Performance Analysis of Three ANN Models Using Improved Fast Evolutionary Programming for Power Output Prediction in Grid-Connected Photovoltaic System

Puteri Nor Ashikin Binti Megat Yunus, Shahril Irwan Bin Sulaiman, and Ahmad Maliki Bin Omar

Abstract—**This paper presents an assessment of three ANN models using hybrid Improved Fast Evolutionary Programming IFEP-ANN techniques for solving single objective optimization problem. In this study, multi-layer feed forward ANN models for the prediction of the total AC power output from a grid-connected PV system has been chosen. The three models were developed based on different sets of ANN inputs. It utilizes solar radiation, ambient temperature and module temperature as its inputs. However, all three models utilize similar output, which is total AC power produced from the grid-connected PV system.**

The mixtures of Gaussian and Cauchy are used during the mutation process in the EP technique. The best predictive model was selected based on the lowest root mean square error (RMSE) and higher regression, R. Besides, the comparison between classical ANN (without evolutionary programming) and hybrid IFEP-ANN was compared to determine which model performs better for single-objective optimization. The IFEP-ANN models showed the best in having the lowest RMSE and significantly better than ANN in terms of highest regression, R.

***Index Terms*—Artificial Neural Network (ANN), Improved Fast Evolutionary Programming (IFEP), Grid Connected Photovoltaic System**

I. INTRODUCTION

In the field of photovoltaic (PV) system, the uncertainty of the energy amount generated from the PV system becomes one of the main concerns of the user. Therefore, many researchers have conducted different types of studies to address this issue.

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One of the prediction techniques used is artificial neural networks (ANN) [1] . The author used maximum temperature, minimum temperature, mean temperature and irradiance to estimate the generated power. Follow by [2] , solar irradiance and module temperature has been used to estimate the energy of a PV generator based on V-I curve. Similarly, in [3] , the prediction of output power also uses by solar irradiance and ambient temperature.

Besides, PV modules has also been predicted using the same architecture, but with different types of input and output [4]. The ANN uses solar radiation, ambient temperature, module temperature and wind temperature as its input while AC output power use as output. Although these studies have produced many important discoveries in the prediction of PV system outputs using ANN, the design of ANN models using specific sets of design constraints relies so much on past experience with the same applications and is subjected to trial and error processes [5]. For instance, in a grid connected PV system, a study has been conducted to predict the total AC power output of a grid-PV system using manually-designed ANN [6]. However, this manual design of ANN is time consuming and prone to inaccuracy issues due to the tedious trial and error process experienced by the ANN designers. Due to this limitation, the evolutionary process has been introduced to provide faster training of the ANN [7].

The ANN evolution can be achieved by developing the connection height, architecture or ANN learning algorithm. In general, there are many types of evolutionary methods to develop ANNs. One of the most popular methods is Evolutionary Programming (EP). Evolutionary Programming (EP) was originally proposed by Lawrence J. Fogel in the United States in 1960 when he studied artificial intelligence. The EP is a stochastic optimization technique based on search algorithms and quite similar to Genetic Algorithm (GA) in terms of the principle of natural evolution where this method is capable of solving constrained and unconstrained optimization problems. The advantages of EP compared to other optimization is that, they make only few assumptions about underlying objective function. Furthermore, the definition of objective functions usually requires only few information about the structure of the problem space. Finally, they can provide a good solution within a reasonable time. As a result, EP is consistently implementing different domains of different problems[8].

EP also such a discipline that has been used to improve the progress of finding optimum solutions in complex issues. For the last decade, EP techniques have been used and applied in several applications and solved many difficult optimization problems[9]. In the field of evolution computation, it is common to compare different algorithms using large test sets, especially when it involves optimization function tests.

However, the IFEP has been outperform the CEP in obtaining the optimum design of transformers of smaller as well as larger ratings in terms of execution time, convergence rate, quality and success rate [10]. Based on the successful finding, this paper present the design of a hybrid model using Improved Fast Evolutionary Programming – Artificial Neural Network (IFEP-ANN), to predicted the total AC power from the grid connected photovoltaic system.

The system used in this study is mounted on the roof of Green Energy Research Centre (GERC), Universiti Teknologi MARA, Malaysia. Data collected from the 5.405 kWp grid-PV consists of solar radiation, SR (in kW/m^2), ambient temperature, AT (in ºC) and module temperature (in ºC) and total AC power output (in W). The data patterns are obtained based on 5 minute interval. Data for 10 days are allocated for training process which consists of 2882 patterns while 5 days data are allocated for testing process corresponding to 1441 patterns.

II. METHODOLOGY

A. Development of ANN Models

ANN is the process of generalization for mathematical models based on the nervous system biology. Neurons is a basic elements of ANN processing. For basic computational models, neurons collect input signals from neurons or other sources and merge them. It will then perform the required computation before mapping them to the output. In general, the ANN model consists of one input layer, one hidden layer and one layer of output. However, it can be used with more than one hidden layer. The main objective of this study is to develop ANN model that can predict the total AC power output of the grid-connected PV system on the rooftop.

In the ANN model, several parameters have been selected before perform the training stage. Firstly, Levenberg-Marquardt algorithm has been chosen as the learning rules for the ANN, since it has showed the best output compared to trainbfg, trainscg and trainrp [11] .According to same author, there are no strict procedure in how to determine the value of ANN parameters, hence the transfer function configuration is set to be 'logsig, pureline'.

Secondly, the number of epochs is set to be 1000 in order to allow accurate convergence of the ANN. After that the value of learning rate, momentum rate and the number of neurons in hidden layer are determined using trial-and-error method, which the value for learning rate and momentum rate lies between 0 to 1, while the number of neurons in hidden layer are between 1 and 20. In this study, three models have been developed based on different types of input configuration with single output AC power.

a) ANN Model 1

The proposed ANN Model 1 is illustrated as in Fig. 1. The ANN model using SR and AT as its inputs and total AC output power as its output. AT is selected since it could influence the performance of PV arrays by cooling down the PV module. Thus, AT is selected to be the second input after the SR.

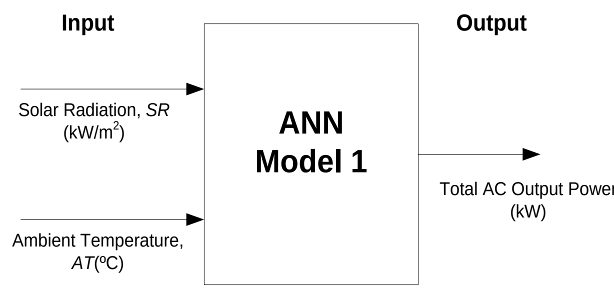

Fig. 1 ANN Model 1 – SR and AT as inputs

a. ANN Model 2

The second model utilizes SR and MT as its input and total AC output power as its output is illustrated in Fig.2. MT is chosen to be the second input in the second ANN model.

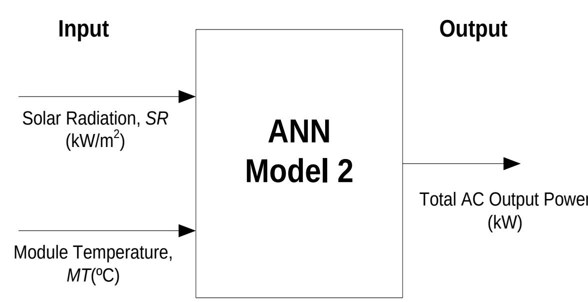

Fig. 2 ANN Model 2 – SR and MT as input

b. ANN Model 3

The third model utilizes SR, MT and AT as its input and total AC output power as its output. This model is comprised of all three factor that could affect the performance of PV array. The model as illustrated in Fig.3.

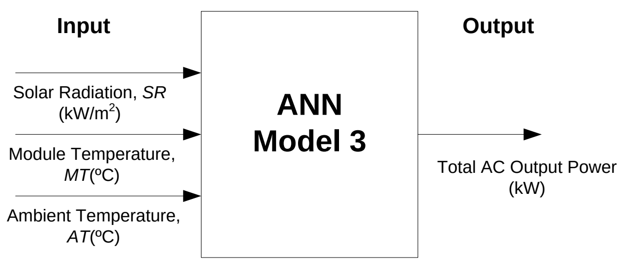

Fig.3 ANN Model3 – SR, MT and AT as inputs

B. Hybrid Improved Fast Evolutionary Programming-Artificial Neural Network (IFEP-ANN)

In this study, the value for learning rate (x_1), momentum rate (x_2) and the number of neurons in hidden layer (x_3) are chosen as ANN parameters and allowed to evolve to reach their optimum values using EP while the type of activation function and learning algorithm were set based on the final topology obtained. The value for learning rate and momentum rate cannot be too high or too low because it will cause slow convergence or more iterative updates are needed to achieve the error goal. The best solution is obtained by achieving the minimum value for RMSE as well as the maximum value for regression, R. Lower RMSE value indicates that the lower error computed by the model while higher R shows the high accuracy of the prediction model. The training network for EP-ANN is implemented using the following steps:

Step 1: Generate N population of sets of random numbers corresponds to learning rate (x_1), momentum rate (x_2), and number of neurons in hidden layer (x_3). Each set of random numbers forms the initial set of parents. Set all constraints needed.

Step 2: Evaluate all sets of parents by training the MLFNN to find the fitness for each parent. At this step, the performance of RMSE and R were evaluated and calculated by using Equation 3.5 and Equation 3.6.

Step 3: Determine the minimum and maximum values for x_1, x_2 and x_3 obtained in parent population. Next, train the ANN model to determine their RSME value. The minimum and maximum value for RMSE also determined from the population.

Step 4: Mutate all parents set to produce children or called offspring. In this study, IFEP is proposed to be combined with ANN. The general equation for Gaussian-Cauchy in IFEP [12] [13]is:

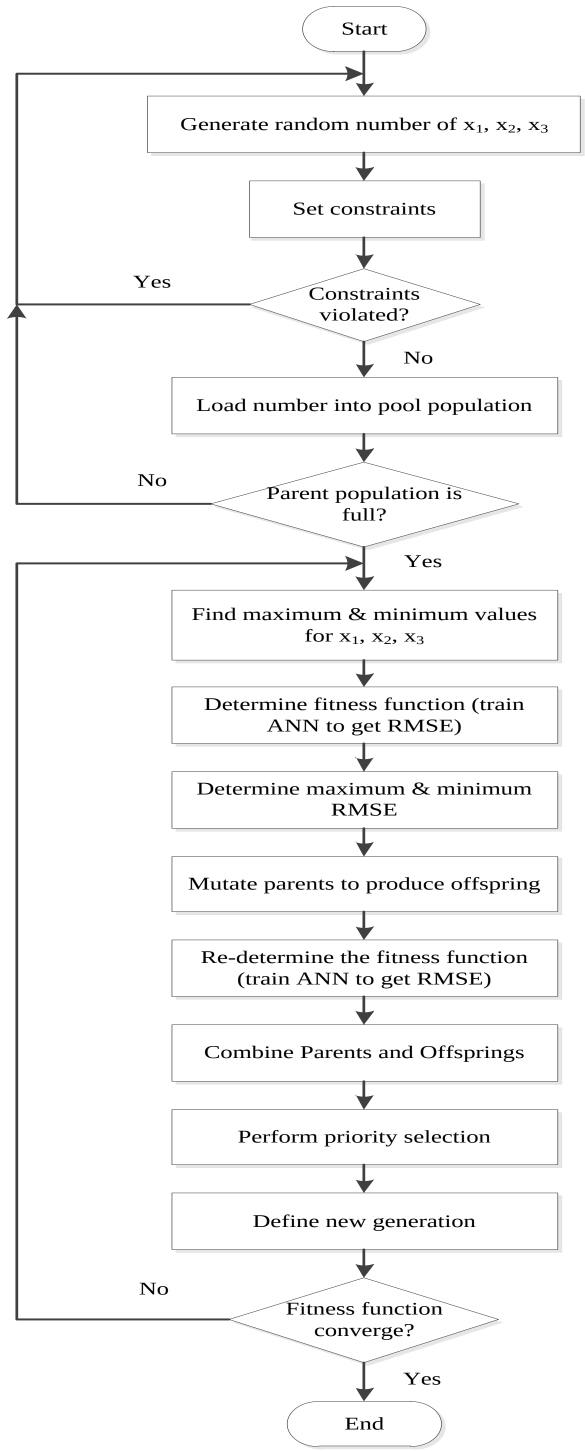

Fig.4 Flowchart for the hybrid Improved Fast Evolutionary Programming IFEP-ANN techniques

$$y1_i' = y_i + \sigma_i . N_i(0,1) \quad (1)$$

$$y2_i' = y_i + \sigma_i . C_i(0,1) \quad (2)$$

Step 5: Evaluate all set of offspring by calculating their RMSE and R.

Step 6: All set of parent and offspring together with their fitness values are combined so that the total generation number become 2N.

Step 7: Selection of the candidates is performed based on their fitness values. In Case 1, candidate with the lowest value for RMSE will become priority to be selected as the best solution. While for Case 2, candidate with the highest value for R will be selected as the best solution.

Step 8: The best solution of N candidates which have been selected in previous step will be as a new parents for the next generation.

Step 9: Perform convergence test to find whether the evolution of population should be continued or stopped. Step 2 will be repeated if the stopping criterion is not met, and will be ended if stopping criterion is met. The overall process of IFEP-ANN algorithm is summarized in flowchart in Fig. 4.

III. RESULTS AND DISCUSSION

There are two section in this result. The first result describe the performance of classical ANN for all three models and the second section describe the performance of IFEP-ANN. After that, the last section will describe the best parameters for the chosen model. The model will be chosen based on the lowest RMSE and the highest regression, R.

In Fig. 5, during training process, Model 2 has experienced the lowest RMSE of 326.472 W. However, in the testing process, the RMSE increase to 1080.3521 W. Similar to Model 1, the RMSE value increase from 351.4745 W in the training process to 971.5679 W in the testing process. Model 3, experienced the highest RMSE in training process of 501.2543 W and the lowest in the testing process of 535.5434W.

In terms of regression, R performance, Model 1 gives the highest values for both training and testing. In training, the value of R is 0.9614 and 0.9716 in testing process. In order to choose the best model, other than considering the lowest RMSE, the highest R also need to be achieved. Thus, the improved fast evolutionary programming (IFEP) has been employed to the classical ANN for all three models. The detailed performance is illustrated in Fig 6.

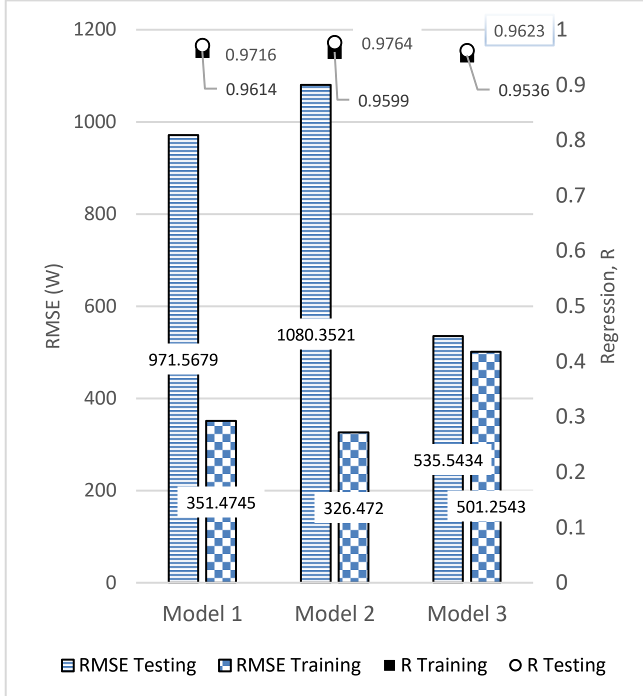

Fig.5 Performance of three model using ANN

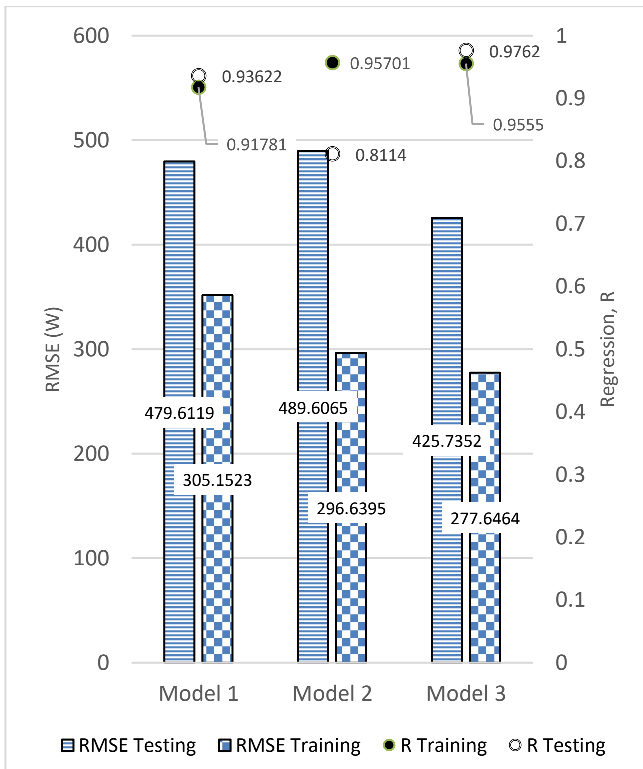

Fig.6 Performance of three model with IFEP-ANN

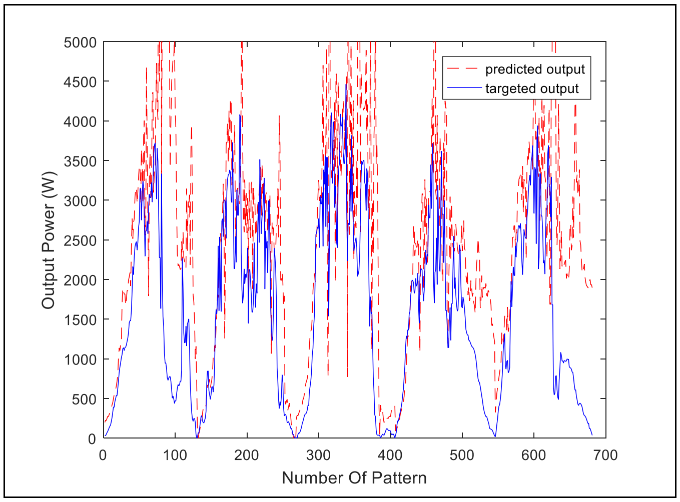

Fig.7 Predicted and targeted output power for Model 3 with classical ANN

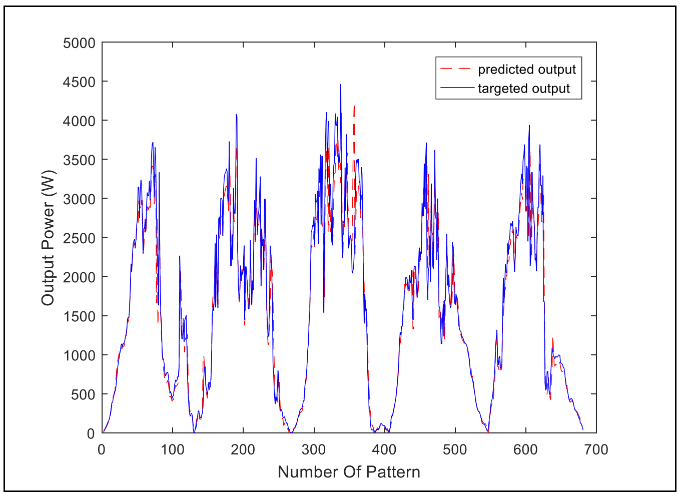

Fig.8 Predicted and targeted output power for Model 3 with hybrid IFEP-ANN

After employed the IFEP-ANN in the models, the performance of all three models yield to the best result. Model 3 clearly showed the best performance based on the lowest RMSE and the highest R compared to other two model. In the training process, the value of RMSE gives as 277.6464 W and it goes to 425.7352 W in the testing process. However, in term of R values, Model 3 still lead to the highest with 0.9555 in the training and 0.9762 in the testing.

Model 1 has experience the highest RMSE both in training and testing process as 305.152 W and 479.6119 W respectively. While in term of R, it gives the second highest as 0.9178 in training and 0.9362 in testing.
However, Model 2 gives the second highest of RMSE in the training as 296.6935 W and increase to 489.6065 W in testing process. For the value of R, Model 2 gives 0.9571 in training and dropped to 0.8114 in testing.

TABLE I: TRAINING PARAMETERS AND RESULT FOR THE BEST MODEL CHOSEN

Parameters	**Model 3 SI, MT, AT**
No. of training	1360
No. of testing	680
Number of Learning Rate (x1)	0.1269
Number of Momentum Rate (x2)	0.0975
No. of hidden layer	20
Type of Transfer Function	Logsig, Purelin
RMSE Training	277.6464
RMSE Testing	425.7352

In short, the Model 3 which represent to the SI,MT and AT as the inputs contributed as the best model since it give the lowest RMSE and the highest R achived.

Fig. 7 and Fig.8 show AC output power prediction for Model 3 with classical ANN and hybrid IFEP-ANN. The result is tabulated for 5 days data in the testing process. It clearly shows that the prediction with hybrid IFEP-ANN has better performance since the value of predicted and targeted AC output power are very close.

Table I illustrated the parameters used in the Model 3. In the training process, the optimum number for learning rate, x1 and momentum rate, x2 are discovered to be 0.1269 and 0.0975 respectively. Number of hidden layer found to be 20 nodes. In addition, the transfer function used is logsig-purelin.

IV. CONCLUSION

This paper was successfully developed hybrid improved fast evolutionary programming and ANN (IFEP-ANN) for predicting total AC power output from a grid-connected PV system. The combination of three inputs of module temperature, ambient temperature and solar radiation gives the best performance. This combination give the lowest root mean square, RMSE and highest regression, R.

ACKNOWLEDGMENT

This work was supported in part by the Fundamental Research Grant Scheme (FRGS), Ministry of Education (Ref: 600-RMI/FRGS 5/3 (120/2015) and Universiti Teknologi Mara (UiTM) Malaysia.

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