Output Prediction of Grid-connected Photovoltaic System Using Artificial Neural Network

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Abstract— **This paper presents an artificial neural network ANN technique for predicting the output from a Grid-Connected Photovoltaic (GCPV) system. In this study, the ANN model utilizes solar irradiance (SI), ambient temperature (AT) and module temperature (MT) as it inputs while the output is the total AC power produced from the grid connected PV system. These data was collected from rooftop of Malaysian Green Technology Corporation (MGTC), Bandar Baru Bangi, Malaysia along January and October 2010. The main objective of this research is to predict AC kWh output from grid-connected photovoltaic system system referring to its performance indicator. The indicators consist of root mean square error (RMSE) and coefficient of determination (R^2), which is for checking the goodness of fit. The performance of ANN model was tested using different algorithm and activation function. The number of neuron has been varied from 1-20 while the momentum rate and the learning rate varies from 0.05 until 1. Levenberg-Marquardt shows the best fit training algorithm.**

Keywords; Artificial Neural Network (ANN), Grid-Connected Photovoltaic (GCPV), performance indicator, prediction.

I. INTRODUCTION

Grid-connected photovoltaic system (GCPV) is a system that has PV arrays that converts sunlight into DC electricity. This DC electricity is then converted into AC electricity via inverters, and this AC will be transmitted to the grid. Although there are many grid-connected PV system install worldwide, there are still a couple of problem that could by any chance slow down the promotion of the grid-connected PV system. One of the problems is the transient of the system output due to the wavering weather conditions throughout the year. Hence customers have difficulties in knowing whether the system is performing, as it should or not. Therefore, this study proposes a method to predict an expected output of the power [1].

Since the earth environment condition is unpredictable, there are a few factors that need consideration to maintain the performance of PV system. First, the variations in sun position and changing climatic conditions may cause the PV array to produce electricity less than the load demand. Naturally, the motion of the sun is dissimilar throughout the year. As a result the total irradiation received at a particular site is different from time to time. Secondly, presence of clouds and rain that will cause scattering and absorption would decrease the irradiation received at a site. Moreover, the performance of PV array is also affected by the ambient temperature and solar cell temperature [2].

In recent years, since the implementation of the grid-connected PV system, many of it's users where concerned about the energy output that can be harvested from the grid-connected photovoltaic system throughout its operation [3]. Prediction of the total AC power output is needed to assure the customers for this type of power system to be reliable. A way to do this is to use artificial neural network (ANN) to construct a multi-model ANN. One researcher did this by configuring the multi model to consider different ANN inputs, which are solar irradiance, ambient temperature, and wind speed and module temperature. These inputs are then broken down into 3 models with 2 inputs and 1 output, which are solar irradiance as one input and the other three as input number two in different models. The outputs of the three models would be similar, the total AC power produced from the grid-connected PV system. The end results of this research have proven to be favoring in heighten the performance of the prediction. Hence, studies were conducted to predict the total AC power output from a grid-photovoltaic system using multi model artificial neural network (ANN). The multi-model was configured from three ANN models considering different sets of ANN inputs where the first model utilizes solar radiation and ambient temperature as its inputs. The second model uses solar radiation and wind speed as its inputs. The third model uses solar radiation, ambient temperature and wind speed as its inputs. Nevertheless, all the three models employ similar type of output, which is the total AC power, produced from the grid-connected PV system. The purpose of this study is to produce to the best model for predicting the total AC power output from a grid-connected PV system based on three input variables. In a nutshell, the data filtering is found to be beneficial in enhancing the performance of the prediction [2]. In March 2009, another study found out that two-variate multi-layer feedforward neural network (MLFNN) using SI and MT or SI and AT as the inputs had presented the best output power prediction model. However, the training parameters of these MLFNN models were chosen using classical approach through a heuristic process [4].

The goal of this study is to predict the output from rooftop of Malaysian Green Technology Corporation (MGTC), Bandar Baru Bangi, Malaysia by using ANN technique. This technique utilizes solar irradiance, ambient temperature and module temperature as its inputs while total AC power produced from grid-connected PV system are used as its output as in Figure 2. The ANN models had been developed by varying the number of nodes in the hidden layers, learning rate, momentum rate, training algorithm and activation function. This include in the training and testing process. This ANN models used different type of transfer function and training algorithm to make sure the performance of ANN model could be enhanced by monitoring the coefficient of determination, R^2 and the root mean square error (RMSE). After the training process is completed, the testing process is performed to decide whether the training process should be repeated or stopped. Besides selecting the best prediction model, this study also exhibits some of the experimental results, which illustrate the effectiveness of the data filtering in predicting the total AC power output from a grid-PV system.

II. METHODOLOGY

A. *System and data collection*

The grid-connected PV system under investigation is located at rooftop of Malaysian Green Technology Corporation (MGTC), Bandar Baru Bangi, Malaysia. The system consists of 45.36 kWp polycrystalline PV array with 40 kW inverter (IG2). Data logger that is part of inverter was connected to solar irradiance and PV module temperature sensors. All irradiance, module temperature and ambient temperature were recorded at fifteen-minute interval. Data collected in January 2010 were used for the training process while data along October 2010 had been used for testing process. The total no of data used are 2400 and 144.000 no of iterations.

B. *Hardware Description*

For this project, all tests were run on a computer with Intel core i3 3.10GHz and memory 4096 MB. Microsoft Windows 7 (64-bit) was installed as the operating system. All tests were implemented using MATLAB version 7.14.0.739 (R2012a).

C. *Model for predicting system output*

As can be seen in Figure 1, an ANN model with single hidden layer was proposed to predict the energy kWh output from the system. This technique was proposed since it involved 2 processes, which is training and testing. This process is implemented in a single program so that the performance from each process can be easily monitored and compared. The ANN model comprises solar irradiance, SI, ambient temperature, AT and module temperature, MT as its inputs while the energy kWh as the output. Besides that, a few fixed ANN parameters were selected before starting the training and testing process as tabulated in table 1.

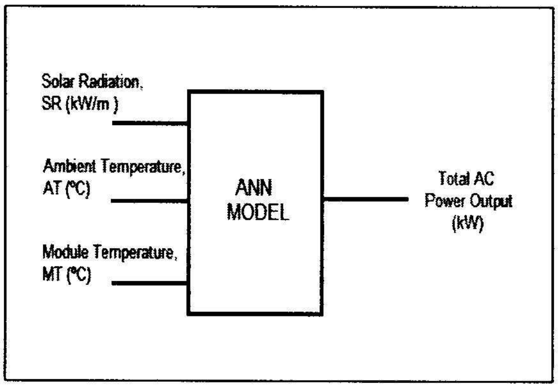


Figure 1. ANN model with 3 inputs and single output

The ANN parameters are presented in Table 1.

TABLE I. ANN PARAMETERS

Parameter	Value
Neuron	1 to 20 (step size 1)
Learning Rate	0.05 to 1 (step size 0.05)
Momentum Rate	0.05 to 1 (step size 0.05)
Transfer Function	logsig, tansig, purelin
Training Algorithm	trainlm, trainbfg, trainscg, trainrp, traingd, traingdx

D. *Proposed ANN*

The ANN models with 3 inputs were developing in this study to improve the performance of the previous research. This technique will improve the data performance by changing the ANN parameters. In this study, maximum iteration of trainings algorithm was set to 1000 epochs. The performance of ANN was calculated using RMSE and R^2 method. The proposed technique was written in Matlab using the following steps.

Step 1: Start the process by loading training and testing data. Initialize ANN parameters (neuron=1, activation function= logsig, training function= trainlm, learning rate= 0.05, momentum rate=0.05).

Step 2: Perform the training process by varying ANN parameters. First, the momentum rate, MR values are varying from 0.05 to 1 with step size of 0.05 follow with the learning rate, LR. Next, there are six training algorithm, AF will be varied which is Levenberg-Marquardt algorithm (trainlm), Scaled Conjugate Gradient (trainscg), quasi-Newton backpropagation (trainbfg), Resilient backpropagation (trainrp), gradient descent with momentum and adaptive learning rate backpropagation (traingdx) and gradient descent backpropagation (traingd). The activation function, AF configurations used are logarithmic-sigmoid (logsig), hyperbolic tangent-sigmoid (tansig) and purely linear (purelin). Lastly, the numbers of neuron; N is varying from 1 until 20 with step size of 1.

Step 3: Test the ANN fitting using R^2 and RMSE.

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(z_{p,i} - z_{t,i})^2}{n}}$$

Where $z_{p,i}$ is the actual output of training data and $z_{t,i}$ is the targeted output of the training data. In addition, n is the number of data patterns for training. Besides that, the coefficient of determination, R^2 was also calculated using

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(z_{p,i} - z_{t,i})^2}{\sum_{i=1}^{n}(z_{t,i} - z_{t\_avg})^2}$$

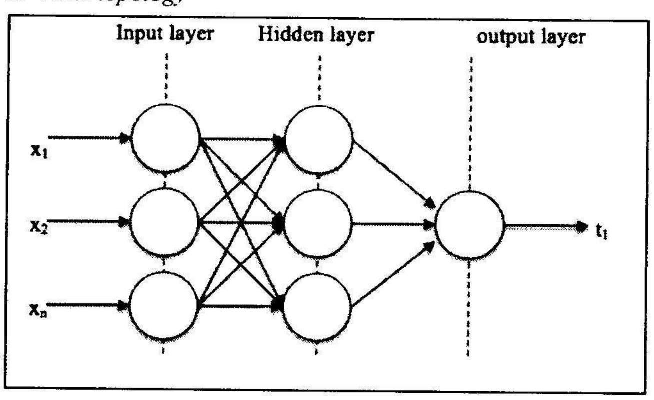
where z_{t_avg} is the average value of the targeted ANN output. In addition, R^2 are commonly used to measure the correlation between parameters in a mathematical model. Nevertheless, RMSE had been chosen as the performance indicator for the prediction while R^2 was engaged to validate the RMSE of the network, i.e. the R^2 of the prediction must be reasonably high.

Step 4: Save all parameter changes and result for further analysis.

TABLE II. RESULT TABLE

N	AF	TA	LR	MR	Training		Testing		Time
					R^2	RMSE	R^2	RMSE	

E. *ANN topology*



This is clearly shown in flowchart.

F. *Flowchart*

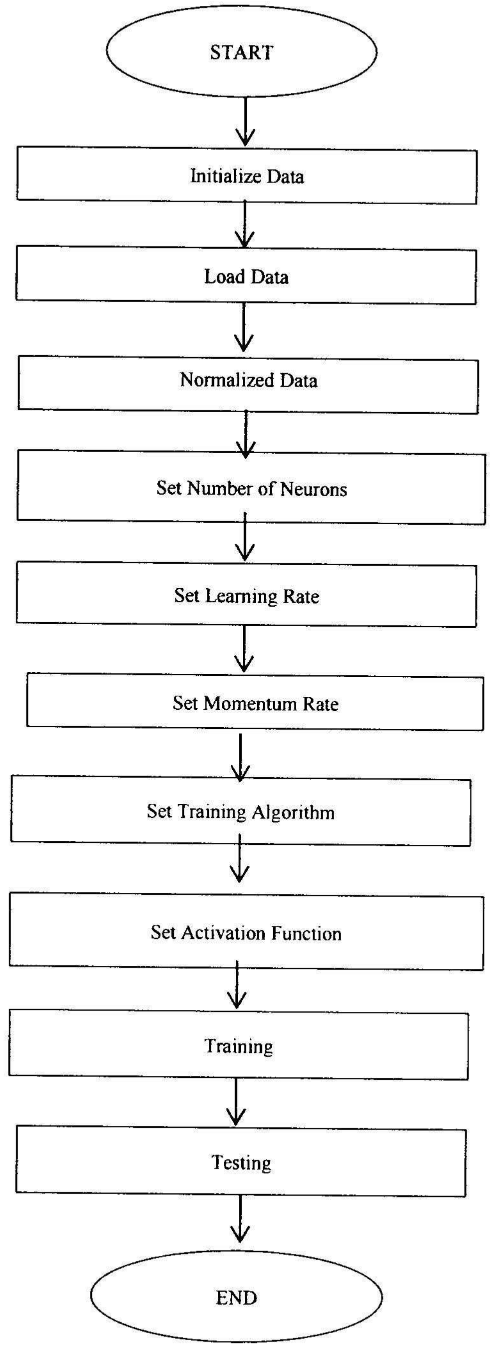


Figure 1. Flowchart for the ANN algorithm

III. RESULTS AND DISCUSSION

The performance of the ANN model for training process is tabulated in Table II while testing process is shown in Table III. Both table shows top 10 ranking with maximum R^2 and minimum value of RMSE. Both training and testing process was completed after 144,000 iterations. In addition, the training process was done using target root mean square error (RMSE) goal of 0.01 and 1000 iterative updates (epochs).

A. Training

TABLE III. TRAINING RESULT

No	N	AF	TA	LR	MR	Training	
						R^2	RMSE
1	1	logsig	trainlm	0.05	0.05	0.9967683	194.32634
2	1	logsig	trainlm	0.05	0.1	0.9967796	193.98889
3	1	logsig	trainlm	0.05	0.15	0.9967796	193.98889
4	1	logsig	trainlm	0.05	0.2	0.9967796	193.98889
5	1	logsig	trainlm	0.05	0.25	0.9969454	188.92788
6	1	logsig	trainlm	0.05	0.3	0.9969454	188.92788
7	1	logsig	trainlm	0.05	0.35	0.9969454	188.92788
8	1	logsig	trainlm	0.05	0.4	0.9969454	188.92788
9	1	logsig	trainlm	0.05	0.45	0.9969454	188.92788
10	1	logsig	trainlm	0.05	0.5	0.9969454	188.92788

B. Testing

TABLE IV. TESTING RESULT

No	N	AF	TA	LR	MR	Testing	
						R^2	RMSE
1	1	logsig	trainlm	0.05	0.05	0.9848638	412.32546
2	1	logsig	trainlm	0.05	0.1	0.9845425	416.67834
3	1	logsig	trainlm	0.05	0.15	0.9845425	416.67834
4	1	logsig	trainlm	0.05	0.2	0.9845425	416.67834
5	1	logsig	trainlm	0.05	0.25	0.9844709	417.64308
6	1	logsig	trainlm	0.05	0.3	0.9844709	417.64308
7	1	logsig	trainlm	0.05	0.35	0.9844709	417.64308
8	1	logsig	trainlm	0.05	0.4	0.9844709	417.64308
9	1	logsig	trainlm	0.05	0.45	0.9844709	417.64308
10	1	logsig	trainlm	0.05	0.5	0.9844709	417.64308

As can be seen from the training results, the activation function and training algorithm produced are logarithmic-sigmoid and Levenberg-Marquardt algorithm respectively. The correlation of determination, R^2 value obtained is found to be 0.9967683, with RMSE of 194.32635. Apart from that, the corresponding number of neuron in hidden layer, learning rate, and momentum rate, are discovered to be 1, 0.05 and 0.05 respectively.

During testing process, the activation function and training algorithm produced are logarithmic-sigmoid and Levenberg-Marquardt algorithm respectively. The correlation of determination, R^2 value obtained is found to be 0.9848638, with RMSE of 412.32546. In addition, the corresponding number of neuron in hidden layer, learning rate, and momentum rate, are discovered to be 1, 0.05 and 0.05 respectively.

Since the ANN model produced maximum value of R^2 and approaching 1 during both process, the proposed technique is justified.

IV. CONCLUSION

In this study, the ANN models have been successfully developed for predicting AC power output from a GCPV system. The regression of determination and root mean square is found to be the suitable criteria with RMSE of 412.32546 and R^2 of 0.9848638 in measuring predicting performance. Apart from that, the best activation function and training algorithm produced are logarithmic-sigmoid and Levenberg-Marquardt algorithm. This study verifies that training and testing can be conducted sequentially and will become simpler and quicker with the selected training parameters and performance comparison. In conclusion, an ANN based technique has been successfully developed to satisfactorily predict the total AC power output from a grid-PV system.

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