Modeling of Operating Photovoltaic Module Temperature Using Hybrid Cuckoo and Artificial Neural Network

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Abstract. Photovoltaic (PV) module temperature is an important parameter in PV system operation as the system output power decreases as the module temperature increases. Therefore, the modeling of operating PV module temperature is crucial to understand the climatic factors which contribute to the variation of the PV module temperature. This paper presents the modeling of operating PV module temperature from a Grid-Connected Photovoltaic (GCPV) system located at Green Energy Research Centre (GERC), Universiti Teknologi MARA, Malaysia. An Artificial Neural Network (ANN) was developed to model the operating PV module temperature with solar irradiance and ambient temperature set as the ANN inputs. In addition, Cuckoo Search (CS) was introduced to search for the optimal number of neurons of ANN hidden layer, learning rate and momentum rate such that the Mean Absolute Percentage Error (MAPE) of the modeling process could be minimized. The results showed that CS had outperformed an Artificial Bee Colony (ABC) algorithm for the ANN training optimization by producing lower MAPE.

Keywords: Operating photovoltaic module temperature, modeling, Artificial Neural Network, Cuckoo Search, Mean Absolute Percentage Error.

1 Introduction

Solar energy is reported to be one of the fastest growing types of renewable energy worldwide [1]. The usage of solar energy in electricity generation is executed using photovoltaic (PV) modules which have become the primary component of a PV system. A PV module basically consists of solar cells that are commonly connected in series to provide the required voltage and current. These cells convert sunlight into DC electricity which will be later channeled to either an inverter in a Grid-Connected Photovoltaic (GCPV) system for power conditioning purpose or both storage and power conditioning in a Stand-Alone Photovoltaic (SAPV) system.

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As solar irradiance increases throughout the day, the ambient temperature correspondingly increases and this subsequently heats up the cells in a PV module. The heating of these solar cells causes the operating PV module temperature, MT to rise gradually. Increasing MT would result in decreasing output voltage of the PV module, and thus reducing the output power from the module. Due to the significant role of MT, several studies had been conducted to model the MT. A review of different mathematical models for MT had been presented [2]. These models were developed based on different factors, i.e. the thermal and physical properties of PV modules, the solar irradiance and other weather parameters, as well as the heat transfer coefficient due to wind. As a result, every model is only applicable for specific conditions covered by the specific factors [3]. Apart from that, these models were formulated using linear mathematical relationship, thus limiting the practicality of the models because any change in MT does not occur instantaneously since any changes in temperature frequently lags behind the changes in solar irradiance [4].

Due to the limitations described earlier, an Artificial Neural Network (ANN) for modeling MT is presented in this study. ANN is a modeling tool which is inspired by biological nervous system. The execution of ANN is unique such that no mathematical models or pre-assumptions are required in its development [5]. Therefore, this feature would offer strong advantage in modeling of MT since no information regarding the thermal and physical properties of PV modules, and the heat transfer coefficient due to wind are required for the modeling process. In addition, ANN is also capable for both linear and non-linear modeling [6]. Hence, the modeling of MT can be performed merely using solar irradiance and other weather parameters without knowing the mathematical relationship among these weather parameters.

Although ANN possesses distinctive advantages compared to conventional mathematical models, one of the difficulties in ANN implementation is the selection of the optimal training parameters such as the number of neurons in the hidden layer, the learning rate and the momentum rate. These parameters are commonly determined using trial-and-error method that can be tedious and time consuming [7]. Therefore, different Computational Intelligence (CI) had been introduced to facilitate the search for these optimal ANN training parameters [8-9]. In this study, a Cuckoo Search (CS) had been used to search for the optimal number of neurons in hidden layer, the optimal learning rate and the optimal momentum rate such that the modeling error could be minimized.

2 Methodology

The CS-ANN was implemented in a few stages. Firstly, an ANN model was created for modeling the MT of a PV array from a GCPV system. Then, the input and output data of the ANN were collected for the learning process. Later, a hybrid CS-ANN was developed to optimize the ANN training parameters. Finally, the CS-ANN was compared with an Artificial Bee Colony (ABC)-ANN in terms of modeling error for benchmarking purpose.

2.1 Multi-Layer Feedforward Neural Network

In this study, the Multi-Layer Feedforward Neural Network (MLFNN) with a single hidden layer had been selected as the ANN architecture since it has been used to solve many complex problems of industry [10]. The inputs to the ANN were set to be the solar irradiance (SI) in Wm^{-2} and ambient temperature (AT) in °C while operating PV module temperature (MT) in °C was set to be the output of the MLFNN, as illustrated in Fig. 1. The MLFNN was developed in two stages, i.e. the training and testing processes, which were performed in Matlab.

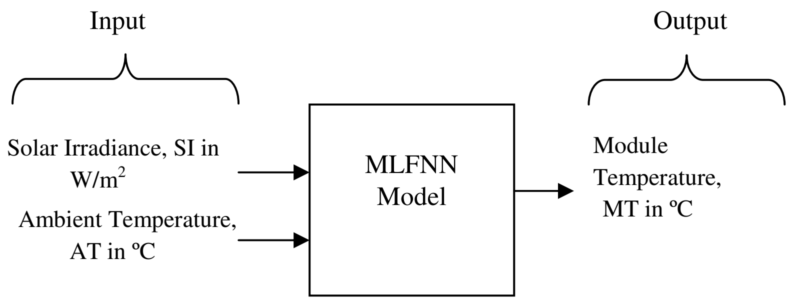

Fig. 1. MLFNN for modeling operating PV module temperature

During training of MLFNN, the number of neurons in the hidden layer, the learning rate, the momentum rate and the learning algorithm are often determined using heuristic method. The heuristic method requires these parameters to be empirically determined using trial-and-error method which can be time consuming and tedious. Therefore, unlike in the heuristic method, these parameters were optimally determined using the CS in this study. Apart from that, different types of learning algorithm were applied in the MLFNN training to determine the most suitable algorithm for the learning scheme. Besides that, the type of activation function at the hidden layer and the output layer were set to be logarithmic sigmoid (LOGSIG) and purely linear (PURELIN) respectively.

2.2 Data Collection

All data comprising SI, AT, MT and Pac were collected from a GCPV system located at the Green Energy Research Centre (GERC), Universiti Teknologi MARA, Shah Alam, Selangor, Malaysia. The system comprises 6 kWp poly-crystalline PV array and a 4.6 kW inverter. The irradiance and temperature sensors were connected to a built-in data logger inside the inverter while all data were recorded at five-minute interval. 70% of the collected data or 2359 data patterns were allocated for MLFNN training whereas the remaining 30% of the collected data or 1010 data patterns had been utilized for the testing process. A summary of the GCPV system specifications is shown in Table 1.

Table 1. System specifications

Parameters	Specification
Type of PV module	Poly-crystalline
PV array configuration	2 string with 13 modules per string
PV array power	6kWp
Type of mounting	Retrofitted
Type of inverter	1 unit X SB5000TL

2.3 Cuckoo Search - ANN

As the routine plan of MLFNN requires far-reaching work and experimentation strategy in figuring out the number of neurons, a hybrid CS-ANN is proposed in this study. CS is a meta-heuristic algorithm inspired by the obligate brood parasitic behavior of a few species of a bird family called Cuckoo [11]. It is a population-based methods derived by emulating the reproduction strategy of cuckoos. Cuckoos commonly lay their eggs in the nests of other birds from different species. Moreover, these cuckoos even tend to destroy the host bird eggs such that the hatching probability of their own eggs increases. Once their own eggs hatch inside the host bird nest, the chicks will be fed by the host birds. However, if the host bird discovered the alien eggs inside its nest, it is most likely abandon the nest or discards the alien eggs from the nest. As a result, cuckoo undergoes an evolution by mimicking the nature of the host birds such that it has better chances to survive in the host bird nest. CS has been successfully used to solve various engineering optimization tasks [12].

In CS, every egg laid by the cuckoo represents a potential solution to an optimization problem. The CS algorithm is developed using three idealized rules:

- Each cuckoo lays only one egg at a time and drops the egg in a randomly chosen nest.
- The best nests with the better quality of eggs will be transcribed to the next generation.
- The probability of an alien egg is discovered by the host bird is from 0 to 1 and the number of available nests is fixed.

The algorithm of CS in an optimization problem [13] can be described as follows:

Step 1: Initialize population of host nests, $x_{i,k}$ where i = 1,2,3,…m, k is the decision variable number, and m is the population size. In addition, the probability of alien egg discovery, Pa and maximum number of iterations are also defined.

Step 2: While maximum number of iterations has not been achieved, move a random cuckoo i from the population via Levy flights. The new position of the cuckoo, x'i,k(t+1) is calculated using

$$x'_{i,k}(t+1) = x_{i,k}(t) + \alpha \oplus Levy(\lambda) \quad (1)$$

where $x_{i,k}(t)$ is the initial position of the cuckoo. α is a positive step size parameter which controls the scale of a random search and is dependent on optimization problem under study. α is determined using

$$\alpha = \alpha_o \left(x_{j,k}(t) - x_{i,k}(t) \right) \tag{2}$$

where $x^t_{j,k}(t)$ is the initial position of random cuckoo for k-th decision variable and α_o is a constant.

The symbol $\oplus$ means entry-wise multiplications. Levy flight provides a random walk derived based on Levy distribution:

$$Levy \sim u = t^{1-\lambda} \tag{3}$$

where λ is set between 1 to 2. In this study, λ is set at 1.5.

Step 3: Evaluate the fitness value of the cuckoo i at the new position, F_i.

Step 4: Randomly choose a nest j among the m nests. If fitness of cuckoo j, F_j is worse than F_i, replace cuckoo j with cuckoo i together with the corresponding fitness value.

Step 5: Abandon a fraction of the worse nest with probability P_a while keeping the remaining nests as potential solutions. Then, new nests by the same fraction are built at new locations via Levy flights.

Step 6: Evaluate the fitness value of the new nests.

Step 7: Rank all nests according to the fitness value and determine the current best nest.

Step 8: Repeat step 2 until maximum number of iterations are achieved.

Step 9: Determine the optimal nest based on the best nest from all iterations.

The CS was later hybridized with an ANN for modeling the operating PV module temperature of a GCPV system. CS was used to search for the optimal number of neurons in the hidden layer, the learning rate, the momentum rate and the learning algorithm, which are defined as the decision variables for the optimization problem. On the other hand, the objective function for the optimization problem is to minimize the Mean Absolute Percentage Error (MAPE) of the MT. MAPE is calculated as follows:

$$MAPE = \frac{1}{n} \sum_{p=1}^{n} \left| \frac{A_p - P_p}{A_p} \right| \times 100\% \tag{4}$$

where p is the data pattern number, n is the total number of data patterns, Ap is the actual value of the MT and P_p is the modeled or predicted value of MT.

Upon completion of training process, the network underwent testing process. Then, the performance of the hybrid CS-ANN was compared with the performance of an Artificial Bee Colony (ABC)-ANN for benchmarking purpose.

3 Results and Discussions

The development of CS-ANN for modeling MT was completed in different stages. The first stage involved the investigation of the optimal population size for Cuckoo. The population of Cuckoos was varied from 10 to 100 at 10 increment and the results are shown in Fig. 2. The best population size is 100 as it produced the lowest MAPE of 2.5659 % for the modeling process. In contrast, population of 30 cuckoos produced the highest MAPE of 2.5997 %.

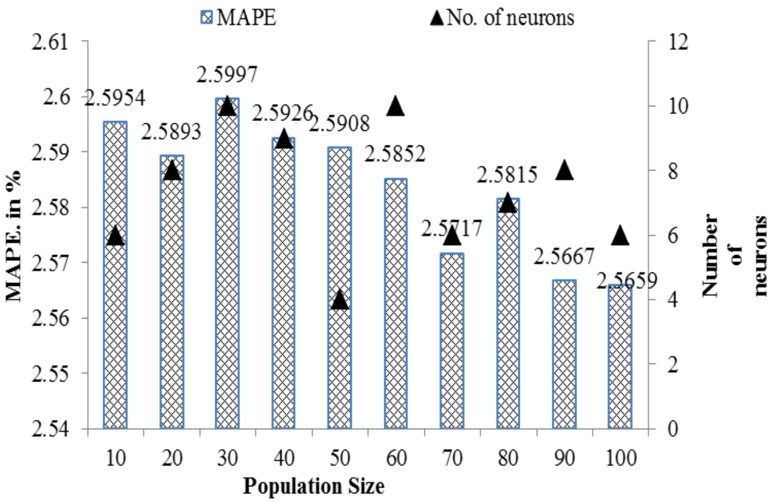

Fig. 2. Performance of CS-ANN using different population size

After determining the population size, the CS-ANN was tested using different learning algorithm to determine the best algorithm for the learning process in ANN. Levenberg-Marquardt algorithm (trainlm), scaled-conjugate gradient algorithm (trainscg), quasi-Newton backpropagation (trainbfg) and resilient backpropagation (trainrp) were used in this investigation and the performance of the CS-ANN with these algorithms are shown in Fig. 3. The learning algorithm which produces the lowest MAPE of 2.5659 % is trainlm, followed by trainbfg, trainscg and trainrp.

Apart from that, the performance of the CS-ANN was compared with the performance of an ABC-ANN for the similar training task. The results of the hybrid ANN training is shown in Table 2. CS-ANN was found to outperform ABC-ANN in terms of producing lower MAPE by approximately 14.76%. In addition, the CS-ANN also requires lower computation time when compared to ABC-ANN. CS-ANN is approximately 1.80 times faster compared to ABC-ANN.

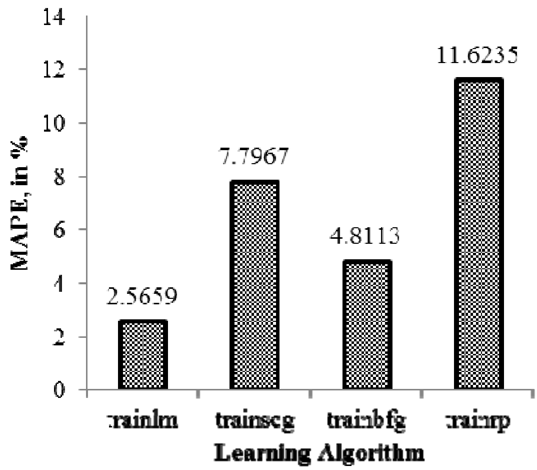

Fig. 3. Performance of CS-ANN using different learning algorithms

Table 2. Optimal ANN parameters and computation time for different hybrid ANNs

Parameters	CS-ANN	ABC-ANN
Optimal number of neurons in hidden layer	6	4
Optimal learning rate	0.4217	0.6382
Optimal momentum rate	0.1000	1.000
Minimum MAPE, in %	2.5659	2.9445
Computation time, hours	2.98	5.36

During testing process, the performance of the CS-ANN and ABC-ANN were again compared in terms of MAPE. A summary of the performance of CS-ANN and ABC-ANN during training and testing is shown in Fig. 3. Similarly, during testing, the CS-ANN had outperformed ABC-ANN by yielding MAPE which is approximately 26.22 % lower compared to ABC-ANN.

Since CS-ANN had produced lower MAPE compared to ABC-ANN during both training and testing stages, CS was discovered to be a more accurate optimizer as compared to ABC in the ANN learning. In fact, CS is also a faster search algorithm when compared to ABC during the hybrid training.

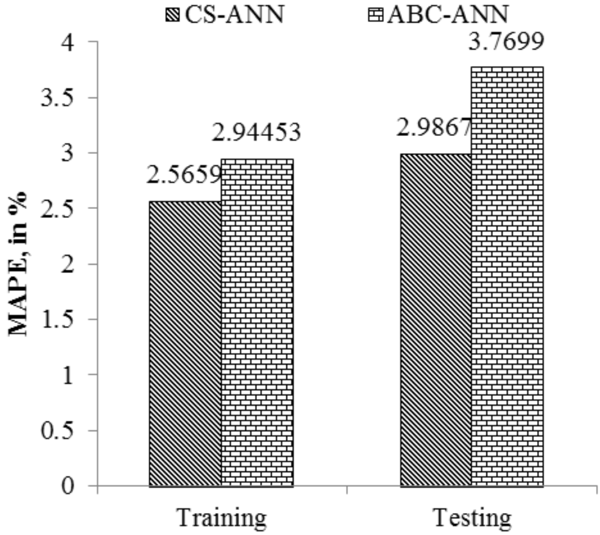

Fig. 4. Performance of CS-ANN and ABC-ANN during training and testing

4 Conclusion

This paper has presented a hybrid CS with ANN for modeling the operating PV module temperature from a PV array of a GCPV system. CS had successfully been used to determine the optimal number of neurons in hidden layer, the learning rate and the momentum rate such that the MAPE of the modeling could be minimized. When compared with the performance of ABC-ANN, the CS-ANN had outperformed the ABC-ANN by yielding a lower MAPE during both training and testing. Moreover, CS-ANN was also found to require lower computation time than ABC-ANN during the optimization task.

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