Journal of Theoretical and Applied Information Technology
20th September 2014. Vol. 67 No.2
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ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

NEW TECHNIQUE FOR SIZING OPTIMIZATION OF A STAND-ALONE PHOTOVOLTAIC SYSTEM

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ABSTRACT

This paper presents a method for sizing optimization in Stand-Alone Photovoltaic (SAPV) system. Evolutionary Programming (EP) was integrated in the sizing process to maximize the technical performance of the system. It is used to determine the optimal PV module, charge controller, inverter and battery such that the expected Performance Ratio (PR) of the SAPV system could be maximized. Two EP models, i.e. the Classical Evolutionary Programming (CEP) and Fast Evolutionary Programming (FEP) were tested in determining the best EP model for the EP-based sizing algorithm. In addition, an iterative-based sizing algorithm was developed to determine the optimal solution for benchmarking purposes. The results showed that CEP had outperformed the FEP by producing higher PR despite having almost similar computation time. However, the sizing algorithm using both EP models was also found to be much faster when compared to the iterative-based sizing algorithm, thus justifying the needs for incorporating EP in the sizing algorithm.

Keywords: *Photovoltaic (PV), Stand-Alone Photovoltaic (SAPV), Evolutionary Programming (EP), Sizing, Optimization*

1. INTRODUCTION

The rapid depletion of fossil fuel sources throughout the world has attracted world community to find the solution regarding the energy security in the future. One of the alternative energy is known as renewable energy which has been widely used to reduce the dependency on the conventional electricity produced by the fossil fuel-based resources. Although there are numerous types of renewable energy technology, solar photovoltaic (PV) has become one of the promising renewable energy technologies especially for remote area which are usually deprived of grid electricity. The solar PV systems used for this application is known as Stand-Alone Photovoltaic (SAPV) systems.

An SAPV system typically consists of PV modules, power conditioning units such as charge controller and inverter, as well as battery bank for charge storage. The battery bank of an SAPV system serves as energy storage for providing a regulated form of electricity to meet the load demand. On the other hand, the charge controller controls the battery charging process using the charge produced by PV modules while the inverter converts the DC electricity into AC electricity. Apart from that, the system channels the electricity directly to the load instead of injecting the generated electricity to a utility grid.

Sizing of SAPV systems becomes crucial since an undersized system may result in failure in meeting the load demand while an oversized system would undermine the techno-economic benefits of having such system. The sizing process in SAPV system appears to be more complex and difficult when compared to the sizing process in grid-connected photovoltaic systems since more components need to be considered in an SAPV system. Moreover, sizing of SAPV system is often more challenging as such system offers no immediate back-up from the utility grid. The sizing of such SAPV system usually requires the system designer to initially select a PV module, charge controller, battery bank and inverter before trying to match the electrical characteristics among these components. Then, the dimensioning of the PV

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20th September 2014. Vol. 67 No.2
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ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

array and battery bank is determined. Eventually, the expected technical performance of the system is computed. However, if there are more than one model of each component needs to be considered, the sizing process is repeated iteratively for each possible set of components before selecting a single best sizing solution. This conventional sizing process is obviously time consuming and tedious although this approach can be made simple using a computer program [1]. Therefore, several studies had been conducted to expedite the overall sizing process using different types of Computational Intelligence (CI).

Genetic Algorithm (GA) and Particle Swarm Optimization (PSO) are found to be among the common CIs used in sizing optimization of SAPV systems. A GA was employed to determine the optimal configuration of renewable energy facilities in selected islands of Japan such that the total cost is minimized [2]. Similarly, another study was conducted to search for the optimal size of each SAPV system components such that the minimal cost can be achieved while ensuring that the load demand is fully served by the system [3]. Besides that, the annualized reliability cost of an SAPV system was minimized by determining the optimal number of PV modules and solar batteries using PSO [4].

This paper presents an Evolutionary Programming (EP) for sizing optimization of SAPV system. EP is branch of CI which was inspired by natural evolution. In this study, EP was used to optimally select the system components such as PV module, charge controller and inverter such that the expected technical performance of the system could be optimized.

2. SYSTEM DESIGN

The SAPV system being investigated in this study is a hybrid PV-battery power system with AC loads as shown in Figure 1. It consists of a PV array that is connected to a battery bank via a charge controller. The charge controller is used to control the charging and discharging process of the battery bank. An inverter is connected to the battery bank to convert the DC electricity to AC electricity that matches the electrical characteristics of the load.

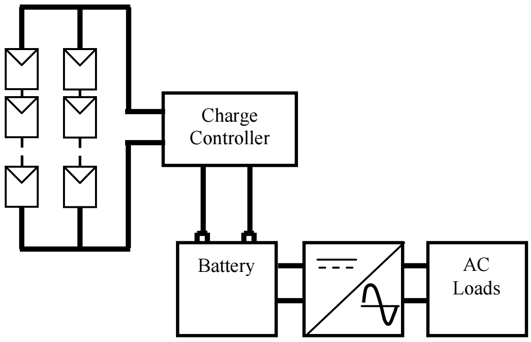

Figure 1: A Block Diagram Of SAPV System

Apart from that, the SAPV system is designed for a small residential house in a rural village of Tawau, Sabah, Malaysia. The estimated daily load demand and monthly solar irradiation are shown in Table 1 and Table 2 respectively.

Table 1: Estimated Typical Daily Load Profile Of A House At Site.

Appliance	Usage time	Usage time	Power	Energy	Energy
	Weekdays	Weekend		Weekdays	Weekend
240Vac, 50Hz	h	h	W	Wh	Wh
FL 1	10	12	20	200	240
FL 2	4	6	40	160	240
TV	5	7	60	300	420
Refrigerator	24	24	50	1200	1200
Radio cassette	11	11	10	110	110
Ceiling fan	2	5	60	120	300
Desk fan	5	6	25	125	150
Daily average load demand				2215	2660

Table 2: Expected Monthly Solar Irradiation at Site.

Month	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Average daily Peak Sun Hours, hours	4.43	4.8	4.96	5.11	4.87	4.83	4.78	4.87	4.99	4.78	4.68	4.37

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The sizing procedure used for this work is described in [5]. The steps for sizing the SAPV system are outlined as follows:

Step 1: Determine the required daily energy demand as appeared at the DC busbar, $E_{required\_daily}$.

$$E_{required\_daiy} = \frac{E_{AC}}{\eta_{inv}} \tag{1}$$

where E_{AC} is the total daily AC load demand in Wh and η_{inv} is the efficiency of inverter.

Step 2: Determine the System Voltage (SV) for the SAPV system. The SV can be chosen as 12V, 24V or 48V depending on size of the load demand.

Step 3: Calculate the Ah demand of the battery bank, $C_{required\_batt}$, as appeared at the DC busbar:

$$C_{required\_batt} = \frac{E_{required\_daily}}{SV} \times \frac{T_{autonomy}}{DOD_{\max}} \tag{2}$$

where DOD_{max} is the maximum depth of discharge of the battery with a value ranges from 0.7 to 0.8. $T_{autonomy}$ refers to a coefficient which determined the number of days that the system should be capable of meeting the load demand without availability of sunlight.

Step 4: Compute the total discharge current from battery bank, I_{bank_disch} and the respective discharge rate, T_{bank_disch} using:

$$I_{bank\_disch} = \frac{1}{SV} \times \left[\sum \frac{AC_{power}}{PF} \right] \tag{3}$$

Bank discharge rate is defined as discharge rate of battery bank and it can be calculated by using this equation:

$$T_{bank\_disch} = \frac{C_{required\_batt}}{I_{bank\_disch}} \tag{4}$$

Step 5: Determine the battery bank configuration, i.e. the number of batteries per string, N_{series_bank} and number of parallel strings of batteries, $N_{parallel\_bank}$ using:

$$N_{series\_bank} = \frac{SV}{V_{batt}} \tag{5}$$

where V_{batt} is the nominal battery voltage. C_{per_batt} is the Ah capacity of the selected battery.

$$N_{parallel\_bank} = \frac{C_{required\_batt}}{C_{per\_batt}} \tag{6}$$

Step 6: Determine the PV array configuration, i.e. the number of PV modules per string, N_{s_pv} and the number of parallel PV strings, N_{p_pv} depending on whether a standard charge controller without MPPT or a charge controller with MPPT is used. If standard charge controller is used, the PV array configuration is determined using

$$N_{s\_pv} = \frac{SV}{V_{module}} \tag{7}$$

$$N_{p\_pv} = \frac{E_{required\_daily} \times f_o}{SV \times I_{mp\_stc} \times PSH \times \eta_{coul\_batt}} \tag{8}$$

where V_{module} is the nominal voltage of PV module. PSH represents the number of daily peak sun hours which is associated to the amount of daily solar irradiation. f_o is a coefficient for oversizing the PV array and η_{coul_batt} is the Coulombic efficiency of the battery. In addition, I_{mp_stc} is the expected current at maximum power at Standard test Conditions (STC).

On the other hand, if an MPPT-based charge controller is used, the PV array configuration is computed using

$$N_{s\_\max} = \frac{0.95 \times V_{\max\_cc}}{V_{\max\_oc}} \tag{9}$$

$$N_{s\_\min} = \frac{1.1 \times V_{\min\_window\_cc}}{V_{\min\_mp} \times \eta_{pv\_cc}} \tag{10}$$

$$N_T = \frac{E_{required\_daily} \times f_o}{P_{mp\_stc} \times PSH \times \eta_{pv\_cc}} \tag{11}$$

$$N_{p\_pv} = \frac{N_{T\_pv}}{N_{s\_pv}} \tag{12}$$

where V_{max_cc} is the maximum allowable input voltage to the charge controller. $V_{max\_window\_cc}$ and $V_{min\_window\_cc}$ are the maximum and minimum allowable input voltage to the MPPT of the charge controller respectively. P_{mp_stc} represents the maximum power of the module at STC while η_{pv_cc} is the sub-system efficiency considered from PV array to charge controller in dimensionless unit. N_{s_pv} is a value selected between the minimum number of PV modules per string going to the charge controller, N_{s_min} to the maximum number of PV modules per string going to the charge controller, N_{s_max}.

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ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

Step 7: Determine the required minimum current capacity of charge controller, $I_{controller\_rating}$ using:

$$I_{controller\_rating} = 1.25 \times I_{sc\_stc} \times N_{p\_pv} \quad (13)$$

where I_{sc_stc} is the short-circuit current of the PV module at STC.

Step 8: Compute the required number of inverter for the system using

$$N_{inv} = \frac{P_{load} \times o_f}{P_{inv}} \quad (14)$$

where o_f is the oversized factor for the inverter to consider load growth and P_{load} is the maximum AC load demand. P_{inv} is the continuous power rating of the inverter in VA.

Step 9: Determine the expected technical performance indicator of the system. In this study, Performance Ratio (PR) was used to characterize the technical performance of the system. It can be calculated using

$$PR = \frac{E_{sys\_\exp}}{P_{array\_stc} \times PSH_{annual}} \quad (15)$$

where E_{sys_exp} is the expected annual energy output from the inverter and P_{array_stc} is the rated power of PV array at STC. PSH represents the estimated annual PSH derived from Table 2.

If a different set of PV module, charge controller, battery and inverter needs to be considered, the sizing process is repeated. In addition, if numerous sets are required for evaluation, all possible sets are evaluated iteratively before determining the best sizing solution. This iterative sizing process is known as Iterative-based Sizing Algorithm (ISA) [6].

3. EVOLUTIONARY PROGRAMMING-BASED SIZING ALGORITHM

Evolutionary Programming (EP) is a branch of Evolutionary Algorithm (EA) that is categorized under Artificial Intelligence (AI) hierarchy. It is a stochastic optimization technique based on search algorithm and it is commonly used as an optimizer in various tasks [7-10]. There are 4 basic processes in EP, i.e. random initialization, mutation, combination and selection. Generally, EP works by evolving a population of possible candidates for optimal solution towards the global minimum through the use of a mutation operator and selection scheme. In this study, EP was used to select the optimal model of PV module, battery, charge controller and inverter for the SAPV system such that the performance ratio (PR) of the system could be maximized. The EP-based algorithm for the optimization task is described as follows:

Step 1: Generate N sets of random number x_1, x_2 and x_3. x_1, x_2 and x_3 represent the decision variables, i.e. the model of PV module, charge controller and inverter respectively. Respective databases consisting 16 PV modules, 18 charge controllers and 38 inverters are considered while the model of battery is fixed in this study. These models are transcribed as integers depending on their respective location in the database. These initial sets of random numbers are known as parent.

Step 2: Calculate the fitness value, i.e. PR for each set of random numbers. Sizing procedure described in Section 2 is followed to determine PR.

Step 3: Mutate each set to produce offspring, thus N offspring is produced. Two mutation schemes were tested in this study using Gaussian and Cauchy mutation. The EP with Gaussian mutation is known as Classical Evolutionary programming (CEP) whereas the EP with Cauchy mutation is known as Fast Evolutionary Programming (FEP) [11].

Step 4: Compute the fitness value for each offspring by repeating step 2.

Step 5: Combine N parents and N offspring into a single population. Then, select the best N candidates based on the fitness value as the next generation of the evolution process.

Step 6: Perform convergence test to determine whether the evolution should be continued or stopped. At this stage, the stopping criterion is if the current generation number is greater than or equal to a specific maximum number of generations, the evolution will stop. Otherwise, steps 3 to 6 are repeated in sequence.

4. RESULTS AND DISCUSSION

The development of EP for this proposed sizing algorithm was aimed at finding the optimal system configuration among a set of system component which are able to meet load demand requirements. At the same time, the PR for the system is maximized. The first phase of the EP-based sizing algorithm involved the investigation of the optimal

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population size for the evolution. The results of this investigation are shown in Figure 2. CEP was discovered to require only 20 sets of random numbers in the population to reached maximum value of PR. In contrast, FEP recorded 30 sets to discover the maximum value of PR.

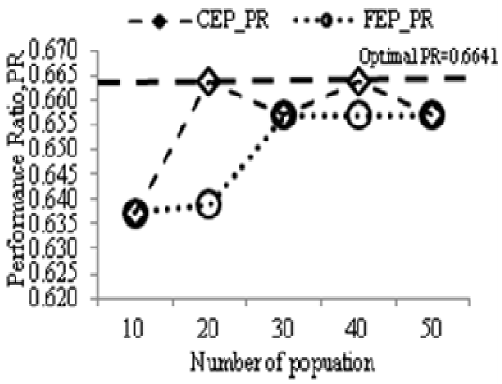

Figure 2: Fitness Value For Different EP Models At Different Number Of Population Using Standard Charge Controller

Apart from that, the performance of CEP and FEP based sizing algorithms were compared with the performance of benchmarked sizing algorithm using iterative approach, known as ISA. The results are tabulated in Table 3. CEP was found to produce similar optimal PR with ISA, i.e. 0.6641 with a computation time approximately 20,551 times faster than ISA. On the other hand, FEP failed to yield the optimal PR produced by ISA although the computation time is much lower than the computation time used in ISA. Moreover, FEP is also less accurate compared to CEP as the PR is approximately 1.0691% less than the PR obtained using CEP.

Table 3: Performance Comparison Of Different EP Models With Benchmarked Algorithm

Results	ISA	EP model	
		CEP	FEP
Optimal PV module code	3	3	3
Optimal battery code	8	8	8
Optimal charge controller code	1	1	1
Optimal inverter code	29	29	25
Npv_s, in integer	1	1	1
Npv_p, in integer	7	7	7
Npv_tot, in integer	7	7	7
Nbatt_s, in integer	2	2	2
Nbatt_p, in integer	1	1	1
Ncc, in integer	1	1	1
Ninv, in integer	1	1	1
Optimal PR, dimensionless	0.6641	0.6641	0.657
APE, in %	-	0	1.0691
Overall computation time, in seconds	69,257.65	3.37	3.4

In addition the performance of different EP models using charge controller with MPPT are shown in Figure 3. Although both models had achieved the optimal PR of 0.6977 as suggested by ISA, CEP requires the lowest number of population of 20 to obtain the optimal PR. On the other hand, FEP requires the minimum population 50 to produce the optimal PR as suggested by ISA.

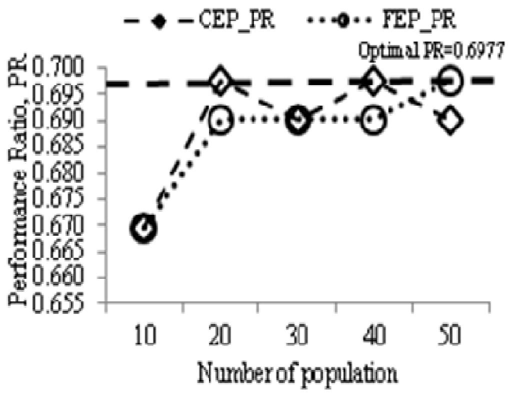

Figure 3: Fitness Value For Different EP Models At Different Number Of Population Using Charge Controller With MPPT

The results of sizing process for EP based sizing algorithm using charge controller with MPPT are tabulated in Table 4. Both optimization techniques had produced APE of 0% with approximately similar computation time, i.e. both techniques are able to produce PR which similar to the target maximum PR recorded using ISA. In addition, these optimization techniques were found to be at least 13,762 times faster than ISA.

Table 4: Performance Comparison Of Different EP Models With Benchmarked Algorithm.

Results	ISA	EP model	
		CEP	FEP
Optimal PV module code	3	3	3
Optimal battery code	8	8	8
Optimal charge controller code	8	8	8
Optimal inverter code	29	29	29
Npv_s, in integer	5	5	5
Npv_p, in integer	2	2	2
Npv_tot, in integer	10	10	10
Nbatt_s, in integer	2	2	2
Nbatt_p, in integer	1	1	1
Ncc, in integer	2	2	2
Ninv, in integer	1	1	1
Optimal PR, dimensionless	0.6977	0.6977	0.6977
APE, in %	-	0	0
Overall computation time, in seconds	53124.72	3.86	3.76

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5. CONCLUSION

This paper presents a methodology for optimal sizing of SAPV system. Two different EP models were investigated before selecting the best EP model for the EP-based sizing algorithm. CEP was found to outperform FEP by producing higher PR value with less computation time when tested with system with standard charge controller. In addition, when compared to the benchmarked sizing algorithm, i.e. the ISA, only CEP succeeded in producing the optimal PR produced by ISA with similar PV module, charge controller, battery and inverter as well as the sizing parameters such as PV array configuration, battery bank configuration, number of inverter and number of charge controller. When tested with MPPT-based charge controller, although CEP and FEP had shown similar performance by producing the optimal PR, CEP comparably perform as fast as FEP. Nevertheless, both CEP and FEP are much a faster algorithm compared to ISA. As the performance of the CEP is equivalent to the performance of ISA in obtaining the optimal solution with faster computation, the proposed EP-based sizing algorithm is justified. Future works could potentially be conducted to apply the EP in multi-source SAPV systems which may involve more decision variables to be optimized.

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