

PAPER • OPEN ACCESS

# Prediction of Photovoltaic (PV) Output Using Artificial Neural Network (ANN) Based on Ambient Factors

To cite this article: Siti Amely Jumaat *et al* 2018 *J. Phys.: Conf. Ser.* **1049** 012088

View the [article online](#) for updates and enhancements.

## You may also like

- [Optimal Control of Li-Ion Battery Energy Storage System for Frequency Regulation](#)  
Jihun LIM, Jin Hyeok Choi, Geon-pyo Lim et al.
- [Performance of chemical engines with a mass leak](#)  
Lingen Chen, Fengrui Sun and Chih Wu
- [A Short-Term Optimal Dispatch Model Considering Uncertain Wind Power Output](#)  
Xuan Zhang, Hua Wei, Wei Gao et al.



The Electrochemical Society  
Advancing solid state & electrochemical science & technology

242nd ECS Meeting

Oct 9 – 13, 2022 • Atlanta, GA, US

Abstract submission deadline: **April 8, 2022**

Connect. Engage. Champion. Empower. Accelerate.

**MOVE SCIENCE FORWARD**



Submit your abstract



# Prediction of Photovoltaic (PV) Output Using Artificial Neural Network (ANN) Based on Ambient Factors

Siti Amely Jumaat<sup>1</sup>, Flora Crocker<sup>2</sup>, Mohd Helmy Abd Wahab<sup>3</sup>, Nur Hanis Mohammad Radzi<sup>4</sup>, Muhammad Fakri Othman<sup>5</sup>

<sup>1,2,4</sup>Green and Sustainable Energy (GSEnergy), Faculty of Electrical & Electronic Engineering, Universiti Tun Hussein Onn Malaysia (UTHM), 86400, Batu Pahat, Johor, MALAYSIA

<sup>3</sup>Computational, Signal, Imaging and Intelligence (CSII), Faculty of Electrical & Electronic Engineering, Universiti Tun Hussein Onn Malaysia (UTHM), 86400, Batu Pahat, Johor, MALAYSIA

<sup>5</sup>Department of Multimedia, Faculty of Computer Science and Information, Technology, Universiti Tun Hussein Onn Malaysia (UTHM), 86400, Batu Pahat, Johor, MALAYSIA

E-mail: sitiately1979@gmail.com<sup>1</sup>, flora.wa90@gmail.com<sup>2</sup>, helmy@uthm.edu.my<sup>3</sup>, nurhanis@uthm.edu.my<sup>4</sup>, fakri@uthm.edu.my<sup>5</sup>

**Abstract.** This paper is proposed an artificial neural network (ANN) to apply in the system of prediction of power output from photovoltaic (PV) panel system. In order to test the efficiency and reliability of a proposed ANN model experimental output will be comparing with mathematical equation. The objectives of this project are to develop the ANN model that capable of predicting power output. The activation functions using for the hidden layer is hyperbolic tangent. The training algorithm is used Levenberg-Marquardt backpropagation. The meteorology data as input data was obtained from RET screen database in the period from 1<sup>st</sup> January 2015 until 31<sup>st</sup> August 2016. There were two locations in Malaysia to be the subject test; Melaka and Kuala Lumpur. From the result, for Melaka, Malaysia the outputs  $V_m$  (MAPE = 0.0003% and RMSE = 8.5%) and  $I_m$  (MAPE = 4.3% and RMSE = 26.8%). Then, for Kuala Lumpur, Malaysia have a less error and good correlation with  $V_m$  (RMSE = 0.2%) and  $I_m$  (MAPE = 0.008% and RMSE = 0.3%). Hence, average power output was high level in January to March for both locations. The conclusion shows that the performance of power output is depending on the level of solar radiation on the day.

## 1. Introduction

The three main important issues that is facing by worldwide power generation are increasing oil prices, the depleting of fossil fuel day to day and increasing the worst issues of environmental [1]. The environmental issues in reducing greenhouse gases (GHG), the utilization of renewable energy sources (RES) is now growing rapidly and widely accepted an alternative power supply [2], [3]. The PV systems provide the direct method to convert solar energy into an electric energy. Therefore, modelling and simulation are important role in the development and investigate the performances of PV modules as well to design of PV system. The PV module performances are relied to provide output

<sup>1</sup> sitiately1979@gmail.com

prediction for proposed and existing PV system under the diverse of ambient environmental condition [4]. With the forecasting and prediction method it will easy to control the operation of harvesting sun energy and energy management and planning [5-6]. Nowadays, ANN technique is popular as use to forecasting due to could reduce the cost, achieving higher processing speed and simpler implementations [7].

There are various methods to implement ANN as the solar radiation as a forecaster. Birinchi Bora *et al* in [8] present Artificial Neural Network method based modeling of PV module to predict the output. İlhan Ceylan *et al* in [9] discussed an artificial neural network that used for prediction of photovoltaic module temperature. There are ambient factor involves to evaluate the PV performance. S.S. Priya in [10] studying the feasibility of an Artificial Neural Network (ANN) based method to estimate and predict global solar radiation (GSR). James Mubiru *et. al* in [11] using ANN could be used to predict monthly typical daily direct solar radiation. In paper [12] presented using the Artificial Neural Network (ANN) model to predict the output. The ANN models create using a neural network fitting toolbox (nftool) and the Levenberg-Marquard (LM) algorithm is used in this analysis. A. Saberian *et al* [13] discussed on modeling and prediction of the photovoltaic power output using artificial neural networks. There two neural network structures use for this model are general regression neural network (GRNN) and feedforward back propagation (FFBP). Valerio Lo Brano *et al* in [14] discussed about predicting the power output of a PV panel by using the ANN model. M. Benghamen *et al* [15] discussed about the ANN model that use for estimating and modeling of the daily global solar radiation. They are used four inputs built six different ANN model using different combination inputs. They are chosen feed-forward neural network (FFNN) with back propagation training algorithms. M.A.Behrang *et al* [16] presented a prediction daily global solar radiation (GSR) on horizontal based on meteorological data using ANN method. They are implemented multi-layer perceptron (MLP) and radial bias function (RBF). In [17] S.A.Jumaat *et. al* proposed ANN to be applied in the system of prediction as fast method used for forecasting output of solar radiation for PV module. The purpose of this study is to predict the solar radiation that receives by PV module. The multilayer perceptron (MLP) with back propagation is used as a network topology.

In this research a create an ANN for forecaster data of PV module for location in Malaysia. The multilayer perceptron (MLP) is selected as network topology for forecast model. Then, the Levenberg-Marquard (LM) algorithm is used in this analysis. This forecast model are divide into two model; Model I to predict amount of solar radiation, Model II to predict current and voltage generated by a PV panel system. In order to test the efficiency and reliability of a proposed ANN Model, the experimental output will compare with mathematical equation.

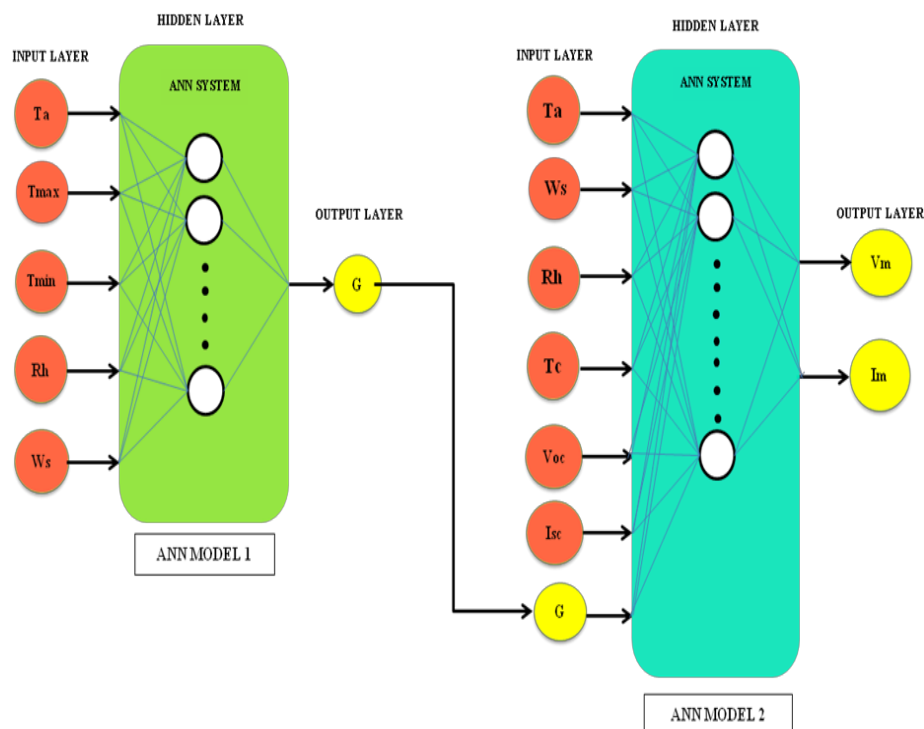
## 2. Artificial Neural Network (ANN)

Simon Haykin in [18] a neural network is a massively parallel distributed processor which is the unit with a simple process, has ability to sorting experiential knowledge and making it available to use. It is two aspect neural network look like a human brain: (i) the knowledge or input is learned by the network through a learning process. (ii) the inter-neuron connection strengths is used as storage the knowledge, which known as synaptic weights. Artificial Neural Network (ANN) is a field of study for human brain system, which is expected to be applied in real life situation. ANN is able to act like a human brain, which to solve the problem by learning method compared to conventional computing which is pre-programmed. ANN has a processing unit to process information and responds to the input given before giving the output desired. Hence, it can be recognized that ANN is used as a method for replacement human brain as a computing device which is far more powerful than conventional logic algebra computation [11] and basic method to optimization technique and minimizes error [19] and [20].

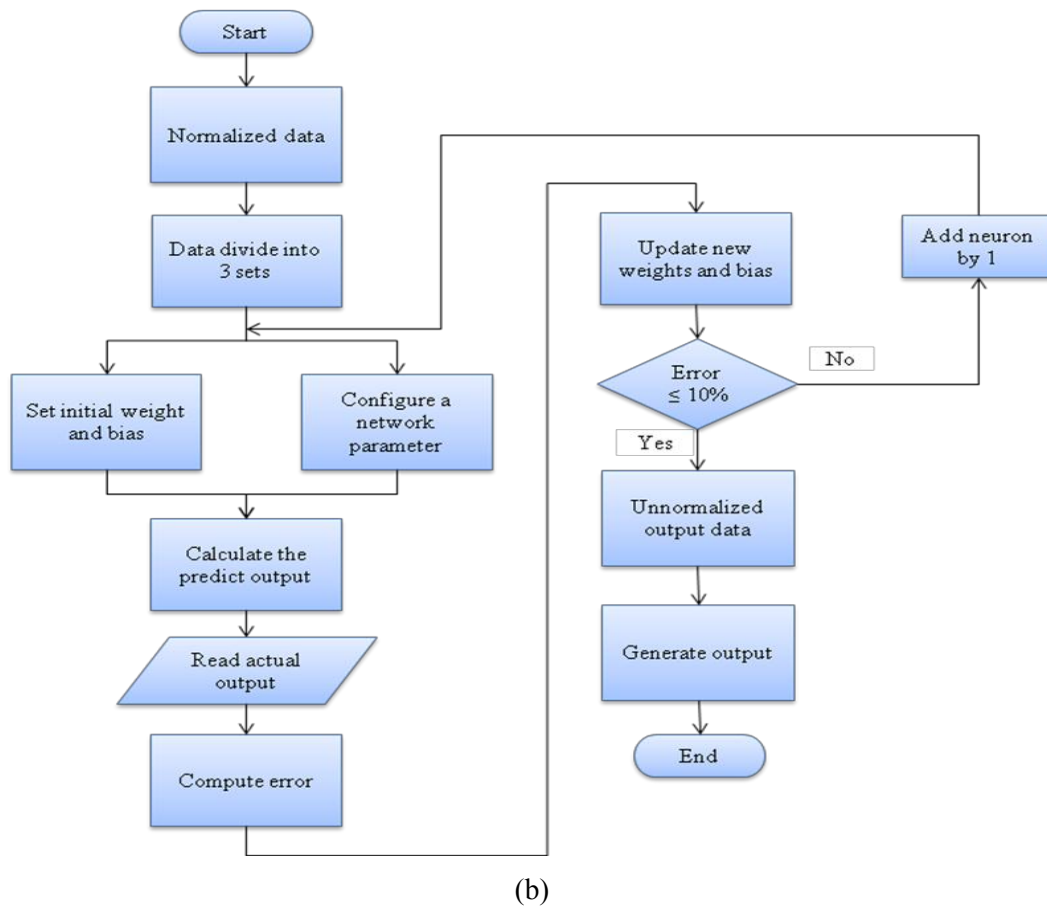
### 2.1 Multilayer Perceptron (MLP)

MLPs are the most common type of feed-forward networks use for prediction data. The MLP which consist of three types of the layers: an input layer, a hidden layer and an output layer. As known that,

bias weight is represented the extra weight for each unit which fixed to 1 and it can be changing by adjusted same value with weight in the network. The important to get the best training performance for MLP is by choosing architecture for giving input parameter. Most an architectural example used is MLP with two-layer perceptron, which with sigmoid transfer function (non-linear). These models can approximate arbitrary accuracy the problem solving with choosing one hidden layer units. Model selection is depending on complexity of the problem that MLP model needed to be solved. However, if there are too many hidden unit will cause the model overfitting and effect the interpolation of test set become poor quality. Then, at least ten network different with different hidden layer should be trained. The initial of the weight is in small random of value near zero and can be both positive and negative. Instead that, the learning rate is considerable to the generalization performance of the network, then reasonable value is in the range 0.05 to 1.0 as default. Before training process, the data should to be partitioned into three types; train, test and validate set. Input data usually need to normalized according to the desired range (0 to 1) or (-1 to 1). The pattern from training set will present the network pattern and one epoch of training is set. It can be hundred epochs occur during the learning process. Nevertheless, this learning process has a stop criterion when validation stop decreases. The validation set is used to decide stopping training. Hence stop criterion should reach the minimum point of error on validation set in order to get good performance [21], [22]. In this paper, there are two ANN Models are created in order to predict solar radiation as for ANN Model I and current and voltage for ANN Model II as shown in Figure 1(a). Figure 1(b) is illustrated developing of ANN model using MLP network topology with Levenberg-Marquardt (LM) algorithm neural network.



(a)



**Figure 1** (a): ANN architecture network (b): The flow chart for developing MLP network

## 2.2 Input Data Vector For System

To occupy and train an ANN Model, there is the large database of specific data which represents the analyzed parameter of system is required. The proposed Equations (4) and (5) are used in calculating the value of voltage and current as actual output for proposed the ANN Model 2. However, for the power value is the product of voltage and current, so power as in Equation (6) use common Ohm Laws [23]. Hence, the cell temperature is used to obtain the current and voltage in consider of using PV panel parameter. Based on ambient temperature, relative humidity, wind speed, and global irradiance the use to calculate cell temperature is consider. The intended equation to predict the module temperature formula of  $T_c$  (°C) adopted from [24] and expressed in Equation (1). The physical data used for the training of the ANN Model were evaluated by using following equations [14], [23], [25 - 26];

- |   |  |
|---|--|
| i. Air temperature, $T_a$ (°C)          | vi. Solar radiation, $G$ (W/m <sup>2</sup> ) |
| ii. Relative humidity, $R_h$            | vii. Cell temperature, $T_c$ (°C)            |
| iii. Wind speed, $W_s$ (m/s)            | viii. Open circuit voltage, $V_{oc}$ (V)     |
| iv. Maximum temperature, $T_{max}$ (°C) | ix. Short circuit current, $I_{sc}$ (A)      |
| v. Minimum temperature, $T_{min}$ (°C)  |  |

These three last parameter are important in order to improve the evaluation of the current and voltage that generated by PV panel. Their values were evaluated by expressions as follow;

$$T_c(°C) = 0.954T_a + 0.03G - 1.629W_s + 0.088R_h + 3.9 \quad (1)$$

$$I_{sc} = I_{sc.ref}(G/G_{ref}) + \mu I_{sc}(T_c - T_{ref}) \quad (2)$$

$$V_{oc} = V_{oc.ref} + \mu V_{oc} (T_c - T_{ref}) \quad (3)$$

In this paper, the electrical parameters for experiment data were obtained from a 175W PV panel [14] system, which utilized in developing the ANN Model. The system specification was shown in Table 1 as follow.

Table 1: Data Sheet of Kyocera KC175GH-2 polycrystalline panel

Maximum Power, $P_{max}$ [W]	175
Maximum Voltage, $V_{mpp}$ [V]	23.6
Maximum Current, $I_{mpp}$ [A]	7.42
Open circuit voltage, $V_{oc}$ [V]	29.2
Short circuit current, $I_{sc}$ [A]	8.09
$V_{oc}$ thermal coefficient, $\mu_{Voc}$ [V/ $^{\circ}$ C]	-0.109
$I_{sc}$ thermal coefficient, $\mu_{Isc}$ [mA/ $^{\circ}$ C]	3.18

### 3. Experimental Setup

There are five basics steps used to designing ANN model such as; (1) Data collection, (2) Pre-processing data, (3) Creating network, (4) Training network and (5) Test performance of the model. These basic steps are to ensure the designing model follow a systematic procedure and will easy to troubleshoot the system.

#### 3.1 Data collection

The RET screen database was used as data collection to obtain the climate data for subject test location such as Melaka and Kuala Lumpur. All data were collected started from 1<sup>st</sup> January 2015 until 31<sup>st</sup> August 2016 and accumulate for the further calculations and comparisons. In fact, Malaysia was experiencing two distinct monsoons there were from October to March was a rainy season (northeast monsoon) and June to September was a dry season (southwest monsoon). Data collection was a first step to collect and prepare the input data for ANN Model. Hence, present study investigates the data of these 20 months start from 1<sup>st</sup> January 2015 until 31<sup>st</sup> August 2016. There will be 609 samples of data for each input and output parameter. All input data was meteorology data which obtain from RET screen database. The output data were current and voltage that generated from PV panel system which calculated with Equations (4) and (5) as shown. This parameter will be calculating using equation which adopted from [14], [23], [25], [26] as follow;

$$V_m = V_{oc} [1 - (b/U_{oc}) \ln a - R_s (1 - a - b)] \quad (4)$$

$$I_m = I_{sc} (1 - a - b) \quad (5)$$

Where

$$a = U_{oc} + 1 - 2 \cdot U_{oc} \cdot R_s, b = a / (1 + a), U_{oc} = V_{oc} / V_t \text{ and } V_t (V) = 0.025 [(T_c (^{\circ}C) + 273) / 300]$$

$$P = V_m \times I_m \quad (6)$$

#### 3.2 Pre-processing data

Pre-processing data also known as normalization, this step was important before train the ANN Model in order to obtain the network more efficient. This data normalization was essential as there were varies of variables for a different unit. The normalization step was applied to both the input and the output in the data set. In this way, the network output always falls into a normalized range. The network output can then be reverse transformed back into the units of the original output data when the network was put to use in the field. The min-max technique was used in the present study to normalize the input data as in Equation (7). The range of data normalization was within the range -1 to 1 [13].

$$y = (y_{max} - y_{min}) * (x - x_{min}) / (x_{max} - x_{min}) + y_{min} \quad (7)$$

##### 3.2.1 Creating network



Creating a network was the stage that includes setting network parameter such the number of the neuron for hidden layer, transfer function, training function, weight and bias learning function, and performance function. During the training process, the parameter like the number of training epochs, learning rate, and the number of hidden layer could be changed depend on the error performance of ANN output. This study, multilayer perceptron (MLP) network was used as it has high accuracy to predict and forecast output compared to other networks as discuss in Section 2. The several numbers of the neuron for hidden layer, the number of epochs and learning rate were approaches in order to create the finest network. The number of neurons was set at range 1 to 10, the learning rate will be set in a range from 0.001 to 1.0 and the number of epoch set from 10 to 1000 [22]. Since the MSE value is very small and correlation coefficient, R is approaching to 1, then it could be considering as the selected network. The lower MSE value was showing a good training of the network [25].

### 3.2.2 Training network

The next step was to train the input data using Levenberg-Marquardt (LM) back propagation. The weight and bias value were set into initial value before training process. Then, out of 609 samples of data will divided into 70% used for training only 427 sample data taken. The rest for testing and validation both were 15% of left data samples. During training process, the algorithm was selects the data randomly from the data set, so every time of train process will got varies of MSE value [27] that depend on 70% of input data was chosen.

### 3.2.3 Test performance of the model

Then, the next step was testing the performance of the developed ANN Model. In order to evaluate the ANN model proposed in this study, three error statistics used which were; the mean squared error (MSE), the mean absolute percentage error (MAPE), and root mean squared error (RMSE). The MSE represents the error between the actual and prediction output. Then, the MAPE was as accuracy indicator for the neural network. RMSE was used indicate the efficiency of the develop ANN Model in prediction. A large positive RMSE indicates that there was a big deviation in the predicted data from the measured data and the lower RMSE show the accurate of the prediction output. It also represents the measurement of the variation of the predicted data around the measured data [27]. All the errors formula expressed in a percentage as defined as follow:

$$MSE = [0.5(Actual - Predict)^2] \times 100\% \quad (8)$$

$$MAPE = \left[ \frac{1}{N} \sum \frac{Actual - Predict}{Actual} \right] \times 100\% \quad (9)$$

$$RMSE = \left[ \sqrt{\frac{1}{N} \sum (Predict - Actual)^2} \right] \times 100\% \quad (10)$$

## 4. Result and Discussion

The trial of investigate the number of neuron, training epochs and learning rate were evaluated to find the MSE of the MLP network. Tables 2, 3 and 4 were represents the percentage of MSE for training and testing and the R value for different number of neuron, training epochs and learning rate. After considering the value of MSE testing at neuron 7 among the other neuron was the lowest compared with MSE training, while the best fit for testing was the finest among MSE training was approaching 1 means a positive linear relationship [25]. It can decide that most suitable number of the neuron was at neuron 7. Additional, insufficient number of the neuron will cause the network overfitting or over training. Aspect to be considered are the MSE value for training data must be smaller than MSE value of testing data and the best fit of training data must be greater than the best fit of testing data [22], [25]. From result experiment, the suitable number of training epochs was 600 and the suitable learning rate was 0.05. If learning rate was set to highest, the algorithm can oscillate and become unstable. If learning rate was lowest, the algorithm takes too long to converge. Then, the MLP network topology for the ANN Model 1 was 5-7-1 and the ANN Model 2 was 7-7-2.

Table 2: MSE for different number of hidden node

<b>No. of hidden node</b>	<b>MSE training</b>	<b>MSE testing</b>	<b>R value</b>
1	0.13	0.22	0.99800
2	0.00252	0.00163	0.99995
3	0.00069	0.00102	0.99999
4	0.00033	0.00078	0.99999
5	0.00086	0.00556	0.99997
6	0.00038	0.00202	0.99999
7	0.00031	0.00023	1.00000
8	0.00051	0.00089	0.99999
9	0.00009	0.00059	0.99999
10	0.00041	0.00036	0.99999

Table 3: MSE for different number of epoch

<b>Epochs</b>	<b>MSE training</b>	<b>MSE testing</b>	<b>R value</b>
100	0.0005	0.0010	0.99999
200	0.00046	0.00103	0.99999
300	0.00009	0.00260	0.99999
400	0.00003	0.00158	1.00000
500	0.00002	0.00001	1.00000
600	0.00001	0.00006	1.00000
700	0.00004	0.00009	1.00000
800	0.00010	0.00362	0.99999
900	0.00005	0.00055	1.00000
1000	0.00031	0.00029	1.00000

Table 4: MSE for different learning rate

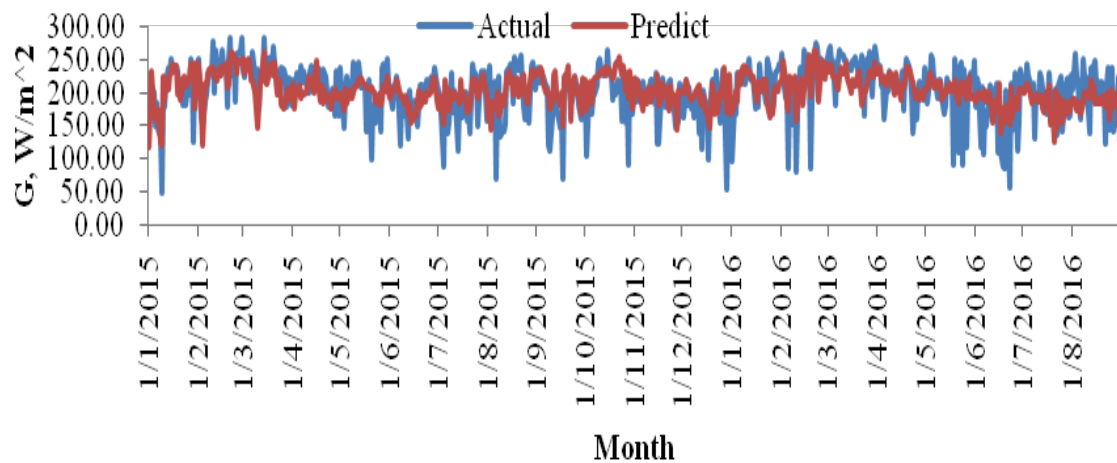
<b>Learning rate</b>	<b>MSE training</b>	<b>MSE testing</b>	<b>R value</b>
0.001	0.00001	0.00015	1.00000
0.05	0.000004	0.00003	1.00000
0.2	0.00150	0.00597	0.99995
0.4	0.00073	0.00112	0.99999
0.6	0.00009	0.00248	0.99999
0.8	0.00002	0.00134	1.00000
1.0	0.00012	0.00062	0.99999

The two locations in Malaysia were selected in order to test and check the efficiency of the developed ANN Model. The chosen locations are Melaka and Kuala Lumpur. The first develop ANN Model was predict the solar radiation,  $G$  ( $\text{W}/\text{m}^2$ ). Moreover, second ANN Model was predicting voltage and current at maximum point in order to forecasting the power generate by PV panel system in different climate condition.

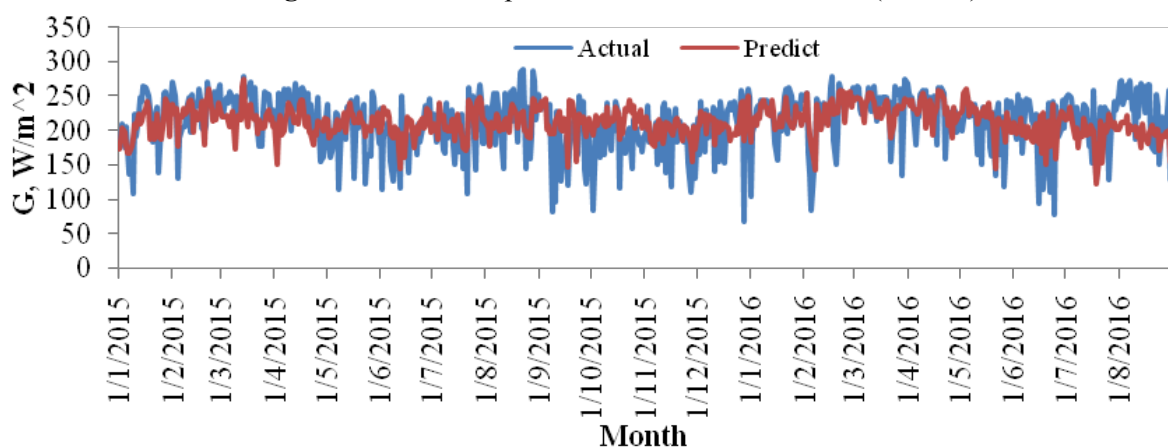
#### 4.1 ANN Model I: Solar Radiation



The model was performed well in this study but it cannot forecast the solar radiation values same as actual very well. For this case, it was obtained low coefficient correlation R in the experiment. The correlation coefficient, R for Melaka was 58%, and Kuala Lumpur was 51%, respectively. Figures 2 and 3 were shows the actual against predict values for selected location. After considering the ambient factor, experiment result for solar radiation that underestimates and overestimates for all location could be affected by these factors; rainy, dry and heavy rainfall. Hence, the findings suggest that the count of an ambient factor as input variable does insufficient to provide improvement for the forecasting model [28]. Therefore is recommended to consider the other variables like latitude, longitude, altitude and sunshine duration, sunshine ratio, mean daily solar irradiance, mean daily air temperature, day and month, sunshine accuracy and mean average temperature, atmospheric data and insolation data [5]. However, the findings obtained here show that the ambient factor does not provide significant precision to forecasting results as support by K.A.Baharin *et al* [28] find that ambient temperature not enough to predict solar radiation. From the experimental result can conclude that the high of solar radiation was recorded in January until March for Melaka ( $117.87\text{--}263.14\text{W/m}^2$ ) and Kuala Lumpur ( $123\text{--}274.73\text{W/m}^2$ ). The harvesting electrical energy is a suitable period during January until March for Melaka, and Kuala Lumpur.



**Figure 2:** Actual vs. predict value of solar radiation (Melaka)

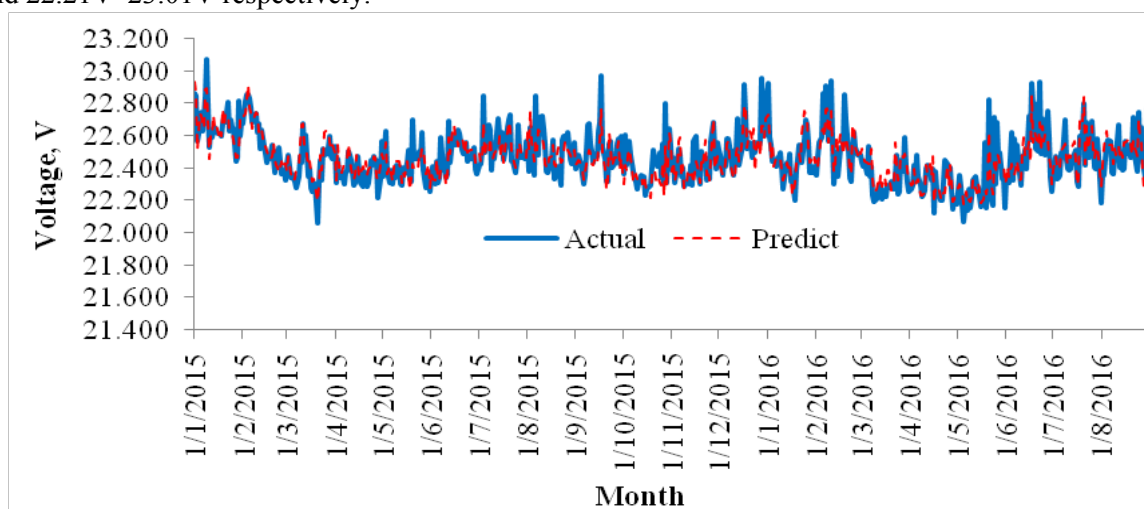


**Figure 3:** Actual vs. predict value of solar radiation (Kuala Lumpur)

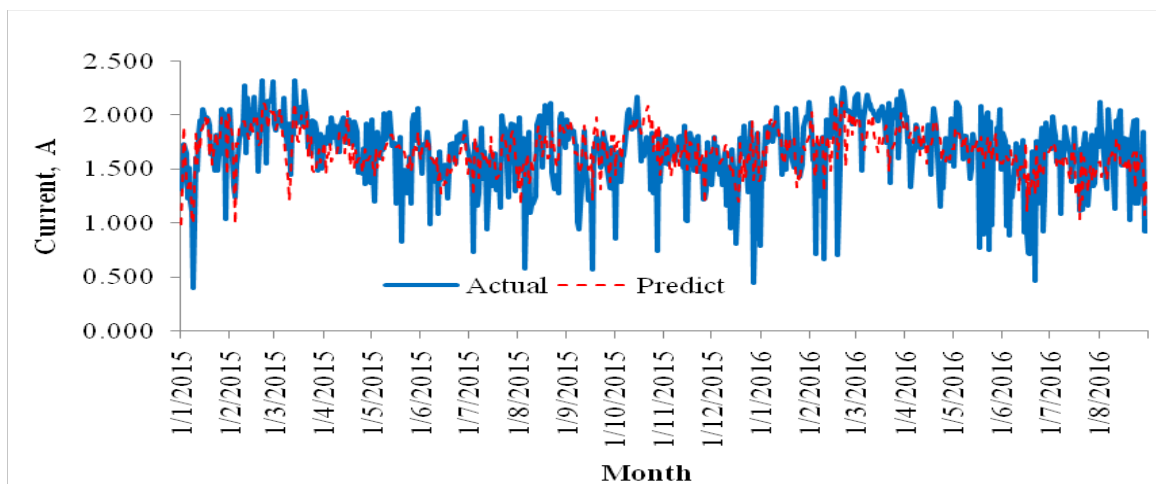
#### 4.2ANN Model II: Voltage and Current

The average actual and estimated voltage values for Melaka were  $22.06\text{V} - 22.08\text{V}$  and  $22.18\text{V} - 22.94\text{V}$ . Figure 4 show the voltage pattern for estimated was similar with actual value. However, there was some error different between estimated and actual value. The voltage value was decreasing trend

on March and May both years due to probably current value fluctuated. Others fact could be a location itself probably have a presence the disturbance such as cloud cluster that could cause the variation in weather that affects the solar radiation. The voltage values produce high on January to February in all probability this location no experience the rainy season. Moreover, the average actual and estimated current values for Melaka were  $0.4\text{A} - 2.23\text{A}$  and  $0.98\text{A} - 2.12\text{A}$ . Figure 5 show the current pattern for estimated was similar with actual value. However, there was big gap different between estimated and actual value. The current value was decreasing trend in January was rainy season and June to August due to the fact there was dry season condition. Hence, the location probably has a presence the disturbance such as cloud cluster that could cause the variation in weather. The current values produce high on February-March in all probability this location no experience the rainy season. In addition, Kuala Lumpur was experiencing the average value of actual and estimated voltage at  $22.19\text{V} - 23.04\text{V}$  and  $22.21\text{V} - 23.01\text{V}$  respectively.



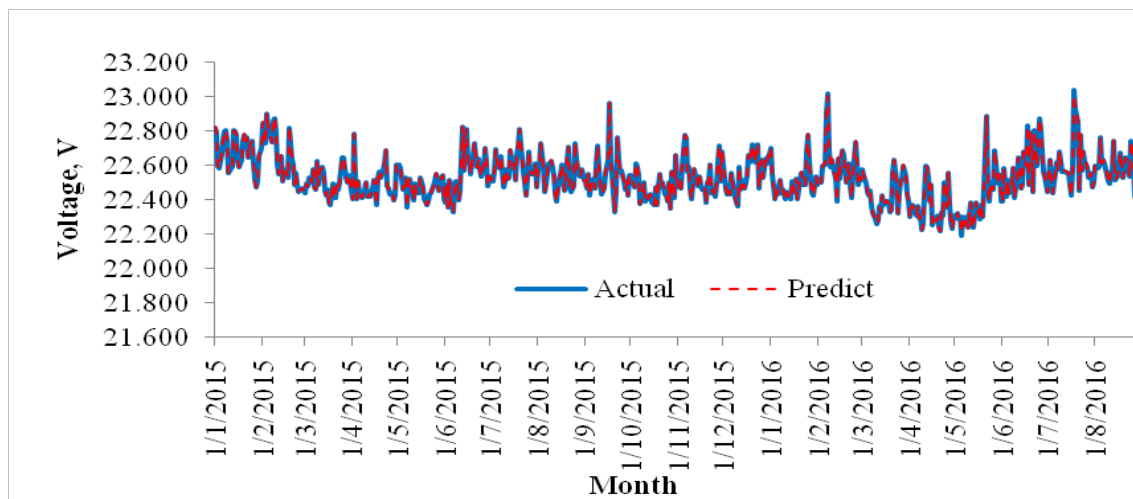
**Figure 4:** Result for actual and predict data voltage for Melaka



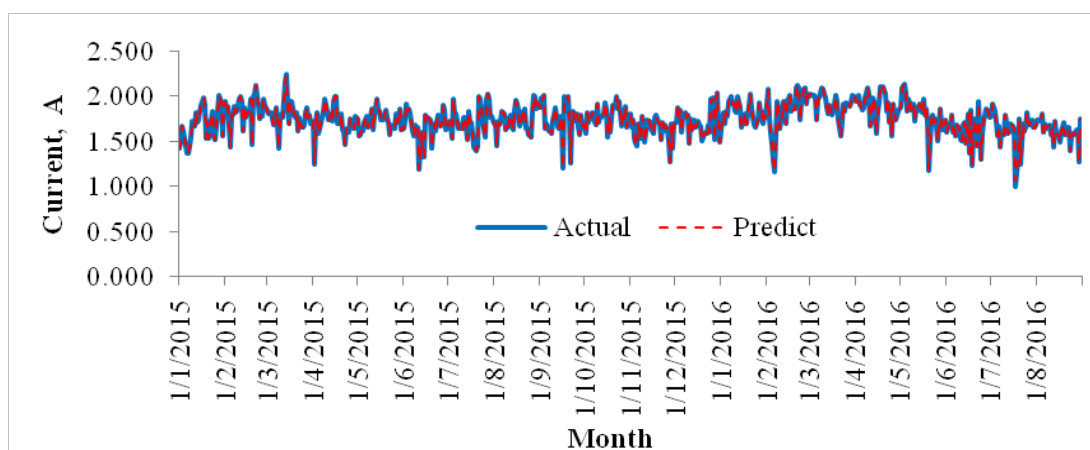
**Figure 5:** Result for actual and predict data current for Melaka

Figure 6 show the actual and estimated voltage was a similar trend with less error different for both values. The voltage was descending trend on March to May at the rainy season and heavy rainfall. The voltage was an upward trend on February and July and same pattern for both years at this location. However, Kuala Lumpur was experiencing the average value of actual and estimated currently at  $1\text{A} - 2.25\text{A}$  and  $1.07\text{A} - 2.22\text{A}$  respectively. Figure 7 show the actual and estimated current was a similar trend with less error different for both values. The current was a downward trend on February at rainy season, May and July of 2016 at dry season. This could be affected by the solar radiation which it

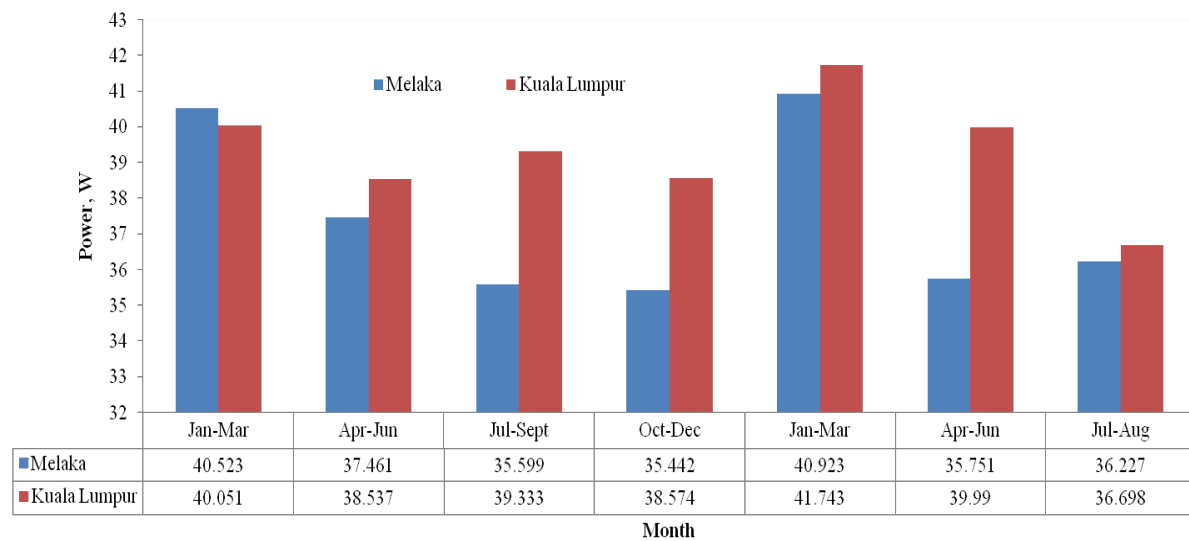
directly depends on value on parameters such as like wind speed, relative humidity, and temperature. This was agreement by A. Babatunde *et al* [30] the parameters which were solar radiation, temperature, humidity and wind speed shows related with each other, especially for solar radiation and temperature. Figure 8 show the power output that generated by PV panel system. Overall from result experiment, the power output produces for polycrystalline PV panel almost certainly up to 25%. This could be a fact due to characteristics of the polycrystalline panel itself which the module efficiency is about 10%-11%. Besides, the meteorology data also could influence the power output for PV panel likes ambient temperature, solar radiation, humidity, or wind speed. However, the most important parameter affect the power output was solar radiation. This could the lower solar radiation value which below  $400 \text{ W/m}^2$ , the power output of PV produces also at low values. This was agreement by A. Ghazali *et al* [30] that polycrystalline show higher power output efficiency at the high level of average solar radiation. This shows that the performance of polycrystalline is depending on the level solar radiation. Hence, from the experimental result, the high potential of producing electrical energy using PV panel for selected locations are in January until March.



**Figure 6:** Result for actual and predict data voltage for Kuala Lumpur

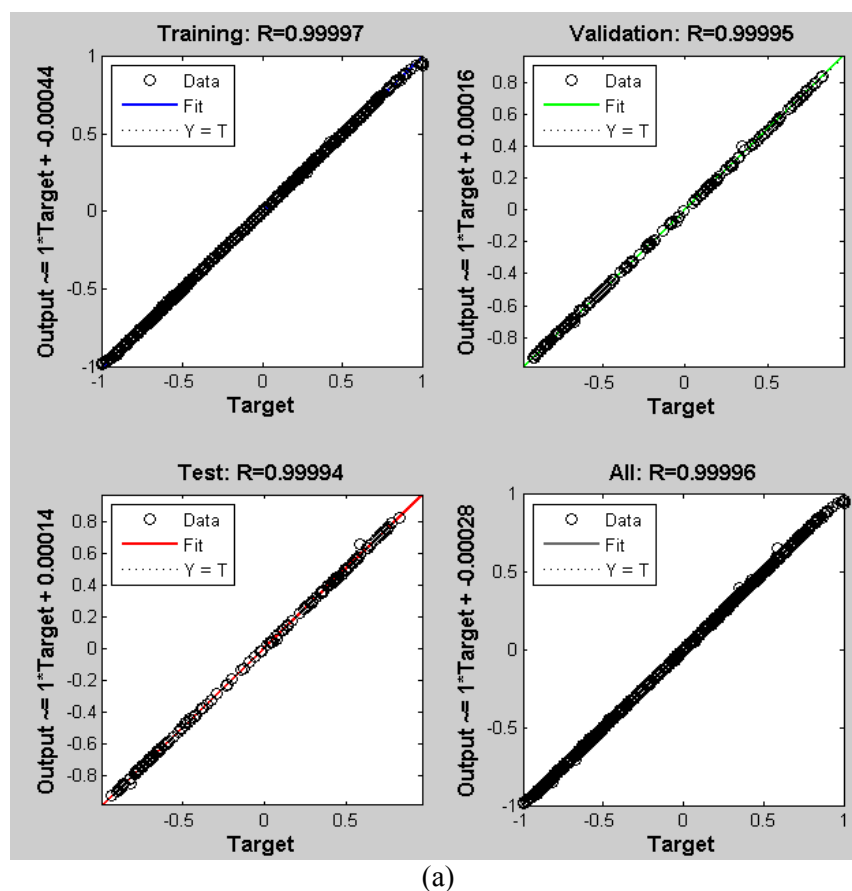


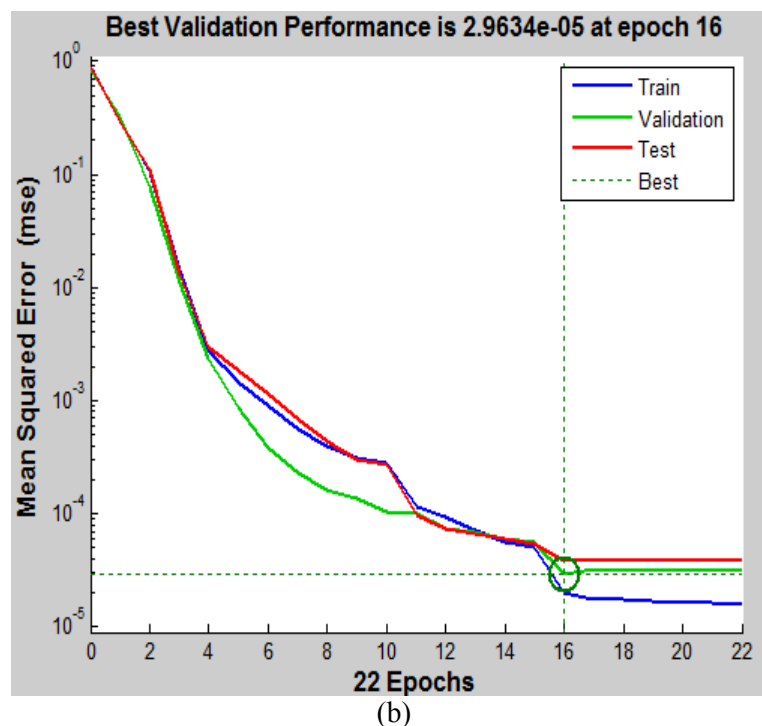
**Figure 7:** Result for actual and predict data current for Kuala Lumpur



**Figure 8:** Average value of power in Watt for predict data in Melaka and Kuala Lumpur regions

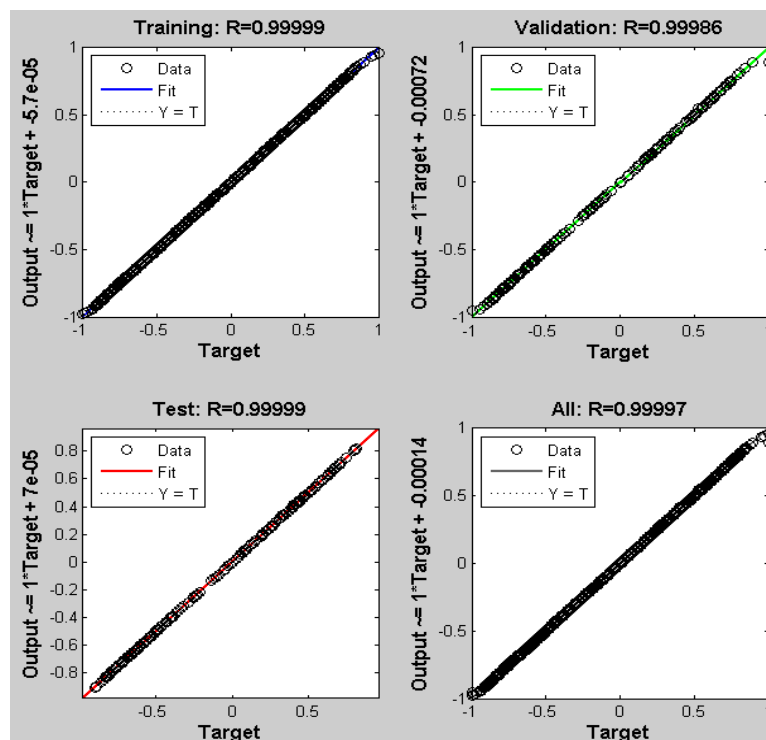
Figures 9 (a) and (b) shows the best curve fit and the MSE performance in order to predict voltage and current for Melaka of ANN Model 2. MSE training of this model was lower than MSE testing and MSE validation. It means the data of model have been learning very well during training.

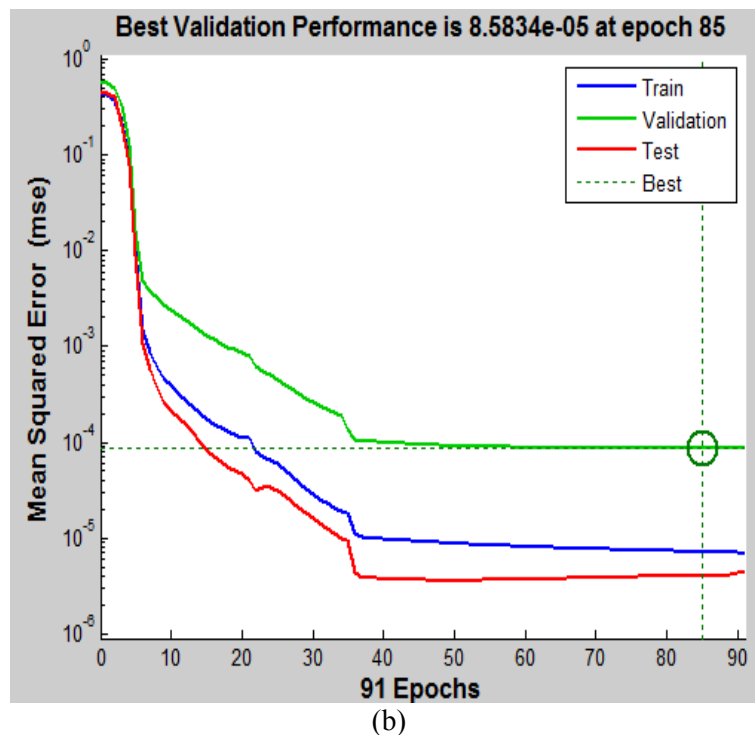




**Figure 9:** (a) The best curve fit and (b) MSE performance of ANN Model for Melaka

Figures 10 (a) and (b) shows the best curve fit and the MSE performance in order to predict voltage and current for Kuala Lumpur of ANN Model 2. The best performance for MSE testing of this model was lower than MSE training and MSE validation. The input data of network was learning well during training and testing.





**Figure 10:** (a) The best curve fit and (b) MSE performance of ANN Model for Kuala Lumpur

Then, Table 5 has listed the MSE value in percentage and total response of system for each locations. As can be concluded from this table, for location of Kuala Lumpur has 0.0007% train and 0.0004% error. It has good correlation between actual and prediction output. As the MAPE is represent as an accuracy indicator for the neural network. RMSE is represented the efficiency of the proposed model in prediction. Hence, from experiment result in Table 5, the current accuracy recorded for two locations were Melaka = 95.7% and Kuala Lumpur = 99.9%. Then, the voltage accuracy recorded for both locations were 99.9% with a small number of the error. Thus, the efficiency of ANN Model 2 were to predict  $V_m$  and  $I_m$  for both location were considered as lower for Melaka because of RMSE was higher than Kuala Lumpur.

Table 5: MSE, R-value, MAPE and RMSE for selected location

Location	MSE Train (%)	MSE Test (%)	R	$R^2$	MAPE (%)		RMSE (%)	
					$V_m$	$I_m$	$V_m$	$I_m$
Melaka	0.002	0.004	0.99996	0.99992	0.0003	4.3	8.5	26.8
Kuala Lumpur	0.0007	0.0004	0.99997	0.99994	0	0.008	0.2	0.3

## 5. Conclusion

This paper represents the two design of ANN Model were used for predicting the solar radiation, voltage,  $V_m$  and current  $I_m$  that presented in MLP neural network topology. However, the output of ANN Model 1 was training well but not has good correlation between output and target. Besides, the value of regression is not fit to MLP's theory which it should get regression most near to 1. There still have many errors between training set and the target. The model develops as to predict the performance of PV module based on changing ambient factors affect the solar radiation. Then, the



output of ANN Model 2 represents the relationship between amounts of ambient factor that affect PV panel output in term of  $V_m$  and  $I_m$  at the both location. The performances of evaluating ANN Model 2 were using MSE, MAPE and RMSE value which presented the accuracy and efficiency of the system itself. Moreover, this model of the network is successfully developed and predicts the  $V_m$  and  $I_m$  output. By using this neural network method are easy and fast to predict the output of the system and to solve the problem. The significant of this study it could help out the electrical production for PV panel system owner to control, estimate and planning the electrical bill.

## Acknowledgement

This research was supported by Office of Research, Innovation and Commercialization Center (ORICC), UTHM.

## 6. References

- [1] M. Bouzguenda, T. Salmi, a. Gastli, and a. Masmoudi, "Evaluating solar photovoltaic system performance using MATLAB," *2012 First Int. Conf. Renew. Energies Veh. Technol.*, pp. 55–59, 2012.
- [2] J. Eynard, S. Grieu, and M. Polit, "Wavelet-based multi-resolution analysis and artificial neural networks for forecasting temperature and thermal power consumption," *Eng. Appl. Artif. Intell.*, vol. 24, no. 3, pp. 501–516, 2011.
- [3] Ayu Wazira Azhari, Kamaruzzaman Sopian, Azami Zaharim, "A New Approach For Predicting Solar Radiation In Tropical Environment Using Satellite Images – Case Study Of Malaysia," *Environ. Dev.*, vol. 4, no. 4, pp. 373–378, 2008.
- [4] F. B. S. Mekhtoub, "PV Cell Temperature / PV Power Output Relationships Homer Methodology Calculation," *IpcO*, vol. 2, no. 1, pp. 1–12, 2014.
- [5] H. G. Chua, B. C. Kok, and H. H. Goh, "Solar Insolation Forecast Using Artificial Neural Network For Malaysian Weather," no. April, pp. 4–9, 2012.
- [6] N. Mahamad, M. Kamal, and B. M. Amin, "Power Prediction Analysis using Artificial Neural Network in MS Excel," *Isbn*, pp. 54–58.
- [7] F. M. Dias, A. Antunes, and A. M. Mota, "Artificial neural networks: A review of commercial hardware," *Eng. Appl. Artif. Intell.*, vol. 17, no. 8, pp. 945–952, 2004.
- [8] B. Bora, O. S. Sastry, and R. Dahiya, "Artificial neural network based modeling of PV module to predict the output," no. December, 2013.
- [9] I. Ceylan, O. ErKaymaz, E. Gedik, and A. E. Gurel, "The prediction of photovoltaic module temperature with artificial neural networks," *Case Stud. Therm. Eng.*, vol. 3, pp. 11–20, 2014.
- [10] S. S. Priya and Mohammad Hashif Iqbal, "Solar radiation prediction using Artificial Neural Network," *Int. J. Comput. Appl.*, vol. 116, no. 16, pp. 28–31, 2015.
- [11] J. Mubiru, "Using Artificial Neural Networks to Predict Direct Solar Irradiation," *Adv. Artif. Neural Syst.*, vol. 2011, pp. 1–6, 2011.
- [12] A. K. Yadav and S. . Chandel, "Artificial Neural Network based Prediction of Solar Radiation for Indian Stations," *Int. J. Comput. Appl.*, vol. 50, no. 9, pp. 1–4, 2012.
- [13] A. M. Saberian, H. Hizam, M.A.M Radzi, M.Z.A Ab Kadir, and Mirzaei "Modelling and Prediction of Photovoltaic Power Output Using Artificial Neural Networks," *Int. J. Photoenergy*, vol. 2014, 2014.
- [14] V. Lo Brano, G. Ciulla, and M. Di Falco, "Artificial Neural Networks to Predict the Power Output of a PV Panel," *Int. J. Photoenergy*, vol. 2014, p. 12, 2014.
- [15] M. Benganem, A. Mellit, and S. N. Alamri, "ANN-based modelling and estimation of daily global solar radiation data: A case study," *Energy Convers. Manag.*, vol. 50, no. 7, pp. 1644–1655, 2009.
- [16] M. A. Behrang, E. Assareh, A. Ghanbarzadeh, and A. R. Noghrehabadi, "The potential of different artificial neural network (ANN) techniques in daily global solar radiation modeling

- based on meteorological data,” *Sol. Energy*, 2010.
- [17] Siti Amely Binti Jumaat, Flora Crocker, Mohd Helmy Bin Abd Wahab, Nur Hanis Binti Mohammad Radzi, Investigate the Photovoltaic (PV) Module Performance by Using Artificial Neural Network (ANN), 2016 IEEE Conference on Open Systems (ICOS), 10-12 Oct 2016 pp. 59-64
  - [18] S. Haykin, *Neural Network: A Comprehensive Foundation*, Second. India: Person Prentice Hall, 2005.
  - [19] B. Vasumathi and S. Moorthi, “Implementation of hybrid ANNPSO algorithm on FPGA for harmonic estimation,” *Eng. Appl. Artif. Intell.*, vol. 25, no. 3, pp. 476–483, 2012.
  - [20] R. Pino, J. Parreno, A. Gomez, and P. Priore, “Forecasting next-day price of electricity in the Spanish energy market using artificial neural networks,” *Eng. Appl. Artif. Intell.*, vol. 21, no. 1, pp. 53–62, 2008.
  - [21] L. Tarassenko, *A Guide Neural Computing Application*. New York, 1998.
  - [22] S. Sumathi, S. N. Sivanandam, and S. N. Deepa, *Neural Network Using Matlab 6.0*, Second. New Dehli: Tata McGraw-Hill Education, 2006.
  - [23] W. Zhou, H. Yang, and Z. Fang, “A novel model for photovoltaic array performance prediction,” *Appl. Energy*, 2007.
  - [24] G. Tamizhmani, L. Ji, Y. Tang, L. Petacci, and C. Osterwald, “Photovoltaic Module Thermal/Wind Performance: Long -Term Monitoring and Model Development For Energy Rating,” 2003.
  - [25] S. S. B. Jamal, “An Application of Artificial Neural Network for DC servo Motor,” *Universiti Teknologi Malaysia*, 2009.
  - [26] K. A. Baharin, H. Abdul Rahman, M. Y. Hassan, and C. K. Gan, “Short-term forecasting of solar photovoltaic output power for tropical climate using ground-based measurement data,” *J. Renew. Sustain. Energy*, 2016.
  - [27] K. Abhishek, A. Kumar, R. Ranjan, and S. Kumar, “A rainfall prediction model using artificial neural network,” *2012 IEEE Control Syst. Grad. Res. Colloq.*, no. Icsgrc, pp. 82–87, 2012.
  - [28] A. M. Ameen and J. Pasupuleti, “Sensitivity Of Artificial Neural Network Based Model For Photovoltaic System Actual Performance,” pp. 241–244, 2014.
  - [29] K. A. Baharin, H. Abdul Rahman, M. Y. Hassan, and C. K. Gan, “Short-term forecasting of solar photovoltaic output power for tropical climate using ground-based measurement data,” *J. Renew. Sustain. Energy*, vol. 8, no. 5, p. 53701, 2016.
  - [30] A. Babatunde and O. Olusola, “Regional Estimation of Solar Radiation using Routinal Meteorological Variables,” *Pacific J. Sci. Technol.*, vol. 5, no. 17, pp. 147–154, 2015.
  - [31] A. Ghazali M. and A. M. Abdul Rahman, “The Performance of Three Different Solar Panels for Solar Electricity Applying Solar Tracking Device under the Malaysian Climate Condition,” *Energy Environ. Res.*, vol. 2, no. 1, pp. 235–243, 2012.