



Power Forecasting from Solar Panels Using Artificial Neural Network in UTHM Parit Raja

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Abstract: This paper presents a step-by-step procedure for the simulation of photovoltaic modules with numerical values, using MATLAB/Simulink software. The proposed model is developed based on the mathematical model of PV module, which based on PV solar cell employing one-diode equivalent circuit. The output current and power characteristics curves highly depend on some climatic factors such as radiation and temperature, are obtained by simulation of the selected module. The collected data are used in developing Artificial Neural Network (ANN) model. Multilayer Perceptron (MLP) and Radial Basis Function (RBF) are the techniques used to forecast the outputs of the PV. Various types of activation function will be applied such as Linear, Logistic Sigmoid, Hyperbolic Tangent Sigmoid and Gaussian. The simulation results show that the Logistic Sigmoid is the best technique which produce minimal root mean square error for the system.

Keywords: Photovoltaic energy, PV module, Simulink model, ANN

1. Introduction

The solar energy is extensively used because it is lavishly accessible everywhere. According to the opportunity of technology, i.e. solar photovoltaic (PV) cells precisely can convert sunlight into electrical energy [1]– [3]. The big installation expenditure of PV module is major defect with the use of solar energy, but industrial improvement has helped in lessening the costs. The PV module is a series / parallel merger of solar cells. Generally, solar cells are connected in series to get vital output voltage. The output power of cell/ module varies with time due to variation in sun irradiance and cell temperature. Several other factors are also liable for variation in output but these two (irradiance and temperature) are major elements [4]. The output characteristics of PV modules are nonlinear, since they are reliant on substantial conditions such as solar irradiation and temperature, as well as local climate conditions such as humidity and wind [5]. Therefore, accurate modelling of PV modules is important to implement a better understanding of their operation and output characteristics, since simulations can be used to figure out the behavior of PV modules under numerous operating conditions. Numerical, analytical and artificial intelligence performance are commonly used in modelling methods [5]. Analytical methods in sequence with an artificial intelligence technique are used to model a PV module.

There are many research focus on the behavior of PV modules under varying conditions that can affect the performance of the PV module using the basic functions in MATLAB/Simulink. The characteristics of PV module also evaluated using various physical parameters. The model of PV module is developed based on mathematical expression.

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250W of PV module are manufactured by Tata solar power and used as reference by Anurag Rai et al. [6] The Artificial neural network is the most used apparatus learning technique in solar irradiance, temperature and PV power output forecasting. The ANN is to forecast further output values based on the set of input data. The efficiency of the model is determined by the correlation to real measured data. Artificial neural networks are widely used in many utilizations such as wind power forecast, solar irradiance forecast, solar power output forecast and temperature forecast [7]. ANN models are easy to model, not expensive and less time consuming than other traditional method for solar irradiance and temperature prediction [8]. In this project, the multilayer perceptron (MLP) and radial basis function (RBF) method are used in the ANN application. The I-V characteristics can be obtained from the PV modelled and therefore, the maximum power can be reached using the power formulas which multiplying the voltage (V) and current (I).

2. Modelling of PV Module

2.1 Equivalent Circuit

A solar cell or photovoltaic cell consists of a p-n junction which is produced in a thin wafer or a semiconductor sheet. A solar cell's I-V performance characteristics have an exponential feature, similar to the diode in the dark. When exposed to light, an electron-hole pair is formed when photons with energy greater than the semiconductor's band gap energy are captivated. The current thus produced when these carriers are swept apart under the influence of the internal electric fields of the p-n junction is corresponding to the incident of radiation [9].

In order to make the solar cells more practical on device, most manufacturers produce solar modules; a group of solar cells linked in series and parallel with the additional unit of blocking and bypass diodes in order to boost the voltage and current handling potential. Assemblies of solar cells are used to make solar modules, which may in turn be related in photovoltaic arrays. A photovoltaic array is tranquil of series and parallel connections of solar modules [9,10].

The strategy to construct the PV module is no different from modelling a PV cell. It consists of the same PV cell model. The parameters are all the same, but only a voltage parameter is different and must divided by number of cells. Some electrical models are used to simulate and modelling the panels of PV. Fig. 1 shows the circuit diagram of PV model [11].

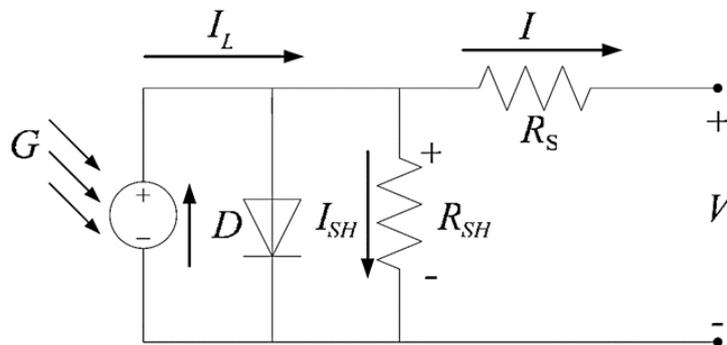


Fig. 1 - The circuit diagram of PV model [10]

2.2 Reference Model

The influence of the ambient irradiation (G) and the cell temperature (T) on the cell characteristics, can be obtained from the model equations. The PV cell photo current I_{ph} (A) is directly proportional to solar irradiance G (W/m^2). When the solar cell is short circuited, inconsequential current flows in the diode. Solar intensities are generally normalized with respect to full solar radiation at sea level with standard humidity and aerosol particulate concentration (1 Sun = $1000Watt/m^2$). Though somewhat contradictory to intuition, PV cell performance does not disgrace significantly between full sun and cloudy conditions. The power output decreases nearly right away with incident solar energy, but efficiency is nearly flat over the region of concern. Based on the Table 1 below, it shows the electrical characteristics data and parameters of the PV module chosen [11]. The model of PV modules is implemented using MATLAB/Simulink program.

Table 1 - Turbidity test of copper solution with rive husk activated carbon after adsorption

Parameter	Value taken for simulation
Maximum Power (P_{max})	200W
Voltage at P_{max} (V_{mp})	26.4V
Current at P_{max} (I_{mp})	7.58A
Open-circuit voltage (V_{oc})	32.9V
Short-circuit current (I_{sc})	8.21A
Shunt Resistance	415.405ohms
Series Resistance	0.221ohms
Band Gap Energy of Semiconductor (E_{g0})	1.1
Boltzmann's Constant (K)	1.38e-23
Ideality factor (n)	1.3
Electronic Charge (q)	1.6e-19
Solar Module Temperature (T)	25°C
Total Number of Solar Cells in Series (N_s)	54
Total Number of Solar Cells in parallel (N_p)	1
Short Circuit Current of Cell at 25 °C	0.0032

2.3 Mathematical Equations of PV Module

The mathematical modelling of the Solar PV Arrays in MATLAB/Simulink are based on several mathematical equations. There are five equations which control the photovoltaic characteristic and shown in Equation 1-5.

Photo Current (I_{ph})

$$I_{ph} = [I_{sc} + k_i \cdot (T - 298)] \cdot \frac{G}{1000} \quad (1)$$

Reverse Saturation Current (I_{rs})

$$I_{rs} = \frac{I_{sc}}{e^{\left(\frac{q \cdot V_{oc}}{n \cdot N_s \cdot K \cdot T}\right)} - 1} \quad (2)$$

Saturation Current (I_0)

$$I_0 = I_{rs} \left(\frac{T}{T_n}\right) \cdot \exp\left[\frac{q \cdot E_{g0} \cdot \left(\frac{1}{T_n} - \frac{1}{T}\right)}{n \cdot K}\right] \quad (3)$$

Shunt Resistor Current (I_{sh})

$$I_{sh} = \left(\frac{V + I \cdot R_s}{R_{sh}}\right) \quad (4)$$

PV Output Current

$$I = I_{ph} - I_0 \cdot \left[\exp\left(\frac{q \cdot (V + I \cdot R_s)}{n \cdot K \cdot N_s \cdot T}\right) - 1\right] - I_{sh} \quad (5)$$

2.4 Simulink Modeling of PV Module

MATLAB/Simulink model for PV simulation is developed using equation (1-5) and shown in Fig. 2. The models are separated based on five main part which are photon current, reverse saturation current, saturation current, shunt

resistor current and PV output current. The parameters used in this developed model are tabulated in Table 1. Fig. 3 shows the block diagram of PV module that develop an output of current, power and voltage using the input from the irradiance and temperature parameters.

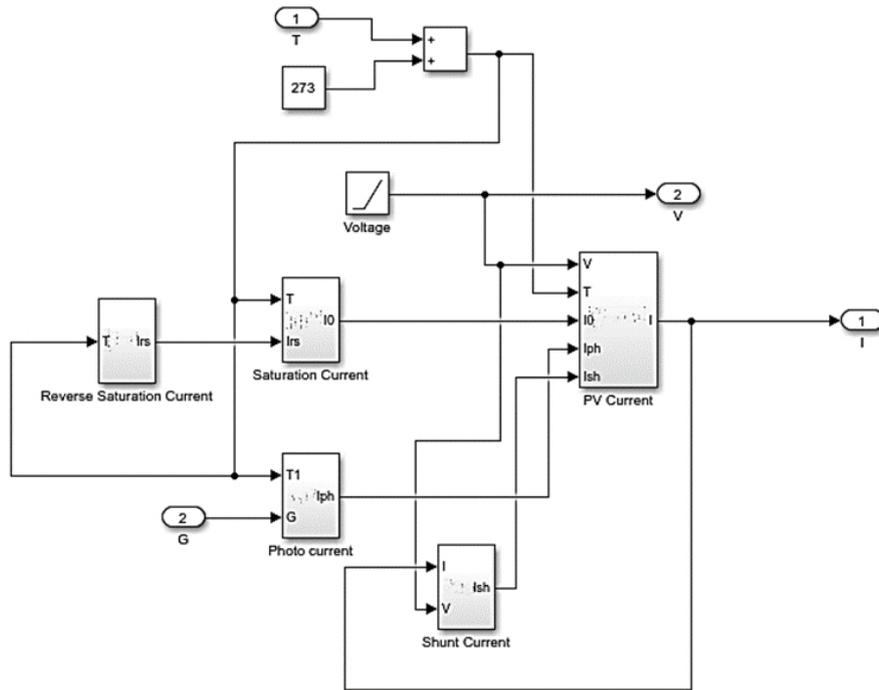


Fig. 2 - Block Diagram of PV Module Simulink

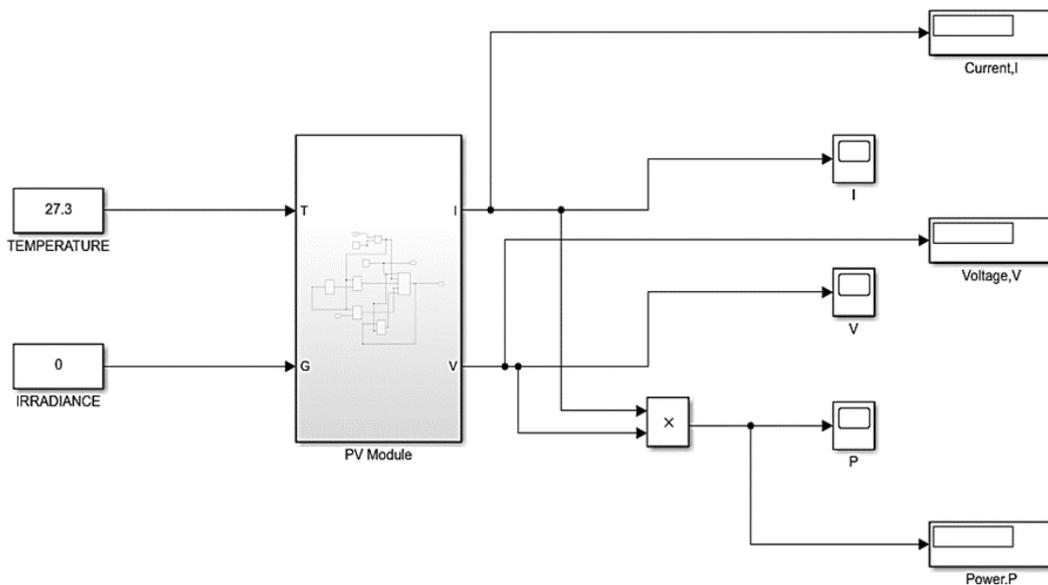


Fig. 3 - Block Diagram of PV module

3. ANN Model Development

3.1 Input and Output Data

There are two inputs data that involves which are solar irradiance and temperature. The inputs data that is fed into the neural network MLP and RBF using different types of activation function are being normalized. The outputs that is develop from the ANN system will be compared with the target that is develop from the PV module.

The real data of solar irradiance and temperature are collected, and 350 set of the input and output data are collected. The data are recorded every half an hour from 5th November 2017 until 18th November 2017 at the building of FKEE in UTHM Parit Raja. Table 2 shows some of the data collected and will be used in the neural network system.

Table 2 - The value of input and output data (example)

Date	Time	Input		Output Display		
		Temperature (°C)	Irradiance (w/m ²)	Current, I	Voltage, V	Power, P
5/11/2017	7.00 AM	24.2	7	- 0.09403	25	-2.351
	7.30 AM	24.6	70	0.4116	25	10.29
	8.00 AM	25.1	134	0.9226	25	23.07
	8.30 AM	26.1	185	1.318	25	32.96
	9.00 AM	26.3	267	1.976	25	49.40

3.1 MLP and RBF Architectures

Two different neural network architectures, namely MLP and RBF neural networks are applied for managing the output of the PV power generation. The MLP architecture employing back-propagation learning and widely used in many applications. The configuration consists of many layers of neurons such as input layer, one or more hidden layer and output layer. The MLP network transforms the unit inputs to the unit outputs through some nonlinear function. The linear, logistic sigmoid and hyperbolic tangent sigmoid activation function is applied in the MLP network. The RBF network architecture also has layers as MLP, but the input values are each allocated to a node in the input layer and sent directly to the hidden layer. The hidden layer represents a series of centers in the input data space with each center having an activation function called as Gaussian function. Table 3 shows the types of activation function of MLP and RBF with graphical illustration and mathematical form.

Table 3 - Types of Transfer Function of MLP and RBF

Neural Network	Activation Function Name	Graphical Illustration	Mathematical Form
MLP	Log-Sigmoid		$f(x) = \frac{1}{1 + e^{-x}}$
MLP	Tan-Sigmoid		$f(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}}$
MLP	Linear		$f(x) = x$
RBF	Gaussian		$f(x) = e^{-x^2/2}$

In the first part of simulation, the PV module system have been designed and model in the MATLAB/Simulink software in order to obtain the set of inputs and outputs for about 350 data. These data will be used to construct the output of PV module using artificial neural network. The set of input and output data were divided into two parts which are data of training and testing data. For ANN model, 75% data are used for training and 25% for testing data. For this

paper, there are two inputs data involved which are solar irradiance and temperature. The set of input data will be fed to the MLP system using Linear, Logistic Sigmoid and Hyperbolic Tangent Sigmoid activation function. There are two outputs which are the current and power. Table 4 shows the parameters used in MLP and RBF neural network.

Table 4 - Parameters of MLP and RBF

Methods	MLP	RBF
Goal (MSE)	0.0001	0.0001
Inputs	2	2
Outputs	2	2
Hidden layer	10	2
Spread	Not applicable	8
Training	263	263
Testing	87	87

4. Results and Discussions

In this section, the result of the comparison between MLP and RBF for PV module performances are presented. The performance of PV module is determined by comparing the results of MLP and RBF network using set of inputs and outputs data obtained from PV model simulation results using MATLAB/Simulink explained before. There are four main results that will be discussed which are regression analysis, network error, pattern of output data and training time. Regression analysis is about statistical process to estimate the relationship between the variables. The statistics show the spread of data at a certain point in the regression process. Fig. 4, 5 and 6 shows the regression analysis of the MLP neural network using three activation function in MLP which are Linear, Logistic Sigmoid and Hyperbolic Tangent Sigmoid, respectively and Fig. 7 shows the regression analysis of RBF neural network. However, the MLP neural network with the Logistic Sigmoid (Log-Sig) has the best value of R which is 0.99973 followed by the RBF with Gaussian function, Linear and Hyperbolic Tangent Sigmoid function which are 0.99966, 0.99960 and 0.99579, respectively. The correlation coefficient (R) for both ANN types is almost equal to 1 that indicates the regression have the strong correlation between the actual output data and target data of neural network output. From the regression results, it can be observed that the MLP network employing logistic sigmoid activation function shows the best result as the data are converges along the best fit line. The maximum and RMS errors are a term that evaluates the performance of each activation function and the error that is generated is compared to the actual output of the system with the output target neural network.

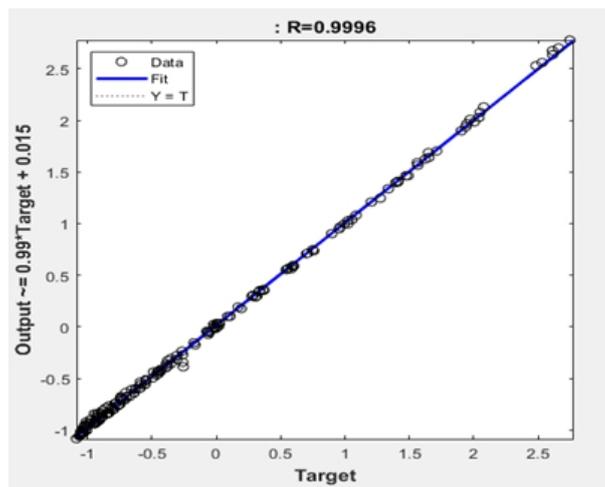


Fig. 4 - Regression of PV solar using Linear activation function

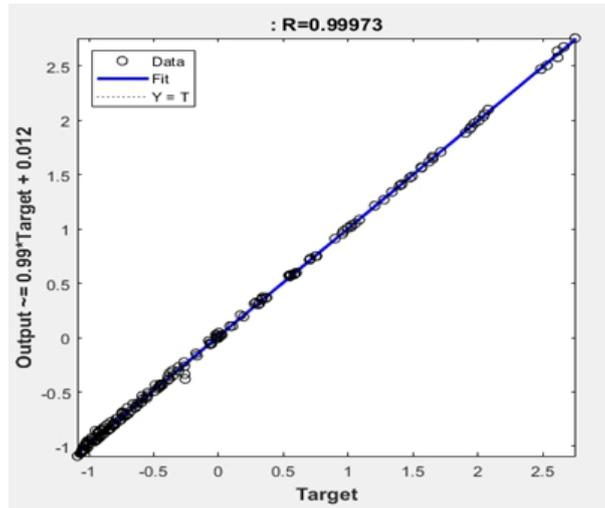


Fig. 5 - Regression of PV solar using Log-Sig activation function

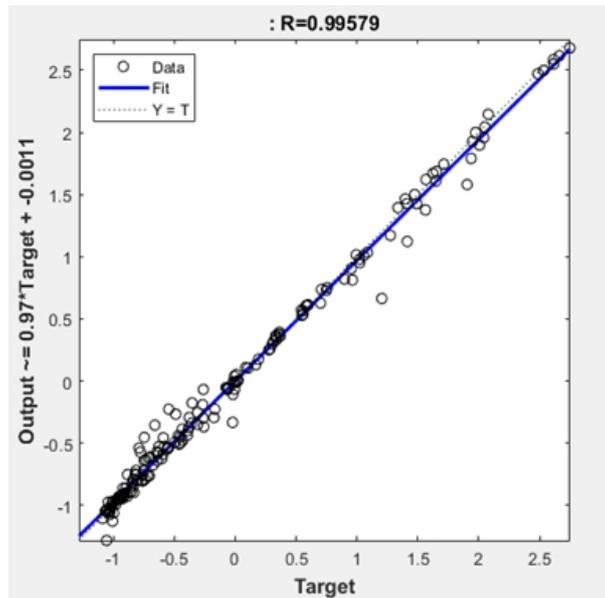


Fig. 6 - Regression of PV solar using Tan-Sig activation function

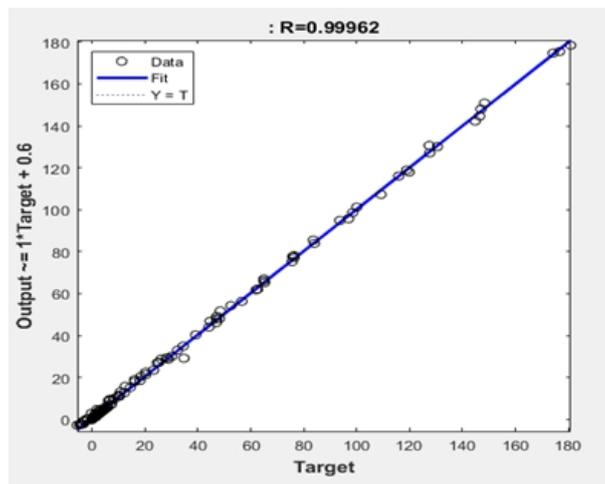


Fig. 7 - Regression of PV solar using Gaussian activation function of RBF neural network

The maximum and RMS errors are a term that evaluates the performance of each activation function and the error that is generated is compared to the actual output of the system with the output target neural network. Table 5 shows the errors with bold figures represent the best performance of RMS errors. From Table 5, the MLP network always achieves the best classification of the RMS errors for the outputs data of PV module. Based on the results, the MLP neural network Log-Sig function shows the lowest value of maximum error and RMS error with the value of 0.00022382 and 0.12533, respectively while for RBF neural networks, the maximum error and RMS error are 0.00046356 and 0.10178, respectively. This indicates that the MLP network with Log-Sig activation function has the best results. It can be concluded that the trained MLP neural network can correctly predict the performances of PV module with minimal errors.

Table 5 - E_{max} and E_{rms} of MLP and RBF

Neural Network	MLP						RBF	
	Linear		Log-Sig		Tan-Sig		Gaussian	
Activation Function	E_{max}	E_{rms}	E_{max}	E_{rms}	E_{max}	E_{rms}	E_{max}	E_{rms}
Output data	0.001026	0.10964	0.00022382	0.12533	0.0033705	0.16054	0.00046356	0.10178

The comparison of the pattern in the graph is used to compare the output data and the target data using the real data of temperature and solar irradiance. Fig. 8 shows the graphs of PV output power using activation function of MLP and RBF neural network. It shows the comparison of output data obtained in the neural network and the Log-Sig activation function has the highest output of voltage compared to the other activation function. The highest the output of target, the better the performance of the systems.

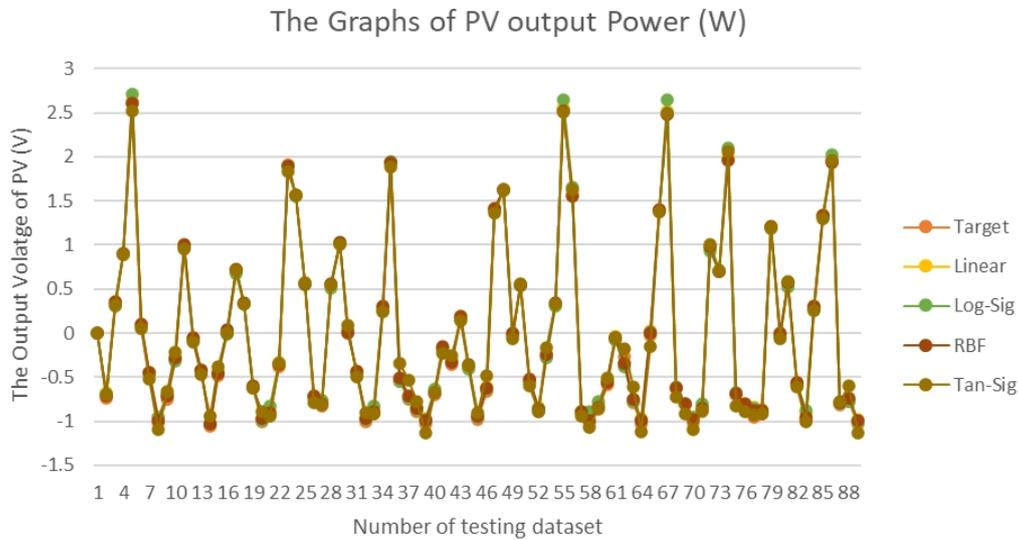


Fig. 8 - The graph of PV solar output voltage using five activation function

In terms of the training time that is required for MLP and RBF neural network to process the data when the result appeared. The shortest training time is the best performance of the neural network. Based on the Table 6, the MLP neural networks with Tan-Sig activation function shows the shortest period of training time which is 0.68925 seconds, followed by linear, log-sig and Gaussian with the values of 1.2488, 1.4588s and 8.285s, respectively.

Table 6 - Training time of MLP and RBF

Neural Network	MLP			RBF
Activation Function	Linear	Log-Sig	Tan-Sig	Gaussian
Time (second)	1.2488	1.4588	0.68925	8.285

4.1 Summary of Comparison

The characteristics to identify the best performance of activation function in neural network are the value of regression is nearest to 1, the smallest value of E_{max} and E_{rms} , highest output voltage and lastly shortest training time. Table 7 shows the summary comparison of characteristics in MLP and RBF neural network.

Table 7 - Comparison between MLP and RBF

Neural Network	Activation Function	Characteristics	Regression nearest 1	Smallest value of E_{max}	Smallest value of E_{rms}	Highest Output voltage	Shortest training time
MLP	Linear		/	/	/	/	
	Log-Sig						
	Tan-Sig						/
RBF	Gaussian						

Based on the Table 7, Log-Sig activation function has the best performance result that Linear and Tan-Sig. Therefore, Log-Sig is the best activation function that represent MLP neural network. Between Log-Sig (MLP) and Gaussian (RBF), Log-Sig mostly has the best performance result for the most characteristics as shown above. Even though Tan-Sig has the shortest training time, however, it cannot beat Log-Sig which has the best result for other characteristics which regression value nearest to 1 and the value of E_{max} and E_{rms} are the smallest.

5. Conclusion

This project shows the development of PV module using Artificial Neural Network. The objective of this project is to have assured the system of PV module can deliver effective power to user using MLP and RBF neural network. The test system of PV module is used to generate the most efficiency value that have been developed using ANN in MATLAB software. The inputs and outputs data are set recorded and used to generate the neural network model as it will describe the features of PV module power generation. The characteristics of PV module are identified by ANN with various activation function in many hidden layers. The results obtained from neural network are used to determine the best activation function which provides the minimum error. Based on the result analysis, the Log-Sig is the best performance result compared to Gaussian because the regression value nearest to 1 and the value of E_{rms} and E_{max} are the smallest.

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References

- [1] González-Longatt, F. M. (2005). Model of photovoltaic module in Matlab™ . 2DO Congreso Iberoamericano De Estudiantes De Ingeniería Eléctrica, Electrónica Y Computación, Ii Cibelec, 1-5
- [2] Nema, S., Nema, R. K., & Agnihotri, G. (2010). Matlab/simulink based study of photovoltaic cells/modules/array and their experimental verification. *International journal of Energy and Environment*, 1(3), 487-500
- [3] Salmi, T., Bouzguenda, M., Gastli, A., & Masmoudi, A. (2012). Matlab/simulink based modeling of photovoltaic cell. *International Journal of Renewable Energy Research*, 2(2), 213-218
- [4] Tsai, H. L., Tu, C. S., & Su, Y. J. (2008). Development of generalized photovoltaic model using MATLAB/SIMULINK. In *Proceedings of the World Congress on Engineering and Computer Science, 2008*, 1-6
- [5] Shannan, N. M. A. A., Yahaya, N. Z., & Singh, B. (2013, November). Single-diode model and two-diode model of pv modules: a comparison. In *2013 IEEE International Conference on Control System, Computing and Engineering*, 210-214
- [6] Rai, A., Awasthi, B., Dixit, A., & Dwivedi, C. K. (2016, October). Modeling of solar photovoltaic module and study parameter variation effect using MATLAB/Simulink. In *2016 International Conference on Control, Computing, Communication and Materials*, 1-6
- [7] Zhang, G., Patuwo, B. E., & Hu, M. Y. (1998). Forecasting with artificial neural networks: the state of the art. *International Journal of Forecasting*, 14(1), 35-62
- [8] Hsiao, Y. T., & Chen, C. H. (2002). Maximum power tracking for photovoltaic power system. In *Conference Record of the 2002 IEEE Industry Applications Conference. 37th IAS Annual Meeting*, 2, 1035-1040
- [9] Sethi, V. K., Rajeswari, C. S., Thapar, V., & Beohar, N. (2010). Evaluating effect of insolation on pv cell Output using Matlab/Simulink. *Journal of Engineering, Science and Management Education*, 1, 34-38
- [10] Shaari, S., & Bowman, N. (1998). Photovoltaics in buildings: A case study for rural England and Malaysia. *Renewable energy*, 15(1-4), 558-561

- [11] Ashok, S., Fonash, S. J., & Fonash, R. T. (2020). Solar cell. In Encyclopedia Britannica, <https://www.britannica.com/technology/solar-cell>