It describes the initial cost and the maintenance plus operational cost of the components. The initial cost is related to the technical specification of the components, capital cost of the components, and the number of the components of PV module, battery, and supercapacitor, which are shown in **TABLE III**. These capital costs also include the installation cost of the devices. The maintenance and operational cost of each unit of the components per year has been set to 2 % of the corresponding capital cost.

B. *Constraints*

Constraints play an important role here because it places the objective function in the proper search space which is related to real life conditions in which we wish to optimize the system. With proper constraints we are able to solve the objective function accurately and implement that solution in the practical situation under consideration. GA searches thoroughly over the search space. With improper constraints the GA will still find the optimal solution, however, it may not be practical to implement. These constraints are implemented by considering the technical characteristic of components in the system such as solar panel, batteries, supercapacitors, charge controller and inverter. Constraints are also made by matching the supply to load demand. There are three constraints computed for this domain.

1. *Constraint for power from Renewable Energy Source, G*

It is defined according to how much the renewable power it can supplies to the DC bus. It is 50 % higher than that of the highest peak power in the simulated load profile. This system is a 2 kW RES, hence, $G \leq 2$ kW.

$$G = (\%_{\mathrm{PPV}} \cdot N_{\mathrm{PV}} \cdot P_{\mathrm{ratedPV}}) \tag{13}$$

where N_{PV} is the number of PV panel, $\%_{\mathrm{PPV}}$ is the percentage of how much the PV panel could generate based on the solar irradiance at that specific site, whose value is 0.96 (based on the weather forecast), and P_{ratedPV} = 0.100 kW (based on the data specification of PV panel).

2. *Constraint for the number of battery, A*

DC bus voltage is determined based on the rated voltage of the battery and also designed by the user. The battery can be sized for voltage and capacity by adding cells in series and parallel respectively. This is the first step of deciding the number of battery in one string. This also means that how many batteries are connected in series based on the battery specification. Hopecake battery (12 V, capacity of 118 A·h and throughput of 1.416 kW) is used. Constraint, A is assigned as follows:

$$A = \frac{C_{\mathrm{U}}, \text{Battery usable capacity}}{P_{\mathrm{A}}, \text{Average power}} \tag{14}$$

where

$$C_{\mathrm{U}} = N_{\mathrm{BAT}} \cdot C_{\mathrm{min}} \tag{15}$$

$$C_{\mathrm{U}} = N_{\mathrm{BAT}} \cdot DOD \cdot \text{rated throughput} \tag{16}$$

$$P_{\mathrm{A}} = \frac{\text{Total load demand in a day}}{\text{Total load hour}} \tag{17}$$

A, autonomous of the system decides the number of batteries used in system with different capacity shortage. This is an autonomous system, operating reserve (battery in this case) plays an important role in the system, and it has a big impact on the net present cost of the system to maintain a zero load rejection.

3. *Constraint for Supercapacitor*

A 48V, 83F supercapacitor is chosen for this simulation.

$$N_{\mathrm{s}} \leq 1 \tag{18}$$

$$N_{\mathrm{p}} \leq 3 \tag{19}$$

$$N_{\mathrm{s}} = \frac{\text{Load Voltage}}{\text{Cell Voltage}} \tag{20}$$

$$N_{\mathrm{P}} = \frac{IN_{\mathrm{s}}}{\Delta V}\left(\frac{\Delta t}{C} + \mathrm{ESR}\right) \tag{21}$$

So the lower and upper bands for the numbers of supercapacitors in parallel are computed as follows.

$$\therefore N_{\mathrm{PUpper}} = \frac{I_{\mathrm{max}} \cdot N_{s}}{\Delta V}\left(\frac{\Delta t}{C} + \mathrm{ESR}\right) \tag{22}$$

$$\therefore N_{\mathrm{PLower}} = \frac{I_{\mathrm{min}} \cdot N_{s}}{\Delta V}\left(\frac{\Delta t}{C} + \mathrm{ESR}\right) \tag{23}$$

where N_{s} is the numbers of the cells in series, N_{p} is the numbers of cells in parallel, ΔV is the voltage drop, and Δt is the discharge period of the supercapacitor, ESR is equivalent series resistance of the supercapacitor.

From (20), it can be said that $N_{\mathrm{s}} = \frac{48}{48} = 1$; and when $\Delta t = 360$ s and $\Delta V = V_{\mathrm{max}} - V_{\mathrm{min}}$, then $\Delta V = 16$ V. By using (21), (22), and (23), and letting $I_{\mathrm{max}} = \frac{P_{\mathrm{max}}}{V_{\mathrm{min}}}$ and $I_{\mathrm{min}} = \frac{P_{\mathrm{max}}}{V_{\mathrm{max}}}$, the upper bound is computed to be 8.

From the data sheet,

$$\mathrm{ESR} = 10\ \mathrm{m}\Omega$$

$$C = 83\ \mathrm{F}$$

$$V_{\mathrm{max}}\ (\text{operating voltage}) = 48.6\ \mathrm{V}$$

From the load profile,

$$P_{\mathrm{max}}\ (\text{power peak}) = 1000\ \mathrm{W}$$

TABLE III shows the data specifications of the components used for the optimization. It has to be mentioned that the crossover and mutation rates are considered x and y, and the number of generations used to get the optimal result is z in this study, and the mentioned values are decided by 'trial and error'.

IV. RESULT AND DISCUSSION

GA only searches one combination of the optimal decision variables with the lowest cost which satisfies all the constraints mentioned above. The cost of the system is $37858.87. The cost of this system is lower than the RES with battery-only system, whose net present cost is $42459. The net present cost is reduced by 10.8 % as shown in the calculation below:

$$\text{Cost reduction} = \frac{(\$42459 - \$37858)}{\$42459} \cdot 100\ \% = 10.8\ \%$$

This is because the supercapacitor aids in prolonging the battery lifetime. It leads to cost reduction by reducing the number of battery replacement throughout the years as the battery DOD is lower compared to the battery-only RES. Besides that, supercapacitor also aids battery in delivering the sudden peak power. Therefore, the battery is sized based on the average power that is required to deliver, whereas, the number of battery in battery-only system is sized based on the highest peak power of the load profile.

Tables below show the result for the supercapacitor-battery hybrid energy storage system and the optimization result for the battery-only system.

TABLE III Cost and specification list of the components

Components/ Specifications	**Manufacturer brand**	**Cost ($)**	
		Capital	**Operational/ Maintenance**
PV module V_{OC} = 21V I_{OC} = 7.22A V_{max} = 17V I_{max} = 6.47A P_{max} = 100W	Grape Solar Monocrystalline Solar	335	7
Battery Nominal capacity = 118 Ah Voltage = 12V Throughput =1.42kW DOD = 80%	Hopecake	361	6.32
Supercapacitor Capacitance = 83F Rated Voltage = 48V Working voltage = 48.6V Absolute maximum voltage = 51V	Maxwell	1498.52	n/a
DC/AC Inverter Efficiency = 80% Power Rating = 1500W	Akku Solar	2068	41
Charge Controller N1 = 95% N2 = 100% Power Rating = 300W	MISOL ELECTRIC	266	2.66

From **TABLE IV**, **TABLE V**, **TABLE VI,** and **TABLE VII,** and **Figure 3**, and **Figure 4**, it is concluded that the cost of this RES with Supercapacitor-Battery hybrid energy storage system (SB-HESS) is reduced as compared with the cost of the conventional PV-wind-battery system. This optimized RES with (SB-HESS) is possible because of the energy control strategies in between these two energy storage devices.

Generally, the overlapping of a battery's high energy density with a supercapacitor's high power density produces a straightforward benefit over either individual system by taking advantage of each characteristic. The resulting performance is the actual fact highly related to the interconnections and controls implemented in the system to exploit their strengths and avoid their weaknesses. The flow coordination and energy control management for improved energy efficiency is critical for any optimized system. There are two main energy control management: supercapacitor-battery direct coupling (passive control), and supercapacitor-battery indirect coupling (active control) [20]. The direct coupling of a supercapacitor and battery energy source is where the supercapacitor connects in parallel with batteries and load. The advantages contributed by this simple design relative to a battery-only system include a capability to elevate power, greater efficiency and extended battery life. However, this design might drain the battery more as the battery tends to charge the supercapacitors when the voltage of the supercapacitor drops (i.e. the stored energy drops). Limitation arising from this direct coupling approach are:

1. The load and supercapacitor voltages float based on the battery voltage that is affected by its SOC, and therefore limit exploitation of the power capability of the supercapacitor. In addition, the requirements of the supercapacitor module or cell voltage must match that of the battery. As a result, control over the module bank size is restricted and is hard to be optimized.
2. The power provided by the hybrid energy storage system is largely governed by the equivalent series resistance of both coupled energy devices. The fixed partitioning of current supply shared by supercapacitor and battery can thus experience rippling during a pulse demand, particularly in the battery where a magnitude of peak power is endured at the end.
3. The terminal voltage of the HESS follows that of the battery rather than being properly regulated; thus the voltage difference between complete charge to discharge of a battery stack can have a significant effect on the power provided to the load.

The optimized size of the RES is built possible with the indirect coupling topologies (active control). Indirect coupling of a supercapacitor and battery via the addition DC/DC power converter affords a means of stepping up or down. This approach leads HESS with higher degrees of freedom for operation and rectifies problems and constraint surrounding the passive direct coupling described above. The power electronics is costly, for an optimized supercapacitor-battery HESS, the porposed approach is to reduce the number of power electronics, and in place with a battery management system which is able to do load forecasting.

TABLE VIII shows the number of batteries used in different systems. It shows that system with hybrid energy storage system has lower number of batteries. It is good for the environment as the supercapacitors are more environmental-friendly as most of the material composition of supercapacitor can be more biodegradable as compared to that of battery. Additionally, the cost of the proposed system is lower than the conventional battery-only system as the initial cost and replacement cost of battery has the big impact on the overall cost.

TABLE IV Optimization result for battery-only system

A, autonomous	DOD, depth-of-discharge	R, lifetime (years)	N_{batt}, No. of batteries	No. of replacement battery	Cost of battery ($)	Net Present Cost ($)	No. of cycles	Usable capacity
63.87	0.5	13.1	12	12	7054	37858.88	1200	8.496

TABLE V Cost summary for supercapacitor-battery hybrid energy storage system

Components	Number of components	Capital Cost ($)	Replacement Cost ($)	O&M cost ($)	Total ($)
PV panels	20	7035	0	2814	9849
Batteries	12	3792	1997.31	1264.68	7053.99
Supercapacitor	4	5994.08	0	0	5994.08
Charge controller	3	756	3024	226.8	4006.8
Inverter	1	2067	8268	620	10955
System		19644.08	13289.31	4925.48	**37858.87**

TABLE VI Optimization result for battery-only energy storage system

A, autonomous	DOD, depth-of-discharge	*R*, lifetime (years)	N_{batt}, No. of batteries	No. of replacement battery	Cost of battery ($)	Net Present Cost ($)	No. of cycles	Usable capacity
100.3	0.8	10.0	20	28	17648	42459	550	22.65

TABLE VII Cost summary for battery-only energy storage system

Components	Number of components	Capital Cost ($)	Replacement Cost($)	O&M cost ($)	Total ($)
PV panels	20	7035	0	2814	9849
Batteries	20	6320	6320	2087.80	17648.80
Charge controller	3	756	3024	226.80	4006.80
Inverter	1	2067	8268	620	10955
System		16178	17612	5748.60	42459.6

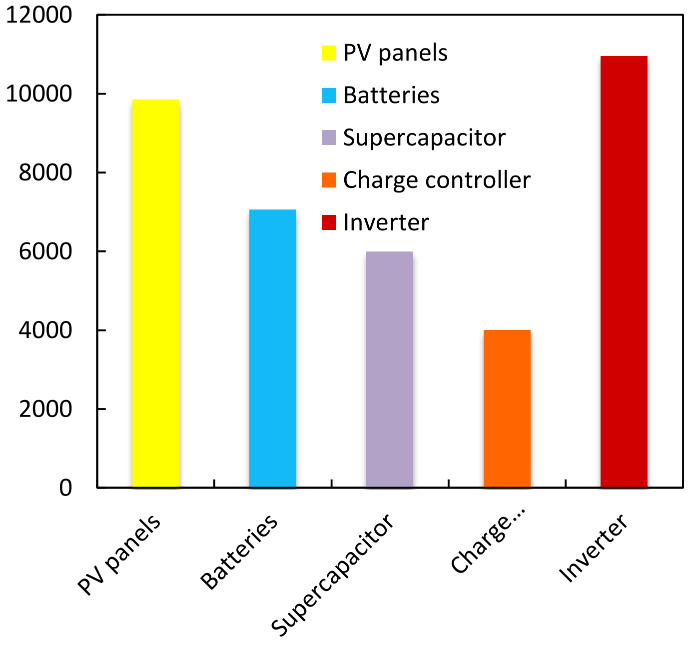

Figure 3 Cost summary for supercapacitor-battery hybrid energy storage system

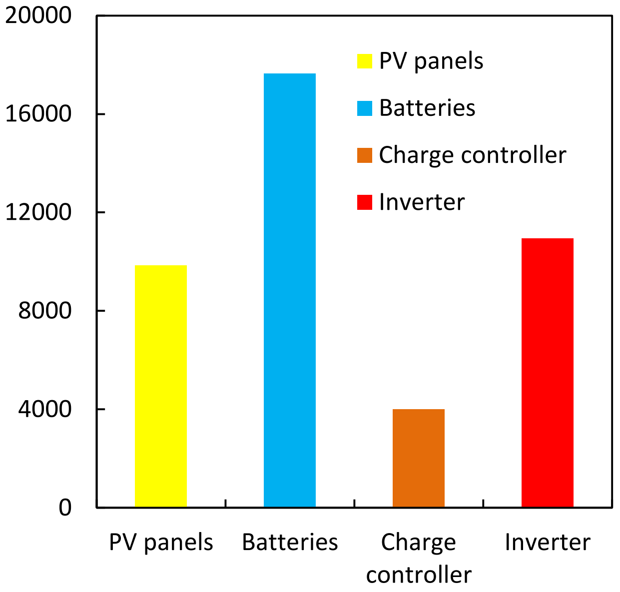

Figure 4 Cost Summary for Battery-Only Energy Storage System

TABLE VIII shows the number of batteries used in different systems. It shows that system with hybrid energy storage system has lower number of batteries. It is good for the environment as the supercapacitors are more environmental-friendly as most of the material composition of supercapacitor can be more biodegradable as compared to that of battery. Additionally, the cost of the proposed system is lower than the conventional battery-only system as the initial cost and replacement cost of battery has the big impact on the overall cost.

TABLE VIII Initial number of batteries and number of replacement battery

Renewable Energy System	Number of Batteries	Number of Replacement battery
PV-Battery	20	28
PV-Battery-Supercapacitor	12	12

TABLE IX Net Present Cost (NPC) of RES found using the GA

Renewable Energy System	Net Present Cost ($)	Battery Lifespan (Years)
PV-Battery	42459	10
PV-Battery-Supercapacitor	37858	13.1

V. CONCLUSION

It was shown that by applying the proposed method the net present cost would be reduced by 10.8 % by coupling the supercapacitor with the battery. The main contribution of the cost reduction is the reduction of the number of replacement batteries throughout the 20 years of project time. Supercapacitor in the proposed hybrid energy storage system prolongs the battery lifespan and increase the power reliability of the system.

The number of batteries used was optimized to a lower number of batteries without jeopardizing the system power reliability. In this paper, the pairing of supercapacitor and battery reduces system cost and is also advantageous to the environment because it cuts down the number of batteries. Supercapacitor can be completely refurbished after its cycle life of 16-20 years with much less chemical hazard.

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REFERENCES

[1] Mekhilef, S.; Saidur, R.; Safari, A.; "A review on solar energy use in industries". Renewable and Sustainable Energy Reviews, 2011;15(4):1777–90. CrossRef

[2] Mekhilef, S.; Safari, A.; Mustaffa, W.E.S.; Saidur, R.; Omar, R.; and Younis, M.A.A.; "Solar energy in Malaysia: Current state and prospects", Renewable and Sustainable Energy Reviews, pp. 386-396, 2012. CrossRef

[3] Nugroho, AM., "The impact of solar chimney geometry for stack ventilation in Malaysia's single storey terraced house", Malaysia's Geography 2010 (January):163–77.

[4] Jamaludin, AFB., "Energy mix and alternatives energy for sustainable development in Malaysia", University Putra Malaysia, 2009.

[5] "Compendium of Energy Efficiency Policies of APEC Economies", 2011.

[6] Glavin, M.E.; Chan, P.K.W.; Armstrong, S.; and Hurley, W.G.; 'A stand-alone photovoltaic supercapacitor battery hybrid energy storage system", in Power Electronics and Motion Control Conference, 2008. EPE-PEMC 2008. 13th, Poznan, September 2008.

[7] Bindner, H,; Cronin, T.; Lundsager, P.; Manwell, J.F.; Abdulwahid, U.; and Baring-Gould, I.; "Lifetime modelling of lead acid batteries", 2005.

[8] Kaiser, R., “Optimized battery-management system to improve storage lifetime in renewable energy systems”, Journal of Power Sources, vol. 168, no. 1, p. 58–65, May 2007. CrossRef

[9] Duryea, S.; Islam, S.; Lawrance, W.; “A Battery Management System for Stand-Alone Photovoltaic Energy Systems”, IEEE Industrial Applications Magazine, Vol.7, Issue 3, May-June, 2001, pp.67-72. CrossRef

[10] Dunlop, J.P.; Farhi, B.N.; “Recommendations for Maximizing Battery Life in Photovoltaic Systems: A Review of Lessons Learned”, Proceedings of Forum 2001 Solar Energy: The Power to Choose, Washington DC, April 21-25, 2001.

[11] Yang, H.; Zhou, W.; Lu L.; and Fang, Z.; “Optimal sizing method for stand-alone hybrid solar–wind system with LPSP technology by using genetic algorithm”, Solar Energy, vol. 82, no. 4, p. 354–367, April 2008. CrossRef

[12] Eftichios Koutroulis, Dionissia Kolokotsa, Antonis Potirakis and Kostas Kalaitzakis, “Methodology for optimal sizing of stand-alone photovoltaic/wind-generator systems using genetic algorithms”, Solar Energy, vol. 80, no. 9, p. 1072–1088, September 2006. CrossRef

[13] Erdinc, O.; and Uzunoglu, M.; “Optimum design of hybrid renewable energy systems: Overview of different approaches”, Renewable and Sustainable Energy Reviews, vol. 16, no. 3, p. 1412–1425, April 2012. CrossRef

[14] Srinivas, M.; and Patnaik, Lalit M.; “Genetic Algorithms: A Survey” IEEE Computer , vol. 27, no. 6, pp. 17-26, June 1994.

[15] José L. Bernal-Agustín, and Rodolfo Dufo-López, “Simulation and optimization of stand-alone hybrid renewable energy systems”, Renewable and Sustainable Energy, vol. 13, no. 8, p. 2111–2118, October 2009. CrossRef

[16] Dunlop, E.D.; Halton, D.; and Ossenbrink, H.A.; “20 years of life and more: where is the end of life of a PV module?”, in Conference Record of the Thirty-first IEEE Photovoltaic Specialists Conference, 2005., 3-7 Jan. 2005.

[17] M. N. G. V. V. G. Kellogg W.D., “Generation unit sizing and cost analysis for stand-alone wind photovoltaic and hybrid wind/PV systems’, IEEE Trans Energy Conversion, vol. 13, no. 1, p. 70–75, March 1998. CrossRef

[18] John Schaeffer, and Doug Pratt, “Gaiam Real Goods solar living sourcebook: Your complete guide to renewable energy technologies and sustainable living”, Gaiam Real Goods, 2005.

[19] Eftichios Koutroulis, Dionissia Kolokotsa, Antonis Potirakis and Kostas Kalaitzakis, “Methodology for optimal sizing of stand-alone photovoltaic/wind-generator systems using genetic algorithms”, Solar Energy, vol. 80, no. 9, p. 1072–1088, September 2006. CrossRef

[20] Yu, A.; Chabot, Victor; and Zhang, Jiujun; “Electrochemical Supercapacitors for Energy Storage and Delivery: Fundamentals and Applications (Electrochemical Energy Storage and Conversion)”, America, CRC Press, April 2013.