Firefly Algorithm-Based Neural Network for GCPV System Output Prediction

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Abstract-**This paper presents a Multi-Layer Feedforward Neural Network (MLFNN) for predicting the AC power output from a grid-connected photovoltaic (GCPV) system. In the proposed MLFNN, Firefly Algorithm (FA) was employed as the optimizer and search tools of the MLFNN training parameters. FA was used to optimize the number of neurons in the hidden layer, the learning rate and the momentum rate such that the Root Mean Square Error (RMSE) was minimized. In addition, the MLFNN utilized solar irradiance (SI), ambient temperature (AT) and module temperature (MT) as its inputs and AC power as its output. Additionally, the optimal population size, absorption confession, learning algorithm and type of transfer functions in FA were also investigated in this study. The performance of the proposed FA-based MLFNN had been compared with the performance of the Classical Evolutionary Programming-based Neural Network (CEP-based MLFNN). The results showed that the proposed FA-based MLFNN had outperformed the CEP-based MLFNN in producing lower RMSE.**

Keywords- Grid-Connected Photovoltaic (GCPV) System; Firefly Algorithm (FA); Root Mean Square Error (RMSE)

I. INTRODUCTION

Photovoltaic (PV) system is a type of renewable energy that converts sunlight into electricity and has been increasing constantly since it helps to produce clean energy. Even during a time of economic crisis, the annual worldwide installed capacity of PV in 2012 was approximately 31.1 GW that is roughly same as in the record installation of year 2011 [1]. In urban areas where the utility-grid is readily available, PV system can be implemented as a distributed power resources as usually demonstrated in grid-connected photovoltaic (GCPV) system to utilize as an alternative source of electricity generation. In GCPV system, the PV array is connected to the grid with an inverter. The PV array generates DC power and the DC power is converted to AC power by the inverter used on the grid. As a result, the energy generated by the PV array could be exported to the grid [2].

The performance of GCPV system is not only depends on the modes of operation but also on power generate by PV array which is extremely dependent on the weather conditions. However, the crucial issue in a GCPV system is highly unpredictable of the AC power output due to the fluctuating weather conditions throughout the day. Due to this fluctuation, it is difficult for the system owners to identify whether their systems are performing as expected. Thus, there is a need for predicting AC power output from the GCPV system such that the performance of the GCPV system could be justified. A Multi-Layer Feedforward Neural Network (MLFNN) was initially developed to predict the AC power from a GCPV system. For instance; S. I. Sulaiman,I. Musirin and T. K. A. Rahman in [3] utilized MLFNN as a prediction tools for predicting output of GCPV system. This study had proved that the MLFNN is capable for predicting AC power output of a GCPV system. Nonetheless, the limitation of the MLFNN are time consuming and tend to become tedious process since it required trial and error method to select the MLFNN training parameters [4-5].

Hence, a Firefly Algorithm (FA)-based on MLFNN was proposed for predicting AC power output of a GCPV system. In addition, FA was employed to optimize the best training parameters for the MLFNN, thus providing a hybrid approach for the prediction technique. Once the training process was completed, testing process was performed to validate the training process. The performance of FA-based MLFNN is expected to be better optimizer and search tools as compared to the Classical Evolutionary Programming-based Neural Network (CEP-based MLFNN)**.**

This paper also presents the optimal population size, absorption coefficient, training algorithm and type of transfer functions in FA-based MLFNN that is used to predict the AC power output of a GCPV system. Numerous work had showed the selected of training algorithm and type of transfer functions may strongly influence the performance of MLFNN training.

II. METHODOLOGY

A. MLFNN Scheme for Predicting System Output

In this study, a MLFNN was proposed to predict AC power from the GCPV system. The MLFNN consists of solar irradiation (SI) ambient temperature (AT) and module temperature (MT) as its inputs and AC power output of a GCPV system as its output as illustrated in Fig. 1.

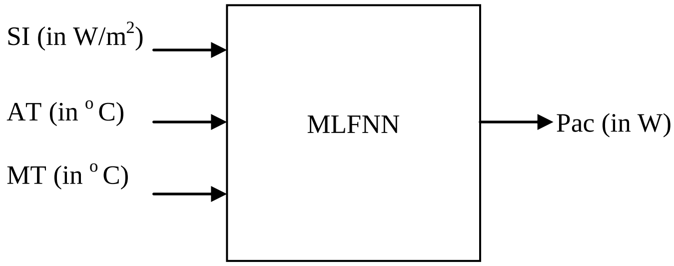

Figure 1. MLFNN scheme for the prediction of AC power of the GCPV System

B. Specfications of the System and Data Collection

The site under study is situated at rooftop of Green Energy Research Centre (GERC), UiTM Shah Alam. This PV system is a collaboration project between GERC with Solarlite Green Energy Sdn Bhd and YingLi Green Energy Singapore. At site, there are two different PV system namely as system 1 and system 2. However, only system 1 is investigated in this study. The details of system 1 are tabulated in Table I.

TABLE I. CHARACTERISTICS OF THE PV SYSTEM 1

Characteristics	**Parameters**
Type of PV system	6 kWp GCPV system
Mounting	Retrofitted
Latitude	3° 04' 08.79''N
Longitude	101° 29' 49.66''E
Total area of PV system	$40.88m^2$
Elevation	18 m
Type of PV module	YGE Polycrystalline
Size of PV module	235Wp
PV module configuration	2 string (13 units module)
Type of inverter	SB5000TL
Size of inverter	4.6kW

At the site, SI (in W/m^2), MT (in ºC), AT (in ºC) were connected to a data logger while AC power (in kWh) was downloaded directly from the inverter. Two thousand data patterns have been recorded at 5-minute interval for the investigation. The data were separated into two set namely as the training data set and the testing data set. Apart from that, 80% of the collected were used for the training process whereas the remaining 20% of the collected data had been used for the testing process. The percentage of training data set is larger as compared to the testing data set to ensure prediction accuracy of MLFNN training. Previous study had showed this ratio of data could give the best performance of AC power output prediction.

C. Proposed Firefly Algorithm-Based MLFNN

Firefly algorithm (FA) is invented by Xin-She Yang for solving multimodal optimization problem [6-8]. This algorithm was inspired by the flash pattern and characteristics of fireflies. Xin-She Yang was stated two significant rules of FA i.e light intensity and attractiveness. The attractiveness is proportional to the brightness or light intensity, which is directly related to the distance between two fireflies which is given as:

$$\beta=\beta o \, e^{\gamma \, r\wedge 2} \qquad (1)$$

Where, βo is the attractiveness at r=0 and γ is the attenuation.

Besides, the less bright of a firefly *i* move towards the brighter firefly *j* is determined by:

$$x i = x i + \beta o e^{-\gamma r i j \wedge 2} (xj-xi) + \alpha \, (\text{rand} - ½) \qquad (2)$$

$$r ij = ||x i - x j|| \qquad (3)$$

Where, r*ij* is the distance between any two fireflies *i* and *j* and α is the size of the random step.

Based on these two significant rules many researchers were interested to used FA as an optimizer tools for selection training MLFNN parameters [9].A few MLFNN parameters and characteristics have been fixed before training MLFNN is performed. Firstly, the light intensity of the FA is set to be RMSE such that RMSE would be a constraint. Lower RMSE would imply the best performance of AC power output prediction. Thus, the success of the prediction had been demonstrated by the low RMSE. The R^2 was introduced to indentify the validity of RMSE value. The R^2 must be very close to unity to represent a good fit between the predicted and actual output [10].The mean square error (MSE) value is set to be sufficiently small (10^{-02}) .In addition; the number of iteration was chosen to be large (1000 epochs) to ensure the prediction precision. Ultimately, the FA-based MLFNN has stopped after fifth generation.

In this study, the development of FA-based MLFNN begin with the selection of the best training MLFNN parameters i.e the optimal population size, the optimal absorption coefficient, the optimal training algorithm and the optimal type of transfer functions. Afterward, FA-based MLFNN was re-trained using the optimal training MLFNN parameters. Later, the performance of FA-based MLFNN was compared with the performance of the CEP-based MLFNN.

The simulations of FA-based MLFNN was performed in MATLAB (R2010b) was carried out based on Intel ® PENTIUM® P6200, 2GB Memory (RAM), windows 7 (64 bit) operating system. The flowchart of the FA-based MLFNN is illustrated in Fig. 2.

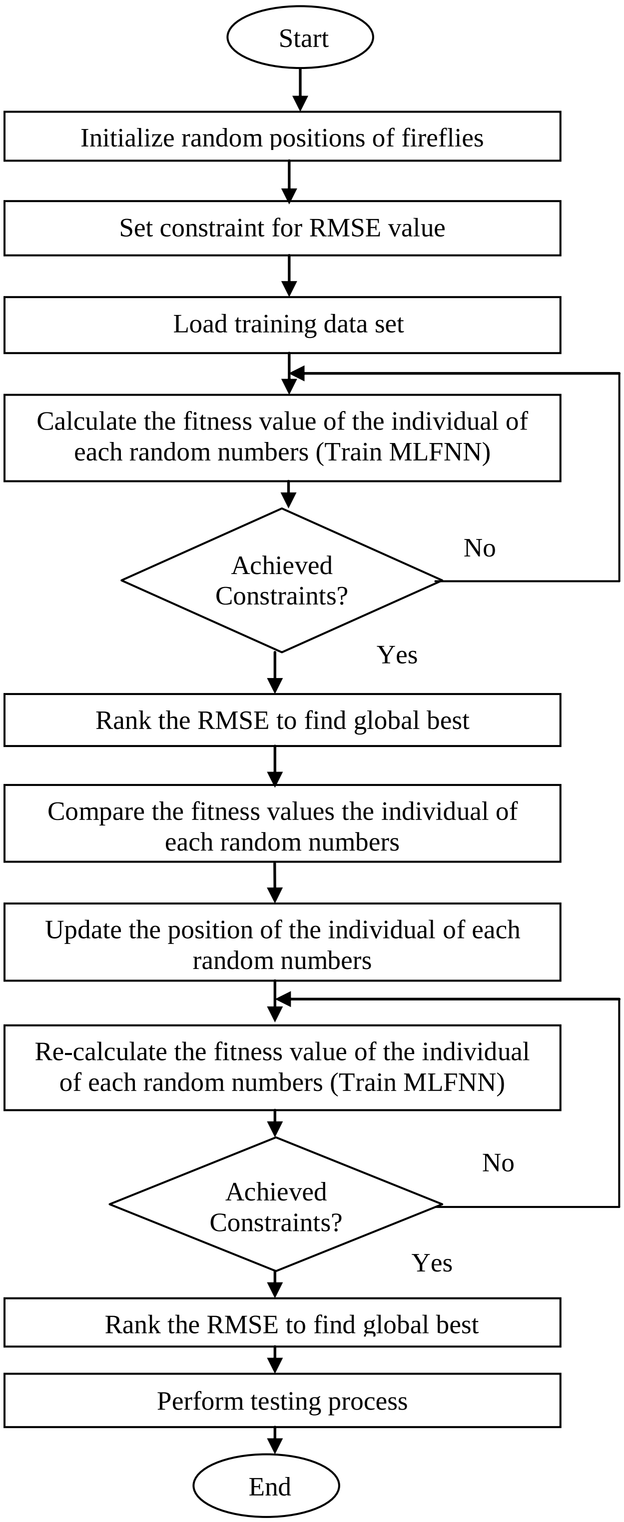

Figure 2. Flowchart of the FA-based MLFNN

The program begins with the initialization of the firefly's population size based on three random numbers that represent the number of neurons in the hidden layer, learning rate and momentum rate. Each three random numbers that comprises of number of neurons in the hidden layer, learning rate and momentum rate was generated for each individual in the firefly where 20 individuals were initially created to form the firefly.

After a set of random numbers of fireflies have been generated, constraint of the search are determined. In this study, the RMSE had selected as a fitness value and main performance indicator whereas RMSE value is the constraint for this investigation. Afterward, load the training data set that had collected from GCPV system previously.

Next, calculate the fitness value of the individual of each random numbers. This step can be done by training the MLFNN with the training data set. This step should be repeated until 20 individual in the random number obtained their RMSE value .Consequently, the RMSE value that had produced was arranged in descending order according to the individual fitness value. Thus, the set of random numbers with lowest RMSE value will be on the top while the set of random numbers with highest RMSE value will be ranked at the bottom. The lowest RMSE obtained known as a global best.

Subsequently, compare the fitness value of each 20 individual in the random numbers due to their brightness or light intensity to find the best fitness, i.e lowest RMSE. Then update the position of the individual, i.e the less bright move toward the brighter individual. Since the position of the individual had been changed, it required to re-calculate the fitness of the individual thus it compute the RMSE value again to find the global best. Once the training MLFNN has been successfully, the trained MLFNN was saved. Later, the trained MLFNN performance was used for testing process using testing data set. The performance of testing process was also demonstrated using lowest RMSE.

III. RESULTS AND DISCUSSIONS

The development of FA-based MLFNN for GCPV system AC power output prediction was first analyzed by determining the population size of firefly. In Fig. 3, shows the optimal population size was found to be 40 in which the FA-based MLFNN produced the lowest RMSE. The population size was varied from 10 to 50 at an increment of 10 fireflies.

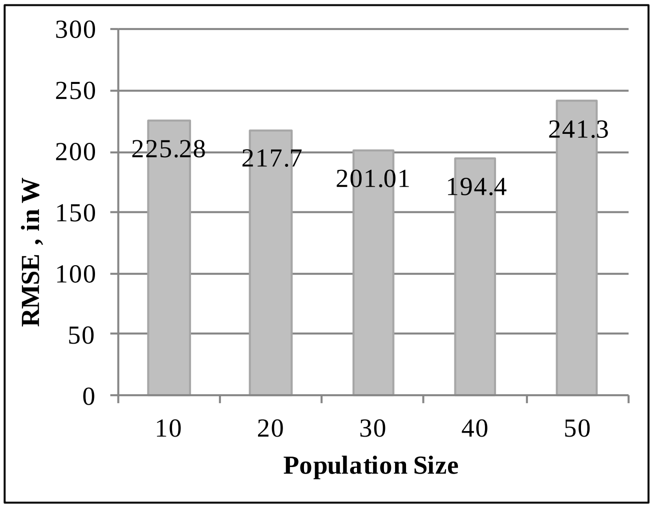

Figure 3. RMSE performance of the FA-based MLFNN using different population size

Afterward, the FA-based MLFNN was conducted with two configurations of absorption coefficients namely as set A and set B. The set A consists of [α=0.2 γ=1.0 β=1.0] that was stated by Yang [11].On the other hand, set B consists of [α=1.0 γ=0.25 β=0.2] that was used by A.Chatterjee and G.K Mahanti as in [12].As a result, set B is capable to produce lower RMSE as compared to the set A as showed in Fig. 4.

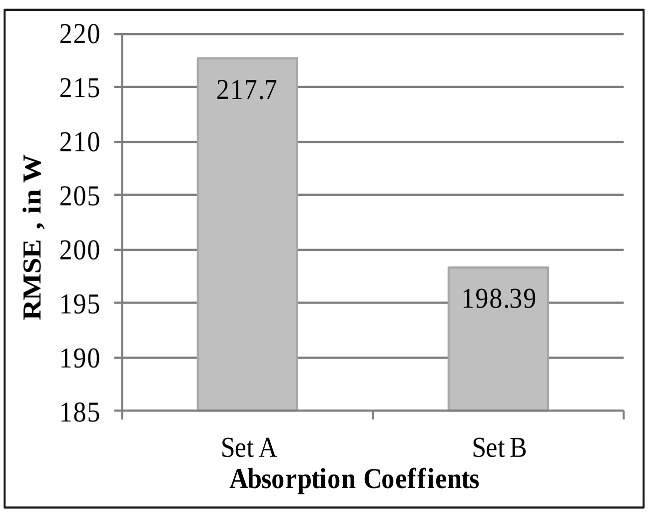

Figure 4. RMSE performance of the FA-based MLFNN using different absorption coefficient

Next, the FA-based MLFNN was examined with different training algorithm such as Levenberg-Marquardt algorithm (TRAINLM), scaled–conjugate gradient algorithm (TRAINSCG), quasi-Newton back-propagation (TRAINBFG) and resilient back-propagation (TRAINRP). Fig. 5 shows that the lowest RMSE was obtained using FA-based MLFNN with TRAINLM while the highest RMSE was obtained using FA-based MLFNN with TRAINRP. Thus, TRAINLM had proved as the best training algorithm.

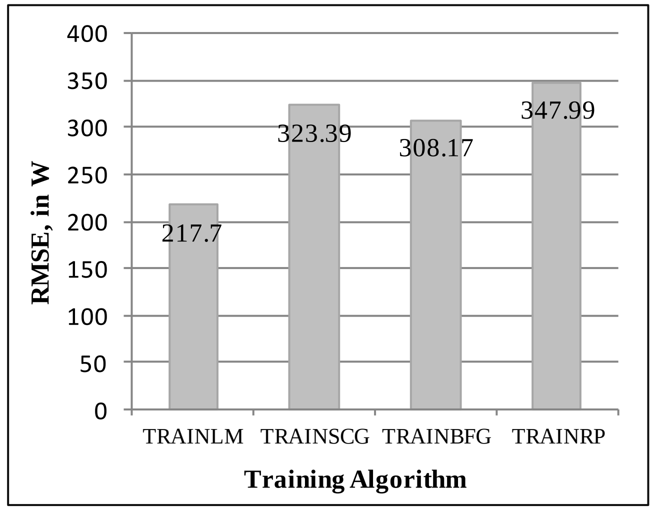

Figure 5. RMSE performance of the FA-based MLFNN using different training algorithm

Subsequently, the FA-based MLFNN was tested different type of transfer functions i.e logarithmic-sigmoid, purely linear (LOGSIG-PURELIN) and hyperbolic tangent-sigmoid, purely linear (TANSIG-PURELIN). As a result, the LOGSIG-PURELIN is able to produce lower RMSE as compared to the TANSIG-PURELIN as showed in Fig. 6.

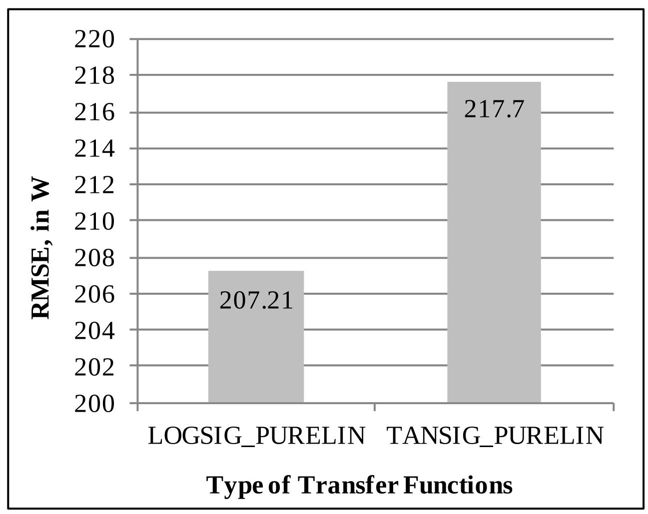

Figure 6. RMSE performance of the FA-based MLFNN using different type of transfer function

Later, FA-based MLFNN was re-trained using the optimal population size, absorption coefficient, training algorithm and type of transfer function. The parameters obtained during training MLFNN was tabulated in Table II.

TABLE II. FINAL MLFNN PARAMETERS

MLFNN Parameters	Value
Optimal number of neurons in the hidden layer	33
Optimal learning rate	0.4
Optimal momentum rate	0.9

Consequently, testing process was performed and the RMSE and R^2 from testing process were compared with RMSE and R^2 from training as illustrated in Fig. 7. It observed the RMSE during testing process is 623.07 W, which is almost tripled the RMSE during training is 207.1 W. Although, the R^2 in both training and testing are almost equally good as the values were very closer to unity.

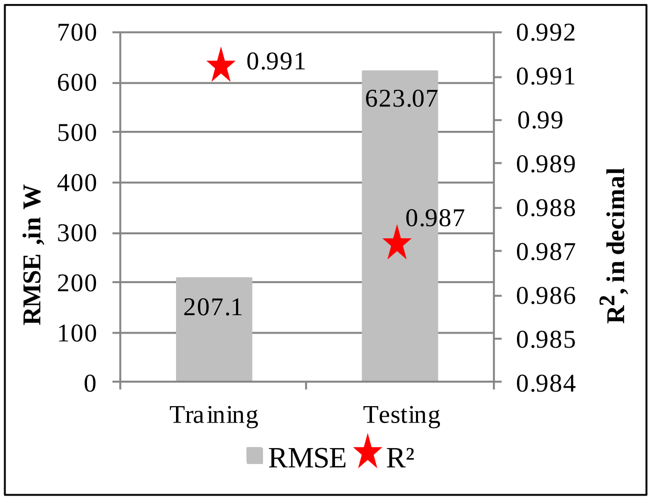

Figure 7. RMSE and R^2 performance of the FA-based MLFNN during training and testing

Eventually, the performance of the FA-based MLFNN was compared with the performance of CEP-based MLFNN using similar training and testing data. Fig. 8 shows that the FA-based MLFNN had produced lower RMSE when compared to the CEP-based MLFNN during training and testing processes. However, the CEP-based MLFNN was found to have faster computation time as compared to the FA-based MLFNN, which create a scope for future study.

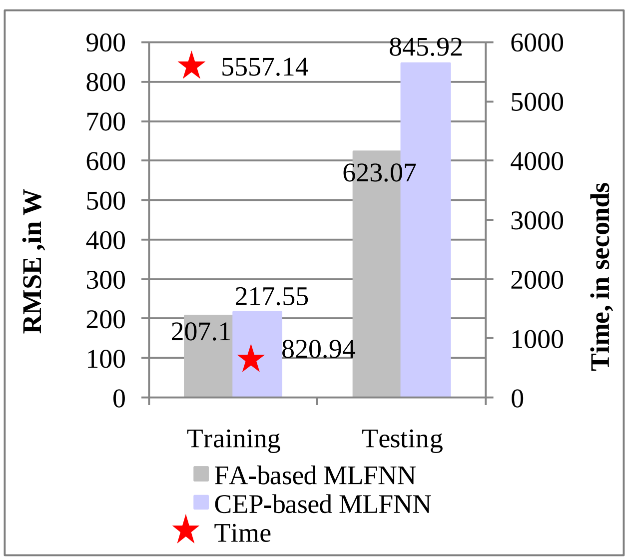

Figure 8. Performance of FA-based MLFNN and CEP-based MLFNN during training and testing

IV. CONCLUSION

This paper has presented a FA-based MLFNN for predicting the AC power output of a GCPV system. FA was used to optimize the number of neurons in the hidden layer, the learning rate and the momentum rate during MLFNN training process. The best MLFNN training parameters had selected to predict AC power output from the GCPV system. Results showed that the FA-based MLFNN had outperformed the CEP-based MLFNN in producing lower RMSE in both training and testing processes. In short, the proposed FA-based MLFNN for predicting AC power output of a GCPV system was justified.

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