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Optimal Sizing of Stand-alone PV System using Artificial Bee Colony Algorithm

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Abstract: The alarming rate of depletion of fossil fuels due to the increasing energy demands has increased the reliance on renewable energy. Renewable resources, such as solar and wind, are excellent alternatives to fossil fuels due to their sustainability and they do not produce harmful gases to the environment. The most promising renewable energy resource is the solar energy since it is available almost everywhere. Renewable energy systems have considerable high initial cost. In order to reduce the cost, the size of the system should be optimized. Optimization means increasing the output energy while reducing the cost. Recently intelligent optimization techniques have been used to solve complex engineering problems. Artificial Bee Colony (ABC) is one of these techniques. In this paper we present a sizing and optimization technique for renewable energy systems using ABC algorithm. The model for the PV panel, the battery, and the loads are used to optimize the system. The method is applied to optimize a typical system and the results of the design are optimum as proved by simulation and comparison with the results of the published methods.

Keywords: Artificial bee colony, stand-alone PV system, optimization

1. Introduction

The most promising renewable energy resource is solar energy since it is available almost everywhere [1]. Solar energy is the energy that comes from the sun. Various technologies have been developed to capture this energy and convert it into electrical energy, such as the solar photovoltaic (PV) system. PV system could be classified into two main categories; stand-alone PV systems and grid-connected PV systems. In the grid-connected system, the generated power is directly fed into the grid. While the stand-alone PV system is usually used for remote areas without access to the grid. However, the stand-alone PV system is becoming more widely used as they have an excellent potential to be the more economical option since it does not require the expensive installation of utility lines to the grid for remote areas.

Renewable energy systems have a considerable high initial cost. To reduce the cost, the size of the system should be optimized [2]. Optimizing the system design reduces the system cost [3]. Conventional sizing methods have been used based on practice. Artificial intelligence techniques have been recently used to design and optimize renewable energy systems. Artificial intelligence (AI) techniques have been applied to solve numerous engineering optimization problems due to their powerful and efficient ability to solve complex problems with multiple objectives [4]. Many types of research and studies have been done on different Artificial Intelligence (AI) optimization techniques, such as neural networks, particle swarm optimization, genetic algorithms, ant colony, and bee-inspired algorithm, for finding the optimum sizing of PV systems [5]. One of the recent bee-inspired algorithm, the artificial bee colony, proposed by Karaboga, has been gaining a lot of attention due to its flexible algorithm [6]. The artificial bee colony algorithm has

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been used to optimize the size of the PV system and showed better results than the genetic algorithms and the particle swarm optimization [7].

One of the challenges faced in implementing renewable energy systems is the high initial cost of the system. Optimization techniques have been widely used to solve this problem since they could help to reduce the cost. According to [8], optimization of the PV system is defined as "*The process for determining the cheapest combination of PV array and battery that will meet the load requirement with an acceptable availability level over the expected lifetime*". The optimization method could be based on either power reliability analysis or system cost analysis [9]. According to [10], the optimization of the PV system could be divided into intuitive methods, numerical methods, and analytical methods. In intuitive methods, simple calculations are normally used. This method is designed based on the month with the lowest solar radiation which is the worst-case scenario. However, the disadvantage of using this method is oversizing or under-sizing of the system which could result in increased cost of the system or inability to satisfy the load demands.

The numerical methods use computer simulations and are based on the loss of load probability (LLP) index. In [11], the simulation is used to size the PV system which is based on the statistical models for the solar radiation and the loads. For the analytical methods, the size of the system is modelled as a function of its reliability. In [12], the sizing methods are categorized into probabilistic methods, analytical methods, iterative methods, and hybrid methods. The intelligent methods are classified as iterative method and according to [13], the artificial intelligent methods are considered to be new generation approaches for optimization.

Recently, artificial intelligence (AI) techniques have been used widely to solve more complicated problems. The author in [14], has reviewed the AI techniques that have been used in the sizing of PV systems. The earliest AI techniques used in the optimization of a PV system are fuzzy logic, artificial neural networks, and genetic algorithm [15]. The commonly used AI techniques are the Genetic Algorithm (GA), Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO), and Artificial Bee Colony (ABC) optimization. There are also several methods available but they are not widely used, such as the Cuckoo Search (CS), Simulated Annealing (SA), Bacterial Foraging Algorithm (BFA). A detailed review of the mentioned methods can be found in [5], [12-15] and the references therein.

In this paper, we present an optimization method for a stand-alone PV system based on the artificial bee colony algorithm. In the following sections, the models of the stand-alone PV system components are presented. Then the economic analysis model is briefly described. The artificial bee colony algorithm is also briefly explained. A case study for a typical stand-alone PV system is presented and the results are discussed.

2. Mathematical Model of Stand-alone PV System

To optimize the size of the PV system it should be modelled. The stand-alone PV system is shown in figure 1. The basic components of the system are the PV array, the battery bank, the MPPT charge controller, the DC/AC inverter and the loads. To optimize the system, the mathematical model of each of the system components should be derived. In the following sections, the models of the system components are presented.

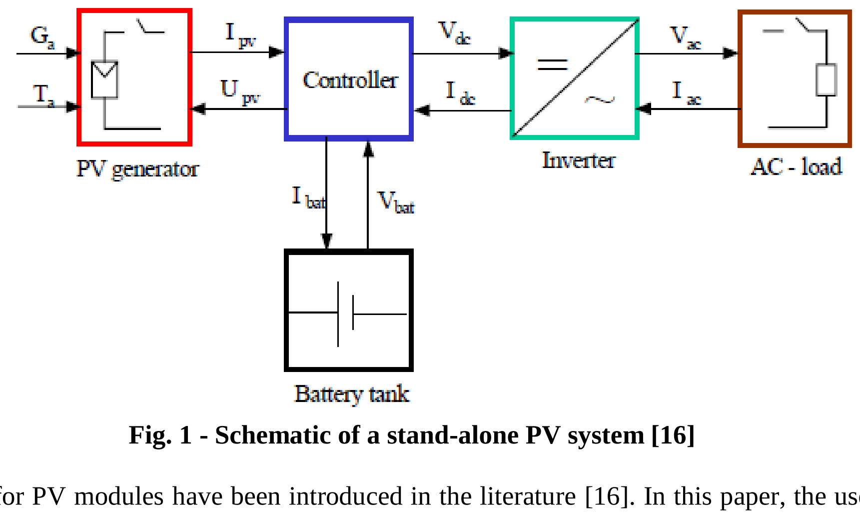

Fig. 1 - Schematic of a stand-alone PV system [16]

Several models for PV modules have been introduced in the literature [16]. In this paper, the used model is based on the single-diode model [17] with parameters obtained from the manufacturer data sheet [18]. An electrical circuit model has been chosen, as shown in figure 2. In this model, the temperature is dependent on the dark saturation current, I_0, the photocurrent, I_{ph}, and the open-circuit voltage, V_{oc}. The temperature dependency on the parasitic series resistance R_s, and shunt resistance R_{sh} are also considered. To match the simulated data with the provided manufacturing data, an ideality factor will be used. The mathematical model of the solar cell based on the single diode model is given as [17]:

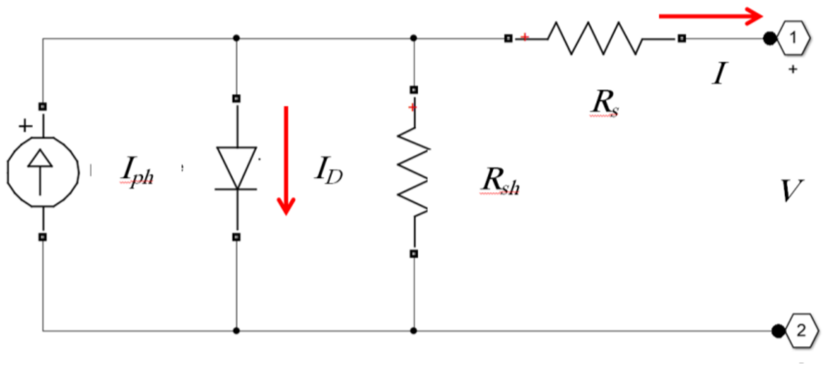

Fig. 2 - Circuit model of a solar cell.

$$I(T,G,V) = I_{ph} - I_0(e^{(V+IR_s)/nV_{th}} - 1) - (V + I \cdot R_s)/R_{sh} = I_{ph} - I_D - I_{sh} \quad (1)$$

The variables are calculated as follows:

$$I_{ph} = I_{ph0} \cdot G / G_{nom} \quad (2)$$

$$I_{ph}(T) = I_{ph} + K_0(T - T_{meas}) \quad (3)$$

$$K_0 = [I_{ph}(T_2) - I_{ph}(T_1)]/[T_2 - T] \quad (4)$$

$$I_0 = I_{SC(T_1)} \cdot (T/T_1)^{3/n} \cdot e^{-\frac{E_g}{V_s}\cdot(\frac{1}{T}-\frac{1}{T_1})} \quad (5)$$

$$I_0(T_1) = I_{SC(T_1)} / \left(e^{qV_{OC(T_1)}/nkT_1} - 1\right) \quad (6)$$

$$R_s(T) = -dV/dI_{V_{OC}} - 1/(I_{0(T_1)} \cdot q/nkT_1 \cdot e^{qV_{OC(T_1)}/nkT_1}) \quad (7)$$

$$R_{sh} = V_{OC} /[I_{ph} - I_0\left(e^{\frac{qV_{OC}}{nkT_{meas}}} - 1\right)] \quad (8)$$

$$R_{sh}(T) = R_{sh} \cdot (T/T_{meas})^{\alpha} \quad (9)$$

I_{ph0} is the photogenerated current at the nominal radiation. I_D is the diode dark current. I_{sh} is the shunt current. G is the solar radiation in W/m^2. The G_{nom} is the radiation of the PV module. n is the ideality factor. e is the electron charge. k is Boltzmann's constant. E_g is the energy gap of the semiconductor. K_0 is the short-circuit current temperature coefficient. N_s is the number of cells connected in series, and N_p is the number of cells connected in parallel, which are obtained from the data provided by the manufacturer, V_{th} is the thermal voltage that could be calculated using the equation below:

$$V_{th}=nkT_c/e \quad (10)$$

Economic optimization is based on the simulation of the system. Figure 3 shows the flowchart of the optimization problem. Different combination of the types and ratings of the PV system components are selected, and each set of combinations are optimized to determine the optimal number of the components. Artificial Bee Colony (ABC) algorithm is used for optimization.

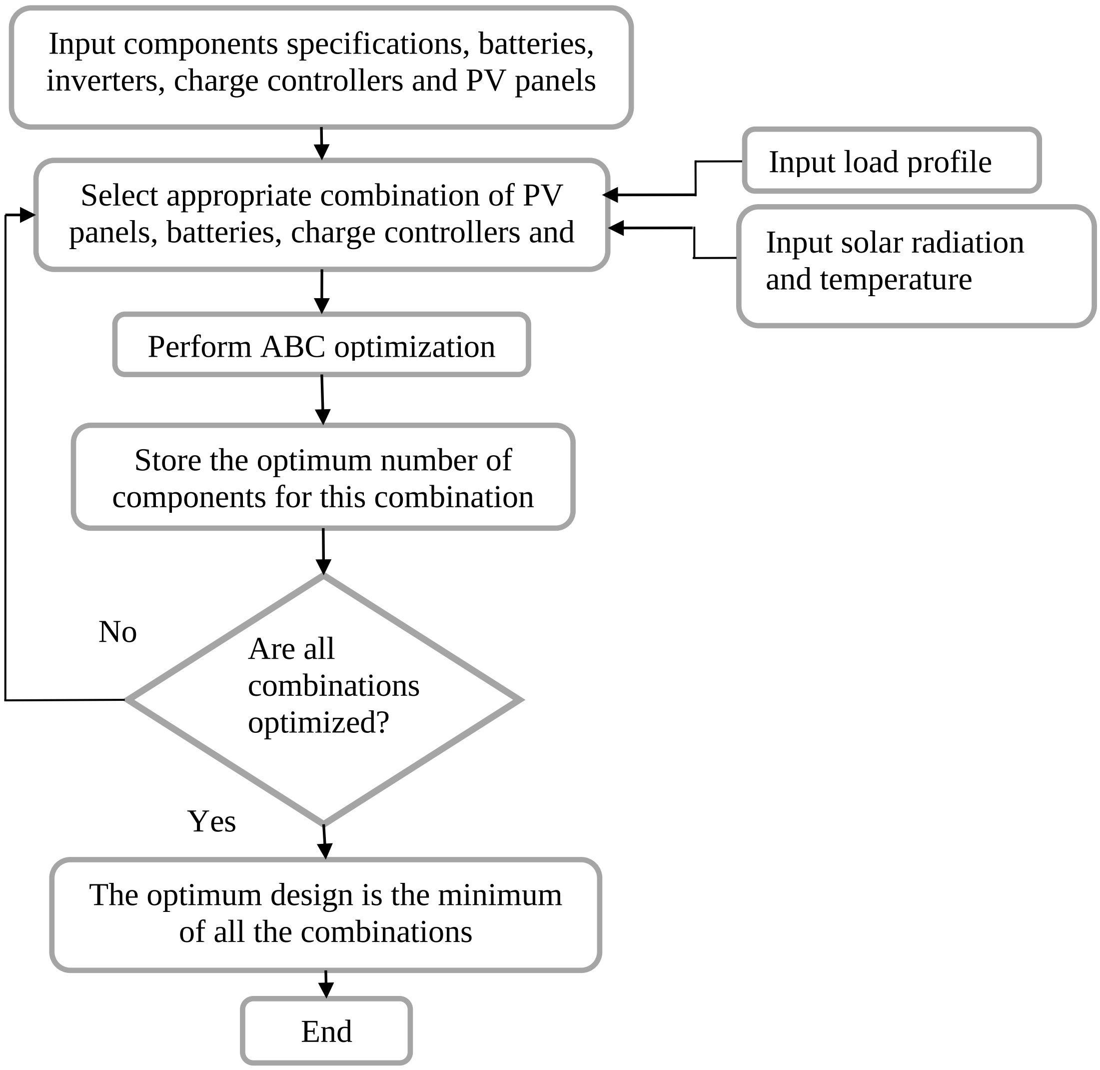

Fig. 3 - Flowchart of the PV system optimization

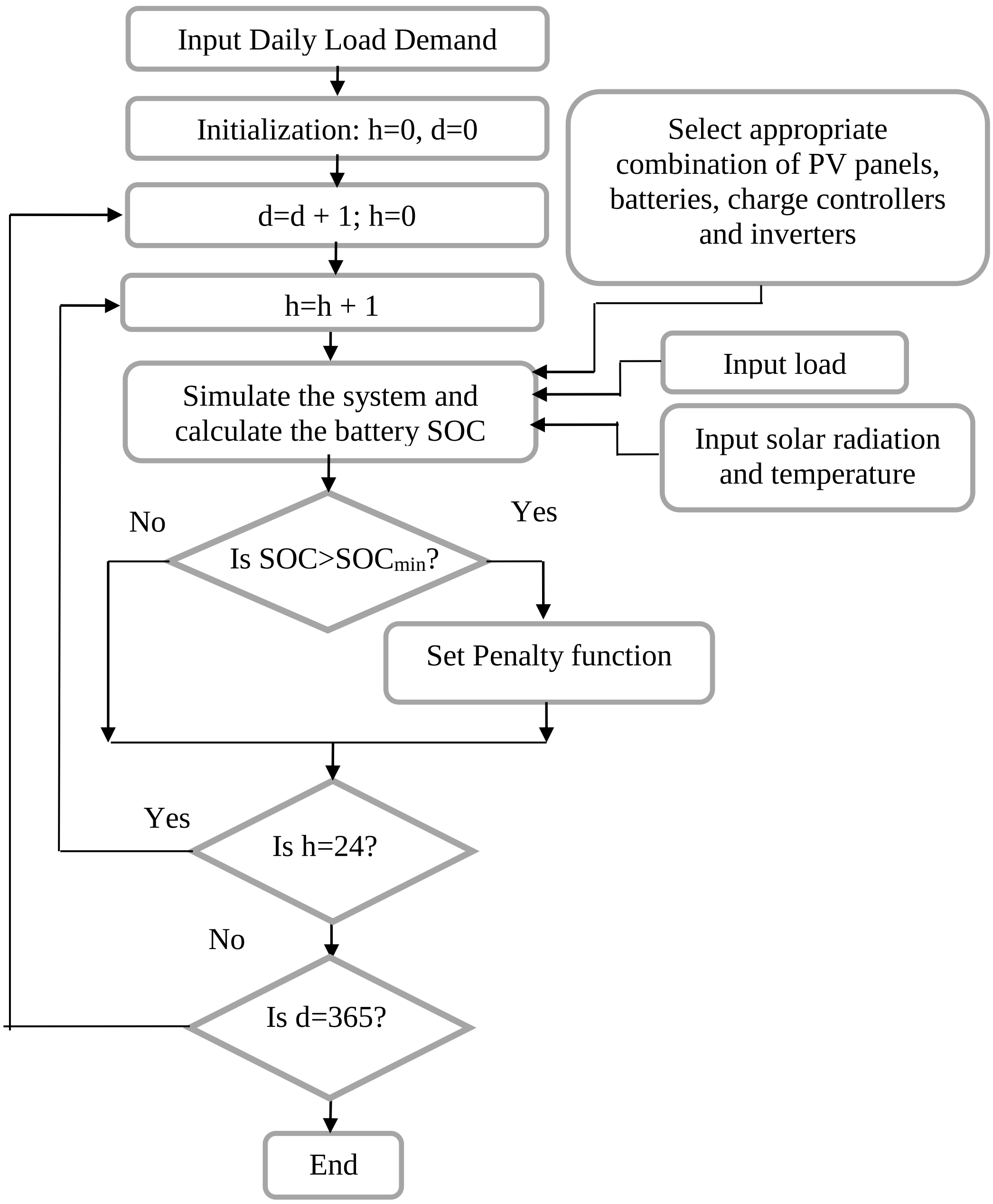

Fig. 4 - Flowchart of the PV system simulation

Figure 4 shows the flowchart of the optimization procedure for each set. With the daily load demand as the input, the simulation of the PV system is performed for all hours and days in the year. If the SOC of the battery is found to be lower than the minimum SOC allowed, a penalty function is added. This is to ensure the solution would not be the optimal solution since it violates the prepared constraints. In the simulation, the output power of the PV array should be optimized. The PV module output depends on many factors; the maximum output power is calculated by maximizing the following equation. The output of the PV array could then be determined using the following equation:

$$P_{PV\_Array}(t) = N_{PV} \cdot P_{PV\_\max}(t) \tag{11}$$

where N_{PV} is the number of PV modules in the PV array. The output of the PV array will supply the load and the deficit will charge or discharge the battery. The load power is then given by:

$$P_{Load}(t) = \frac{P_L(t)}{\eta_{inv}} \tag{12}$$

where, P_L is the load power, and η_{inv} is the inverter efficiency. The battery power is the difference between the PV array power and the load power and is given by [19]:

$$P_{Battery}(t) = P_{PV}(t) - P_{Load}(t) \tag{13}$$

If the battery power is positive, then the battery will be charged and if the battery power is negative then the battery will be discharged. The battery capacity is given as:

$$C_R(t) = C_R(t-1) + \frac{P_{Battery}(t)\cdot \Delta t \cdot \eta_{battery}}{V_{battery}} \qquad \text{for } 1 < t < 24 \tag{14}$$

where, $C_R(t)$ and $C_R(t\text{-}1)$ are the available battery capacities (Ah) at hour t and t -1, respectively, of day i, $\eta_{battery}$ is the battery efficiency, usually 80%. Δt is the time sampling which is 1 hour. $V_{battery}$ is the battery voltage. The battery should not be overcharged or discharged below the minimum state of charge. This can be used as a constraint for optimization. The constraint is given as:

$$C_{R\_\min} < C_R(t) < C_{R\_\max} \tag{15}$$

Where $C_{R\_\min}$, and $C_{R\_\max}$ are the minimum and maximum capacities of the battery bank. The minimum capacity is given by:

$$C_{R\_\max} = DOD \cdot C_{R\_N} \tag{16}$$

Where DOD is the depth-of-discharge and C_{R_N} is the nominal capacity.

3. The Levelized Cost of Electricity (LCOE)

The LCOE is chosen as the objective function in the optimization. To achieve minimum cost this function should be minimized. The cost is divided into two parts; initial cost and operating & maintenance cost. The total objective function, with subject to N_{PV} >0 and N_{Bat} > 0, is given as:

$$TLLC = \left(\frac{\sum_{i=1}^{N_{PV}} i(C_{pvi} + 20\cdot M_{pvi})}{L\cdot T_{pv}}\right) + \left(\frac{\sum_{j=1}^{N_{Bat}} j\cdot C_{Batj}(1 + y_{Batj} + M_{Batj}(20 - y_{Batj}))}{L\cdot T_{Bat}}\right)$$
$$+\left(\frac{\sum_{k=1}^{N_{CH}} k\cdot C_{CHk}(1 + y_{NCHk} + M_{NCHk}(20 - y_{NCHk}))}{L\cdot T_{CH}}\right) + \left(\frac{C_{inv}(1 + y_{inv} + M_{inv}(20 - y_{inv}))}{L\cdot T_{inv}}\right) \tag{17}$$

where, the lifetime for PV module is denoted as $L\cdot T_{pv}$, the life time of battery as $L\cdot T_{Bat}$, the lifetime of battery charger as $L\cdot T_{CH}$, and the inverter's lifetime as $L\cdot T_{inv}$. C_{pvi} is the capital cost of one module and C_{Batj} is the cost of each battery. The maintenance cost per year of one PV module is represented as M_{pvi}, while the battery maintenance cost per year as M_{Batj}. C_{CHk} is the cost of one battery charger and C_{inv} is the cost of one inverter. y_{NCHk} and y_{inv} are the expected number of battery chargers and DC/AC inverter replacement during the 20-year lifetime of the system, which is assumed to be 4 times. The expected number of battery replacement during the system lifetime is y_{Batj}. The maintenance cost per year of one battery charger and DC/AC inverter is indicated by M_{NCHk} and M_{inv}, respectively. The lifetime of the PV panel is between 20 and 25 years. While the lifetime of a battery is 5 years. The lifetime of both the charge controller and inverter is 10 years. The objective function of cost is minimized to determine the optimal number of PV modules, N_{PV} , and the optimal number of batteries, N_{Bat} . The LCOE is given by:

$$LCOE = \frac{TAC}{E_{tot}} \tag{18}$$

TAC is the total annualized cost and E_{tot} is the total electricity generated during the whole lifetime of the system. The problem of optimization of the sizing is summarized as:

Minimize

$$f(u) = \left(\frac{\sum_{i=1}^{N_{PV}} i(C_{pvi} + 20 \cdot M_{pvi})}{L \cdot T_{pv}} \right) + \left(\frac{\sum_{j=1}^{N_{Bat}} j \cdot C_{Batj}(1 + y_{Batj} + M_{Batj}(20 - y_{Batj}))}{L \cdot T_{Bat}} \right)$$

$$+ \left(\frac{\sum_{k=1}^{N_{CH}} k \cdot C_{CHk}(1 + y_{NCHk} + M_{NCHk}(20 - y_{NCHk}))}{L \cdot T_{CH}} \right) + \left(\frac{C_{inv}(1 + y_{inv} + M_{inv}(20 - y_{inv}))}{L \cdot T_{inv}} \right)$$

Subject to

$N_{PV} > 0$
$N_{Bat} > 0$
$N_{Ch} > 0$
$C_{R\_\min} < C_R(t) < C_{R\_\max}$

In the ABC algorithm, there are three groups of bees; the employed, onlookers, and scout bees. The bee colony splits into two halves, the first half contains the employed bees and the other half is the onlookers. In this algorithm, the possible solution to the optimization problem is represented as the position of the food source and the quality of the solution corresponds to the amount of nectar in the food source. For every food source, there is one employed bee. The employed bees are responsible for searching the food source and gathering information regarding the source's distance, direction, and fitness. Then, the information is shared with the onlooker bees around the hive. The employed bees with their food source have been exhausted becomes scout bee. The onlooker bees evaluate the information shared by the employed bees and send the scout bees to explore a new feasible food source. The source with the greatest fitness is memorized by the onlooker bee. The main steps for the ABC algorithm for optimization problems are as follows [6]:

1. Initialize the population of solutions $x_{i,j}$, where i=1,2,…,D, j=1,2,…,N; , ;
2. Evaluate the population;
3. Repeat;
4. Produce new solutions $v_{i,j}$ for the employed bees by using equation (19) and evaluate the new solution;
5. Apply the greedy selection process for the employed bees between x_i and v_i ;
6. Calculate the probability values, P_i, for the solution x_i based on their fitness values using equation (21);
7. Generate new solutions v_i for the onlooker bees from the selected solution x_i based on its P_i and evaluate them;
8. Apply the greedy selection process for the onlooker bees between x_i and v_i;
9. Determined any abandoned solutions and replaced it with a new randomly produced solution x_i using equation (20) for the scout bees;
10. Memorize the best solution obtained so far;
11. Repeat the cycle until the condition of termination is met.

The ABC algorithm is shown in Figure 5.

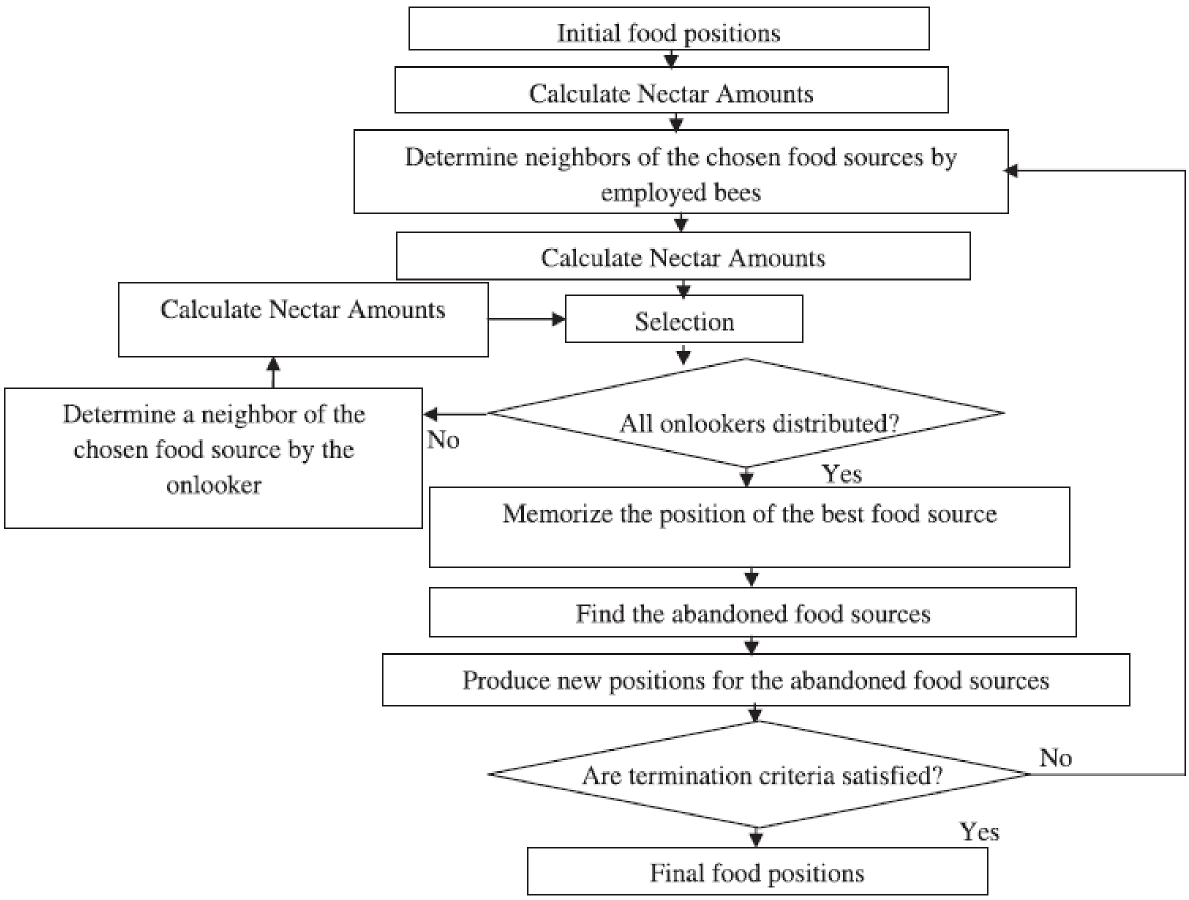

Fig. 5 - The ABC algorithm [6]

To find the new food position based on the old position that has been stored in the memory, the algorithm uses the following equation [20]:

$$v_{i,j} = x_{i,j} + \varphi_{i,j}(x_{i,j} + x_{k,j}) \tag{19}$$

Where, $k \in \{1,2,...,SN\}$ and $j \in \{1,2,...,D\}$ are random indexes. While, $\varphi_{i,j}$ is a random number between [-1, 1], and $x_{i,j}$ is the food position.

$$x_{i,j} = \min{}_j + rand(0,1) \times (Max_j - \min{}_j) \tag{20}$$

The onlooker bees select the food source depending on the probability function as follow:

$$P_i = \frac{fit_i}{\sum_{i=1}^{N} fit_i} \tag{21}$$

Where, fit_i is the fitness value of solution i, which depends on the nectar amount of the source in the position i, N is the number of food sources [20].

4. Case Study

Since the ABC algorithm does not consider the constraint of the problem, certain modification is required. For a constrained optimization problem, a penalty function is usually used to handle any solution violating the constraint. In this paper, to prevent from selecting a solution that has fallen into the prohibited zone, a penalty factor, has been added to the cost function in (17). To ensure the validity of the algorithm, we optimize the system based on the data in [7].

The data of the system are shown in table 1. The results were verified by comparing them to the one obtained in the referred paper [7].

Table 1 - Specifications of PV system components [7]

Type	Power rating (W)	Capital cost ($)	Maintenance cost per year ($/year)
PV module			
1. CS5C-90	90	450	4.50
2. Bpsx150	150	750	7.50
3. CS6P-200	200	1000	10.00
4. CHSM6610M-235	235	1175	11.75
5. IM72C3-310-T12B45	310	1550	15.50

Type	**Nominal capacity (Ah)**	**Voltage (V)**	**DOD (%)**	**Capital cost ($)**	**Maintenance cost per year ($/year)**
Battery					
1	230	12	80	341	3.41
2	100	12	80	163	1.63
3	150	12	80	256	2.56
4	300	6	80	512	5.12
5	420	6	80	716	7.16

Type	**Power rating (W)**	**Capital cost ($)**	**Maintenance cost per year ($/year)**
Battery charger			
1	300	259	2.59
2	240	121.5	1.22
3	288	140	1.40
4	120	198	1.98
5	1152	289	2.89

Type	**Efficiency (%)**	**Power rating (W)**	**Capital cost ($)**	**Maintenance cost per year ($/year)**
DC/AC inverter				
1	80	1500	2510	25.10

Using the data from table 1 above, the optimum design for the 125 combinations of different types of devices are summarized in Tables 2-11. The minimum cost using charger type 1 is 0.6549 $/kWh obtained using 7 panels of type Bpsx150 and 7 150Ah batteries. The required number of chargers is 20. Using charger type 2, the optimum cost is 0.6 $/kWh which is achieved with 25 charger controllers, 7 panels of type Bpsx150 and 7 150Ah batteries. The optimum cost with charger type 3 is 0.5939 $/kWh obtained with the same previous combination. The optimum cost with type 4 is 0.7505 $/kWh. The overall minimum cost is 0.5604 $/kWh which is obtained using a type 5 charger controller and using 7 panels of type Bpsx150 and 7 150Ah batteries.

Table 2 - Optimum number of PV panels and batteries using charger type 1

N_{PV} /N_b	CS5C-90	Bpsx150	CS6P-200	CHSM6610M-235	IM72C3-310-T12B45
230	12/7	7/7	6/7	5/7	4/7
100	12/14	7/14	6/14	5/14	4/14
150	12/7	7/7	6/7	5/7	4/7
300	12/7	7/7	6/7	5/7	4/7
420	12/7	7/7	6/7	5/7	4/7

Table 3 - Optimum cost using charger type 1

$/kWh	CS5C-90	Bpsx150	CS6P-200	CHSM6610M-235	IM72C3-310-T12B45
230	0.6744	0.6700	0.6922	0.6885	0.6981
100	0.6718	0.6673	0.6895	0.6858	0.6954
150	0.6594	0.6549	0.6771	0.6734	0.6830
300	0.7048	0.7003	0.7225	0.7188	0.7284
420	0.7410	0.7365	0.7587	0.7550	0.7646

Table 4 - Optimum number of PV panels and batteries using charger type 2

N_{PV} /N_b	CS5C-90	Bpsx150	CS6P-200	CHSM6610M-235	IM72C3-310-T12B45
230	12/7	7/7	6/7	5/7	4/7
100	12/14	7/14	6/14	5/14	4/14
150	12/7	7/7	6/7	5/7	4/7
300	12/7	7/7	6/7	5/7	4/7
420	12/7	7/7	6/7	5/7	4/7

Table 5 - Optimum cost using charger type 2

$/kWh	CS5C-90	Bpsx150	CS6P-200	CHSM6610M-235	IM72C3-310-T12B45
230	0.6195	0.6151	0.6373	0.6336	0.6432
100	0.6169	0.6125	0.6346	0.6309	0.6405
150	0.6045	0.6000	0.6222	0.6185	0.6281
300	0.6499	0.6454	0.6676	0.6639	0.6735
420	0.6861	0.6816	0.7038	0.7001	0.7097

Table 6 - Optimum number of PV panels and batteries using charger type 3

N_{PV} /N_b	CS5C-90	Bpsx150	CS6P-200	CHSM6610M-235	IM72C3-310-T12B45
230	12/7	7/7	6/7	5/7	4/7
100	12/14	7/14	6/14	5/14	4/14
150	12/7	7/7	6/7	5/7	4/7
300	12/7	7/7	6/7	5/7	4/7
420	12/7	7/7	6/7	5/7	4/7

Table 7 - Optimum cost using charger type 3

$/kWh	CS5C-90	Bpsx150	CS6P-200	CHSM6610M-235	IM72C3-310-T12B45
230	0.6135	0.6090	0.6312	0.6275	0.6371
100	0.6108	0.6064	0.6285	0.6248	0.6345
150	0.5984	0.5939	0.6161	0.6124	0.6220
300	0.6438	0.6394	0.6615	0.6578	0.6674
420	0.6800	0.6755	0.6977	0.6940	0.7036

Table 8 - Optimum number of PV panels and batteries using charger type 4

N_{PV} /N_b	CS5C-90	Bpsx150	CS6P-200	CHSM6610M-235	IM72C3-310-T12B45
230	12/7	7/7	6/7	5/7	4/7
100	12/14	7/14	6/14	5/14	4/14
150	12/7	7/7	6/7	5/7	4/7
300	12/7	7/7	6/7	5/7	4/7
420	12/7	7/7	6/7	5/7	4/7

Table 9 - Optimum cost using charger type 4

$/kWh	CS5C-90	Bpsx150	CS6P-200	CHSM6610M-235	IM72C3-310-T12B45
230	0.7700	0.7656	0.8131	0.8094	0.8190
100	0.7674	0.7629	0.8105	0.8068	0.8164
150	0.7549	0.7505	0.7980	0.7944	0.8040
300	0.8004	0.7959	0.8435	0.8398	0.8494
420	0.8365	0.8321	0.8796	0.8760	0.8856

Table 10 - Optimum number of PV panels and batteries using charger type 5

N_{PV} /N_b	CS5C-90	Bpsx150	CS6P-200	CHSM6610M-235	IM72C3-310-T12B45
230	12/7	7/7	6/7	5/7	4/7
100	12/14	7/14	6/14	5/14	4/14
150	12/7	7/7	6/7	5/7	4/7
300	12/7	7/7	6/7	5/7	4/7
420	12/7	7/7	6/7	5/7	4/7

Table 11 - Optimum cost using charger type 5

$/kWh	CS5C-90	Bpsx150	CS6P-200	CHSM6610M-235	IM72C3-310-T12B45
230	0.5799	0.5755	0.5976	0.5939	0.6035
100	0.5772	0.5728	0.5950	0.5913	0.6009
150	0.5648	0.5604	0.5826	0.5789	0.5885
300	0.6102	0.6058	0.6280	0.6243	0.6339
420	0.6464	0.6420	0.6642	0.6605	0.6701

Based on the results, the optimal combination is using the PV module type 5 (310 W, $1550), battery type 2 (100 Ah, $163), and charge controller type 5 (1152 W, $298). The optimum number of PV modules is 4, the optimum number of batteries is 14 for the whole lifetime of the system and 5 charge controllers. Since the output of the PV modules is 1116 Wp, one charger is enough for the system. The optimum cost of the system is 0.6009 $/kWh. Figure 6 shows the output power of the PV array, the load, and battery power. Figure 7 shows the SOC of the battery throughout the year. The figure shows that the batteries can remain within the predesigned range. To ensure the validity of the result, a system with a reduced number of components was studied. Since the number of charge controller used is 1, reducing the number of batteries or PV panels are the only possible scenario. By reducing the number of batteries to 1, the SOC is found to drop below the predetermined requirement, which is 20%, this is shown in Figure 8. When the number of PV panels used was reduced to 4, the SOC was observed to drop below 20% after five days. This can be seen in Figure 9. Therefore, this verifies the results of the ABC algorithm.

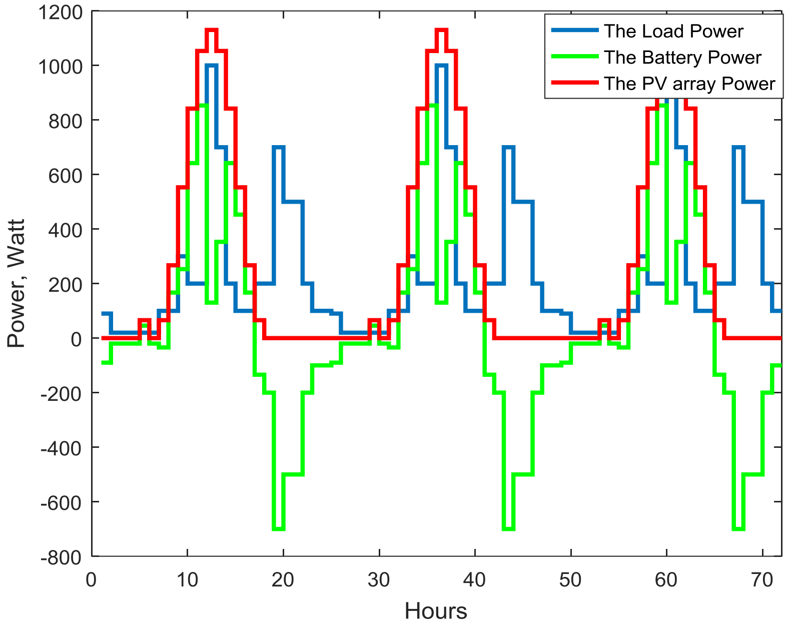

Fig. 6 - The PV output power, the load power and battery power

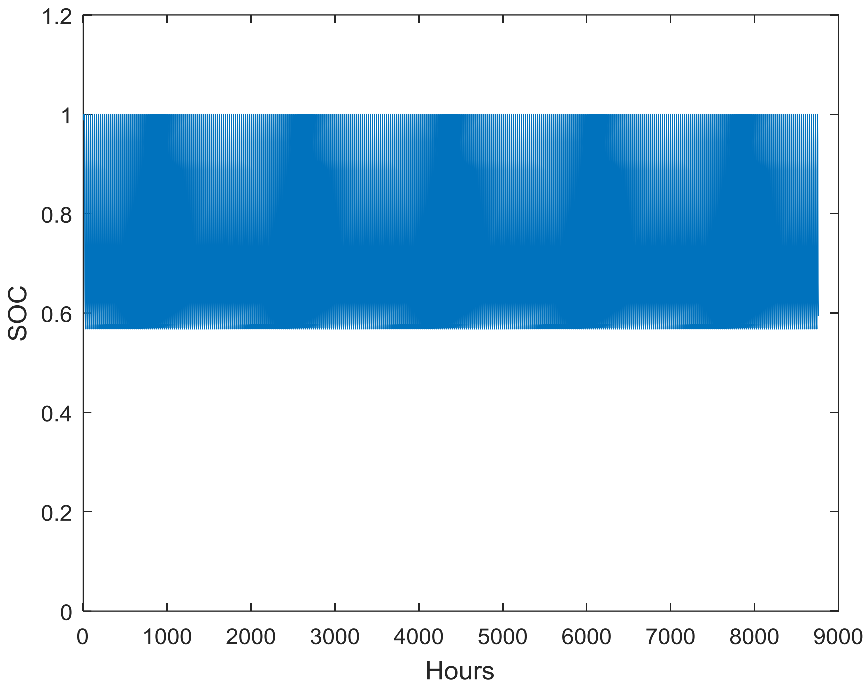

Fig. 7 - The SOC throughout the year with the optimum number of PV panels and batteries

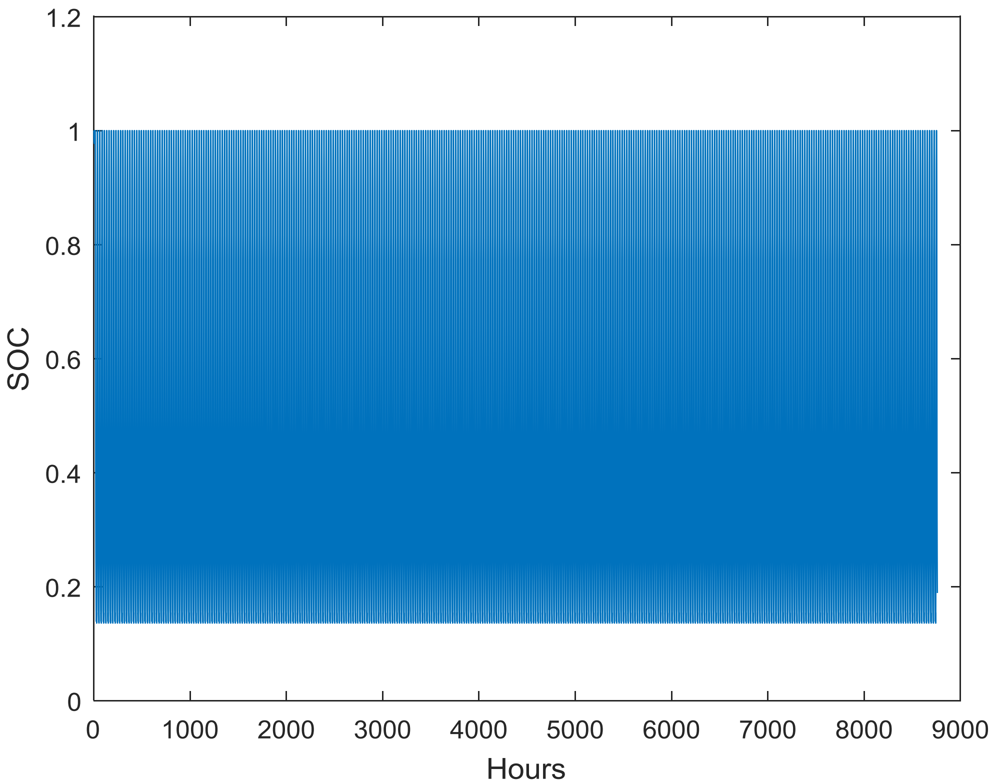

Fig. 8 - The SOC throughout the year 4 PV panel and 1 battery

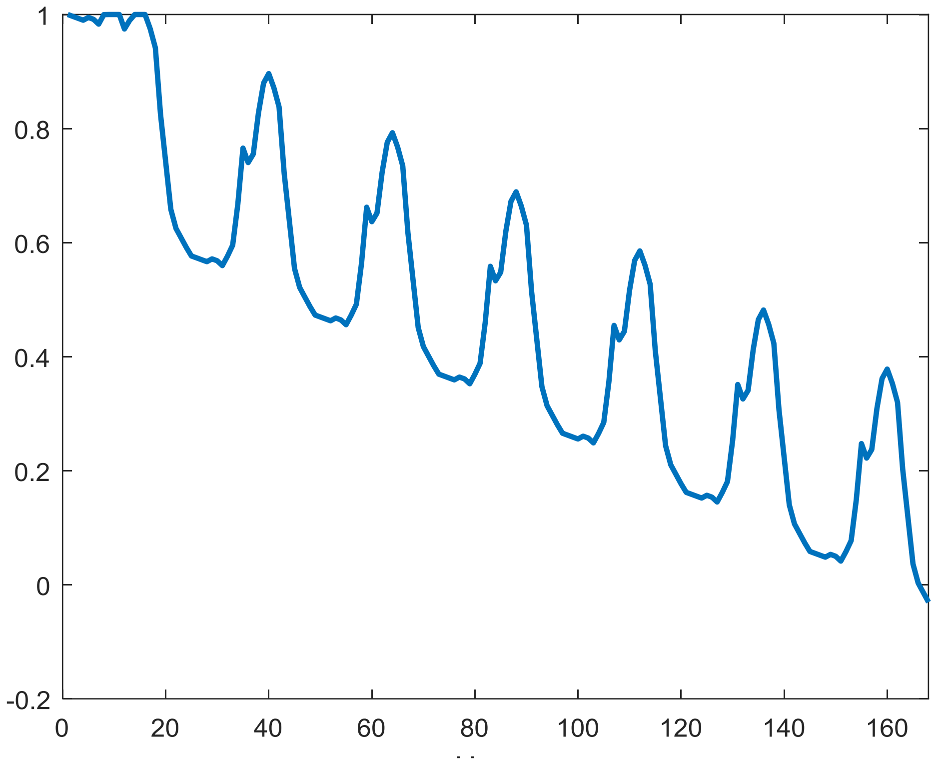

Fig. 9 - The SOC for six days with 3 PV panel and 2 batteries

The optimization presented in this paper is based on the stand-alone PV system structure. It should be noted that different PV system structure could lead to different cost [21]. For the storage, we consider only chemical batteries, other storage technologies or standby diesel generator can also be considered [22].

5. Conclusions

The high initial cost is one of the challenges facing the wide expanse of the renewable energy system. Artificial intelligence techniques have been applied to solve complex engineering problems. In this paper, we present optimal sizing techniques for a renewable energy system. The optimization of the system cost is done using an artificial bee colony. The cost function includes the initial cost in addition to the operation and maintenance cost. A stand-alone PV system has been chosen as a case study. The state-of-charge of the battery should remain above the required minimum where this case is chosen as a penalty function in the optimization. The method is applied to find the optimum combination and number of components from a large data set. The optimum size of the system has been verified through Matlab simulation. Other factors can affect the optimization, for example, inflation rate, uncertainties in the weather conditions and the degradation of the system components, adding these imperfections could lead to more realistic optimization.

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