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RESEARCH ARTICLE - ENGINEERING (MISCELLANEOUS)

Optimization of Neurons Number in Artificial Neural Network Model for Predicting the Power Production of PV Module

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Abstract

In this work, an Artificial Neural Network (ANN) with a backward-propagation technique was used to predict the power generation of the Photovoltaic (PV) module in weather conditions of Baghdad city-Iraq. Experimental tests were conducted in the summer of 2022. Three weather parameters, including solar radiation, ambient temperature, and wind speed, as well as the output electrical characteristics of the PV module (voltage, current, power) and module temperature, were measured. Therefore, the dataset of the ANN system consists of four input and one output parameter. Furthermore, the structure of ANN includes a single hidden layer with a backward propagation technique. The main goal of this study was to optimize the number of neurons in the training process. The evaluation of the ANN model depended on the determination coefficient (R) and Root Mean Squared Error (RMSE). The obtained results show that the architecture of ANN is appropriate for predicting the power generated from the PV module. The developed ANN model has good accuracy. The MSE is 0.002747 at epoch 9 in the model. Furthermore, the R values are recorded as 0.99078, 0.98254, 0.99125, and 0.99005 for training, testing, validation, and all respectively in the proposed model. In addition, the optimized number of neurons in the hidden layer provided sufficient accuracy without relying on the trial-and-error method for choosing the number of neurons, which most researchers rely on.

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Keywords: ANN; PV Module; Power Generation; Single Hidden Layer; Neurons.

1. Introduction

In the past years, some countries have taken positive policies to produce electric energy by relying on renewable energy using the photovoltaic module, instead of producing it using fossil fuels [1, 2]. The energy production of the photovoltaic module is affected by real operation conditions such as (solar radiation, temperature, wind, humidity .... etc.). The main factors affecting the output of photovoltaics are solar radiation and temperature. The efficiency of the solar module increases with increasing solar radiation and decreases with increasing temperature. Therefore, the photovoltaic module is a non-linear power source and it is difficult to predict the output power from it [3, 4]. Many studies have been conducted to measure and predict the electrical output parameter of a photovoltaic module. These studies include experimental, numerical, and analytical models [5]. Through literature studies, many methods were used to predict the output characteristics of a photovoltaic module, these methods have been divided into four main approaches: physical approach [6], statistical approach [7], Artificial Intelligence (AI) approach, and hybrid approach [8, 9]. In the AI approach, Artificial Neural Networks (ANNs) are considered a powerful tool to predict the output of a photovoltaic module and are easy to perform and used to model complex operation conditions [10]. ANNs are a branch of artificial intelligence based on machine learning, inspired by the neural networks of the human brain [11]. The basic architecture of an artificial neural network consists of three layers: the input layer, any number of hidden layers, and the output layer [12]. Each layer consists of several processing units called neurons. Neurons transfer data between layers, working in perfect unison, and the weights they carry represent control functions organized based on the output [13]. ANN is used as a theoretical technique for forecasting and the Maximum PowerPoint Tracking (MPPT) of PV modules, with algorithms used to determine the best weights [14].

ANN suggested an approach to predict the output power and the overall efficiency of a PV module using a Recurrent Neural Network (RNN), depending on the Back Propagation (BP) algorithm. The environmental factors (solar radiation, dust, temperature, and wind speed) are the nodes of the input layer of RNN, and the output layer consists of two nodes (power generation and efficiency of PV module). The RNN architecture consists of one input layer, one output layer, and two hidden layers (ten neurons in the first layer, two neurons in the last hidden

Nomenclature & Symbols			
PV	Photovoltaic	V_{oc}	Open Circuit Voltage (V)
AI	Artificial Intelligence	I_{sc}	Short Circuit Current (A)
ANN	Artificial Neural Network	V_{mpp}	Maximum Power Point Voltage (V)
RMSE	Root Mean Squared Error	I_{mpp}	Maximum Power Point Current (A)
SC	Solar Cert	P_{mpp}	Maximum Power (W)
R	Determination coefficient	FF	Fill Factor (%)
MPPT	Maximum PowerPoint Tracking	G	Solar Radiation W/m²
STC	Standard Test Condition	Ta	Ambient Temperature (ºC)
RNN	Recurrent Neural Network	Tpv	Module Temperature (ºC)
BP	Back Propagation	N	Number of Predication Values
MLP	Multilayer Perceptron	W_i	Synaptic Weights
RBF	Radial Basis Function	b	Bias
FFBP	Feed-Forward Back Propagation	d	Desired Output (W)
GRNN	General Regression Neural Network	p	Predicted Output (W)

layer), log-Sigmoid function type is the activation function that is used during training. The trial-and-error approach is used to select the number of hidden neurons in RNN. The results indicate the RNN can provide high-accuracy results [15].

The ANN model was used by Fahmi et al. [16] with Multilayer Perceptron (MLP) and Radial Basis Function (RBF) techniques to predict the parameters of the PV module. The MLP technique uses the BP algorithm with the linear, log-sigmoid, and tan-sigmoid types of activation function, the structure consists of one input layer, one output layer, and ten hidden layers. The RBF technique has the same classes as in MLP with two hidden layers and a Gaussian type of activation function. Solar radiation and temperature are the nodes of the input layer of ANN, and current and power are the output of this. The results of the study showed that log-sigmoid is the best technique with the least root mean square error.

In [17], the data recorded for five months of the year 2017 in Baghdad city were used to train and test two models of artificial neural networks, called Feed-Forward Back Propagation (FFBP) and General Regression Neural Network (GRNN), to forecast the PV output power. Both structures have five input nodes such as (solar radiation, ambient temperature, cell temperature, wind speed, and humidity) and one output node is the power. A trial-and-error approach was used to determine the number of hidden layers and neurons in these layers. In the FFBP case, two hidden layers have been used, the number of neurons in the first and second hidden layers was found to be 32 and 16 respectively. In the GRNN case, the first layer contains as many neurons as there will be input/target vectors with radial basis functions in the input vectors. The second layer's number of neurons is determined by the target vectors with a linear transfer function. As a result, GRNN is more accurate and has proven its ability to forecast in less time than the FFBP model.

Two models of ANN structure were used by Kayri et al. [18] to estimate the output power of the PV module, ANN-model-1 for sunny and mostly sunny days, and ANN-model-2 for cloudy and overcast days. Six atmospheric variables are the nodes of the input layer such as (air temperature, solar irradiance, wind speed and direction, relative humidity, and angle of the sun's elevation), and power generation is the output of the output layer. Between the input and output layers, there are two hidden layers, each consisting of 15 neurons. The results showed that the proposed models can give estimates with high sensitivity.

Through the above presentation, and the literature review, many researchers used an artificial neural network to predict the photovoltaic parameters, they selected the number of neurons in the hidden layer using the trial-and-error method to find the best accuracy of the proposed model. So, the main objective of this paper was to predict the power generation of the Photovoltaic (PV) module in weather conditions of Baghdad city-Iraq based on measured data carried out in the summer of 2022. Furthermore, the number of neurons was optimized in the training process to achieve the best accuracy of the model instead of using the trial-and-error method.

2. Experimental Part

In this study, a solar polycrystalline silicon module type (Protonix Fortuner India FRS-165 W) was selected to achieve the experimental investigation. The technical data of the PV module were shown in Table 1. It was installed on the iron frame with an incident angle of (33º) from the horizontal towards the south (local latitude of Baghdad city) as shown in Figure 1. The weather data, the temperature of the PV module, and the output electrical characteristics of the PV module were measured experimentally. The weather conditions include solar irradiance, ambient temperature, and wind speed while, the output characteristics of the module include: open circuit voltage (V_{oc}), short circuit current (I_{sc}), maximum power point voltage (V_{mpp}), maximum power point current (I_{mpp}), maximum power (P_{mpp}), and fill factor (FF). The I-V tracer (SEAWARD PV200) coupled with a solar survey (SS200R), which has a temperature sensor placed on the back surface of the PV module, was used to measure these data. This tracer is an accurate device to analyze and compare collected data with the Standard Test Condition (STC) data, and it is capable of generating (I-V) and (P-V) curves with a measurement range of (5-1000V DC) for (V_{oc}) and (5-15A) DC for (I_{sc}). All the data collected by the I-V tracer were transferred to the computer and displayed by the Solar Cert (SC) software. 326 measured data were collected from the experimental tests for seven days in summer during July month over some time from (7:00 AM- 6:00 PM). These collected data will be used for training, testing, and validation of the ANN model. Taking a large number of collected data contributes to the input of a larger amount of data of real operating conditions to the ANN model to obtain the best training, testing, and verification process. A sample of measured data was tabulated in Table 2.

Table 1. Technical data of PV module

PV module characteristics	Value
P_{mpp}	156 W
V_{mpp}	18 V
I_{mpp}	9.17 A
V_{oc}	22.05 V
I_{sc}	9.81 A

Fig. 1. Tested PV module and solar survey meter (SS200R)

Table 2. Samples of collected data

NO.	Voc (VDC)	Isc (ADC)	G (W/m2)	Ta (C)	Tpv (C)	Wind (m/s)	Vmpp (V)	Impp (A)	Pmpp (W)
1	20.7	2.696	332	32.88	36.67	0.3	17.44	2.5	43.6
2	20.6	3.401	362.8	36.45	40.75	0.31	16.95	3.2	54.24
3	21.1	3.277	393.1	34.3	34.97	0.12	17.68	3.1	54.808
4	20.4	3.786	400.2	38.07	45.8	0.31	16.83	3.4	57.222
5	20.4	3.643	430.1	41.83	44.92	0.5	16.78	3.5	58.73
6	21.4	3.849	449.7	36.26	32.69	1.1	18.42	3.5	64.47
7	21.1	3.987	476.4	36.21	36.67	1.2	17.61	3.7	65.157
8	21.2	4.262	501.2	37.19	35.85	1.1	17.69	4	70.76
9	21.1	4.277	525.3	36.45	37.79	1.2	17.4	4	69.6
10	21.2	4.791	544.1	37.28	38.13	1.22	17.34	4.5	78.03
11	20.9	4.538	560.3	40.51	41.43	1.2	17.07	4.3	73.401
12	20.2	5.231	579.7	40.81	52.16	1.21	16.38	5	81.9
13	21.2	4.956	591.5	37.43	39.15	1.5	17.24	4.7	81.028
14	20.8	5.372	600.8	40.02	45.02	1.45	16.9	5	84.5
15	20.9	5.074	625.7	42.17	43.47	1.1	18.84	3.7	69.708
16	20.1	6.127	655.6	51.37	57.01	1.87	16.4	6.1	100.04
17	21.3	5.807	675.9	38.75	39.1	1.22	17.37	5.4	93.798
18	21	5.787	694.2	40.41	43.9	1.4	17.22	5.4	92.988
19	20.4	6.317	717.2	45.6	51.82	1.87	16.27	6	97.62
20	21.2	6.306	738.9	39.88	41.48	1.8	17.26	5.9	101.83
21	21.1	6.701	762.2	45.25	42.74	2.1	17.05	6.2	105.71
22	21.3	6.823	789	39.04	41.04	1.7	17.24	6.5	112.06
23	20	7.145	801.2	43.69	58.42	2.1	15.6	6.7	104.52
24	20.7	7.153	826.2	41.73	51.04	2.1	16.33	6.7	109.41
25	20.4	7.463	840.2	44.52	55.6	2.2	15.96	7	111.72
26	20.9	7.538	850.6	47.06	46.09	2.3	16.49	7.1	117.07
27	19.6	7.741	871.3	50.19	65.17	2.2	15.16	7.1	107.63
28	21.4	7.677	878	42.37	40.99	2.41	16.96	7.2	122.11
29	21	7.842	889.8	45.74	45.26	2.31	16.71	7.3	121.98
30	20.4	7.911	894.9	46.67	56.38	2.12	15.89	7.4	117.58
31	20	7.849	901.6	50.93	61.29	2.31	15.49	7.3	113.07
32	21.1	8.082	910	44.18	45.17	2.3	16.72	7.6	127.07
33	21.3	7.983	913.8	43.54	41.43	2.54	17.07	7.5	128.02
34	21.2	8.128	922.6	44.91	43.03	2.52	16.52	7.9	130.50
35	20.9	8.369	933.5	44.96	50.07	2.52	16.29	7.8	127.06
36	20.5	8.36	940.6	47.7	56.38	2.29	15.8	7.8	123.24
37	21.3	8.411	951.7	43.54	42.11	2.52	16.8	7.9	132.72
38	20.4	8.32	955	53.13	57.3	2.3	16.1	7.4	119.14
39	21.1	8.511	964.6	43.74	45.65	2.1	16.59	8	132.72
40	21.1	8.717	999.9	43.69	46.57	2.52	16.42	8.1	133

3. Theory of Artificial Neural Network

Artificial neural networks (ANNs) are computer simulations that are used to perform and represent linear and nonlinear relationships between input and output data [19]. The structure of ANNs consists of an input layer, a hidden layer, and an output layer. In addition, each layer includes some nodes called neurons [20, 21] as shown in Fig. 2.

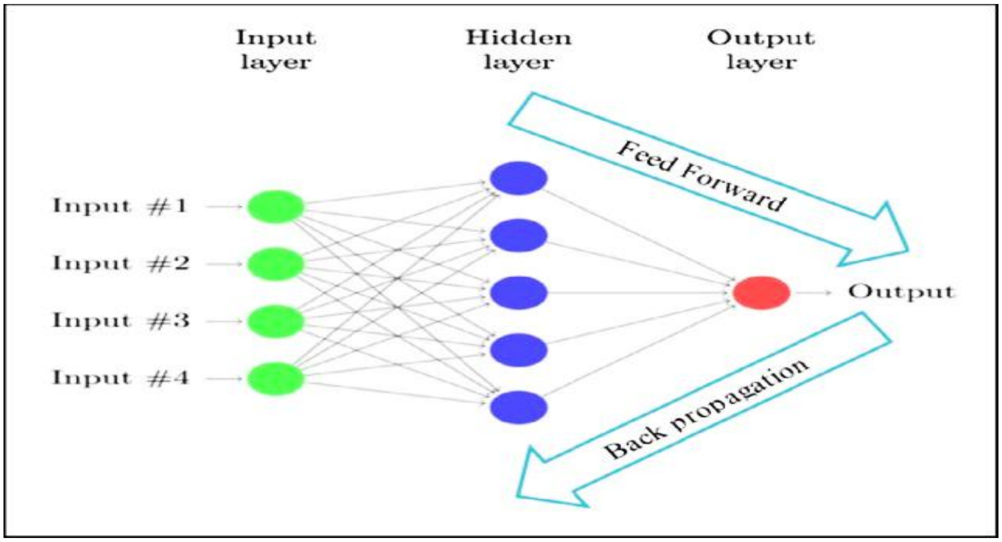

Fig. 2. Basic Structure of Artificial Neural Network [22]

These neurons have weights and biases which are linked together [16]. The function of weight values is to connect neurons, whereas the bias is used to explicitly state the system freedom degree. The basic operation of ANNs is described by adding the output of each layer to the bias. The neurons are mathematically described by [23]:

$$S = \sum_{i=1}^{n} W_i X_i + b \quad (1)$$

where: W_i is the synaptic weights and b is the bias.

The activation function is then used to find and send data to the next layer. Three traditional types of transfer functions are used in ANNs: linear, sigmoid, and hyperbolic tangent transfer functions. The sigmoid transfer function is considered the best of the three types. The mathematical models of three different types of transfer functions are described in the following [24]:

$$f(S) = \begin{cases} S & linear\ function \\ \frac{1}{1+e^{-S}} & sigmoid\ function \\ \frac{e^{+S}-e^{-S}}{e^{+S}+e^{-S}} & hyperbolic\ tangent\ function \end{cases} \quad (2)$$

Backpropagation is the most important algorithm for updating ANN's weights. The mathematical model of the propagation method can be summarized by forward and backward steps based on the chain rule principles according to the block diagram in Fig 3. The error between the predicted and desired output can be calculated as:

$$E = \frac{1}{2}(d - p)^2 \quad (3)$$

where: d is the desired output and p is the predicted =*f(S)*.

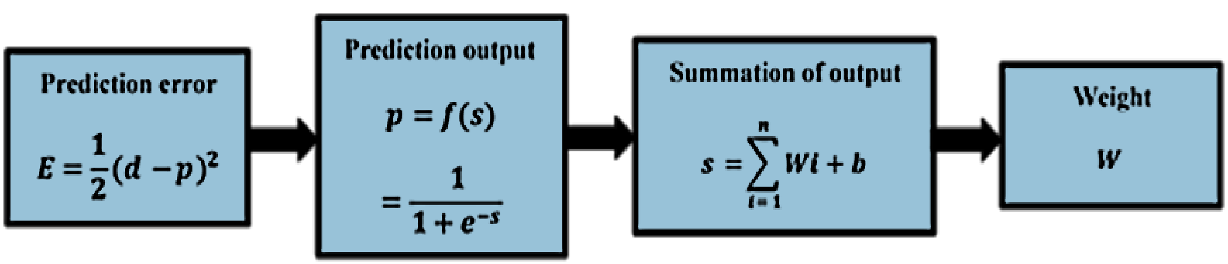

Fig. 3. Block diagram of error calculation

4. Features of the Proposed ANN Structure

In this study, the ANN model was used to predict the output power of the PV module by using MATLAB code. This code has the following features:

- The ANNs operate under a back-propagation learning algorithm to decrease the number of estimate errors in a network.
- The architecture of ANN consists of an input layer with four parameters: (solar radiation, ambient temperature, module temperature, and wind speed), a single hidden layer, and an output layer with one node (output power of PV module).
- The activation function of the hidden layer in this study is the sigmoid tangent function, and the linear transfer function is used in the output layer.
- The dataset used to train and test models was divided into 70% for training and 30% for testing and validation.
- During the training process, the number of neurons in the hidden layer was optimized.
- The Root Mean Square Error (RMSE) and determination coefficient (R) between the target and predicted values were used to assess the performance of the ANN model.

The RMSE can be represented as:

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(p-d)^2} \tag{4}$$

where N is number of predication values.

5. Result and Discussion

In this paper, the ANN model is used to predict the output power of the proposed PV module. The structure of the ANN model consists of four input nodes in the first layer such as solar radiation, ambient temperature, module temperature, and wind speed, and one node in the output layer, which is the power generated by the PV module. The model utilized a single hidden layer. The model optimization code is used to tune and identify the optimum values for the number of neurons in the hidden layer to get better prediction accuracy. The input and output data for the ANN model were collected from the experimental work and classified into 326 readings. In the ANN model, 70% of this data was used to train and 30% was used to test and validate this model.

Initially, the input data under summer conditions are visualized, as shown in Fig. 4. Data visualization helps to reveal the interactions within the data, and these figures show the relationship of solar radiation, ambient temperature, module temperature, and wind speed data under summer conditions with the corresponding output power data of the PV module.

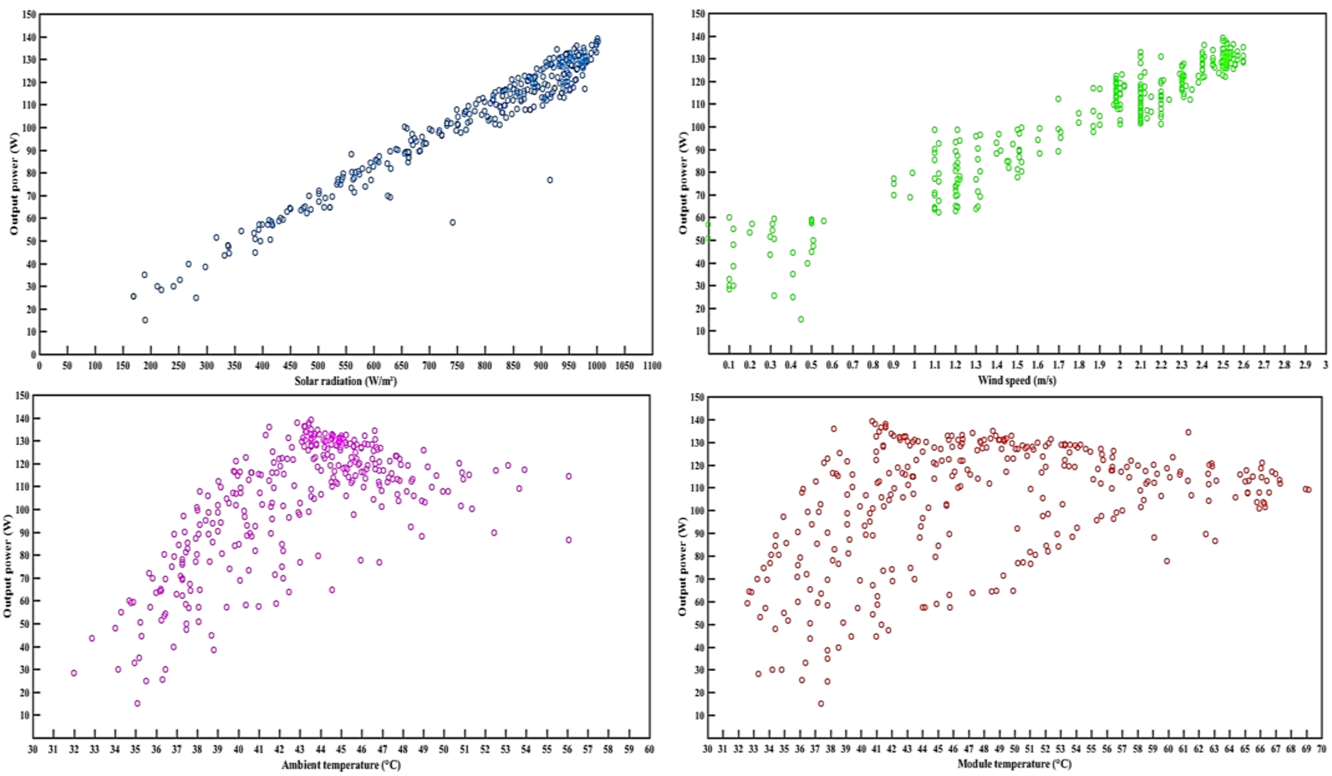

Fig. 4. Visualization of summer conditions data

The data visualization results indicate that the increase in solar radiation exhibits a quasi-linear behavior with the increase in output power. Other figures illustrate differences in the density of data point ranges, which are not comparable to any specific approach. Thus, solar radiation is more influenced by other input parameters in relation to the output power of the PV module.

Then, an optimization code was used to tune the number of neurons from 1 to 100, trying each one sequentially to identify the best number of neurons in the hidden layer for the model. It was observed to be 17 neurons in the hidden layer. Fig. 5 demonstrated the root mean squared error (RMSE) values for the validation and training at each number of neurons. The optimal number of neurons is chosen based on the minimum RMSE value for the validation process, with a minimal difference in RMSE from the training process. We observe from these curves that they begin to deviate from each other when the number of neurons is larger than 30.

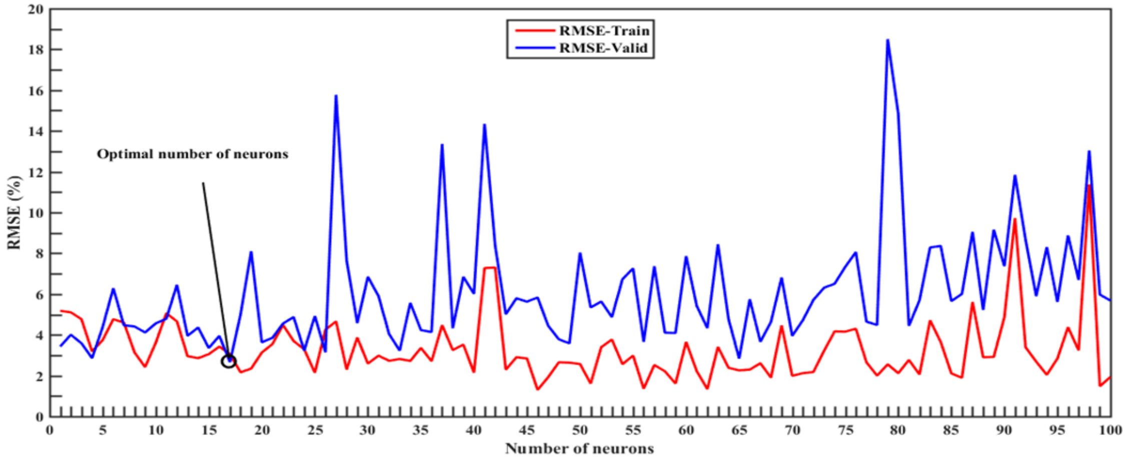

Fig. 5. Optimal number of neurons in the model

Through it, the ANN model was run with 17 neurons in a single hidden layer as shown in Fig. 6. The best validation performance can be observed and recorded in the mean squared error (measured versus estimated power) is 0.002747 at epoch 5 as shown in Fig. 7. This result shows that the weight and bias of the networks are well adapted, and the model can replicate the output power with good accuracy.

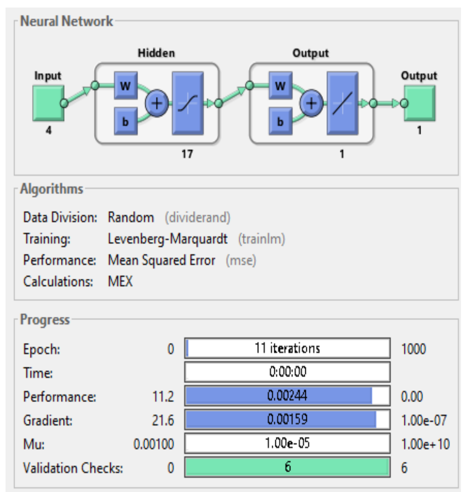

Fig. 6. Structure of ANN models

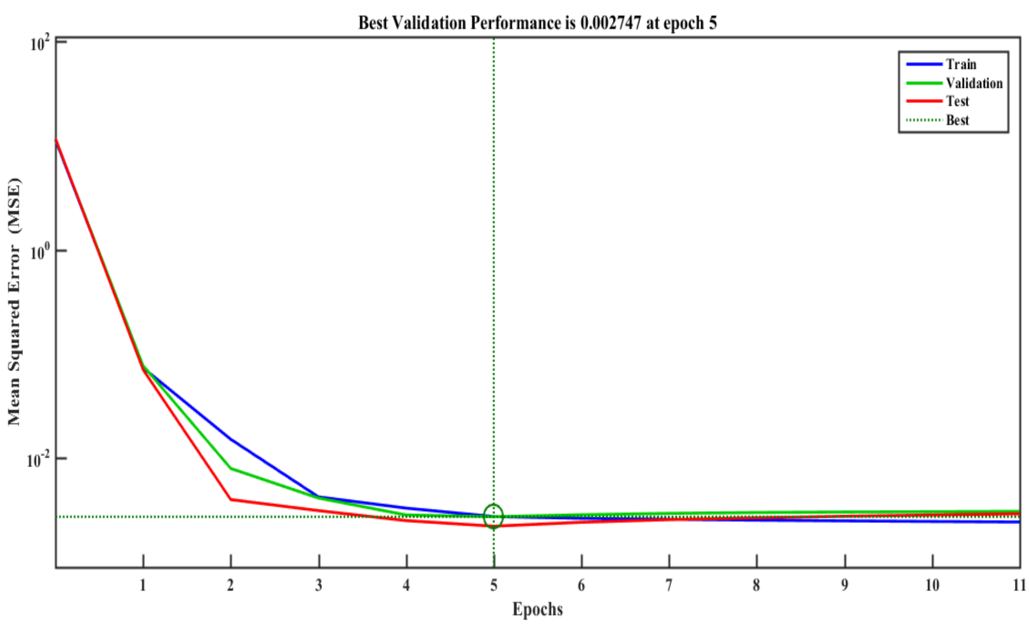

Fig. 7. Best Validation Performance in the model

The determination coefficient (R) was observed as 0.99078, 0.98254, 0.99125, and 0.99005 for training, testing, validation, and all, respectively, in the proposed model as shown in Fig. 8. This means that the measured and predicted output power are relatively close.

The predicted line of the model is represented in Fig. 9, the measured and predicted output power values are close to the trend line. So, the model is accurate for predicting the output power of the PV module.

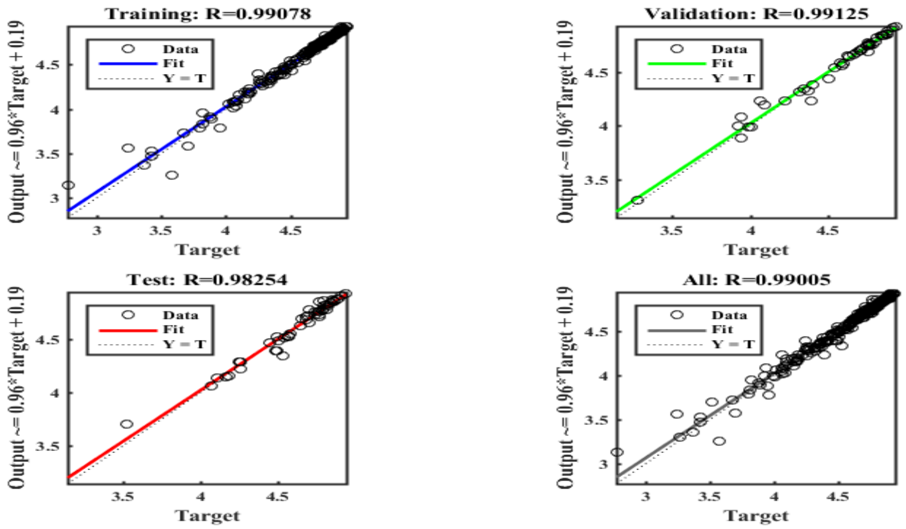

Fig. 8. Determination coefficient of the proposed model

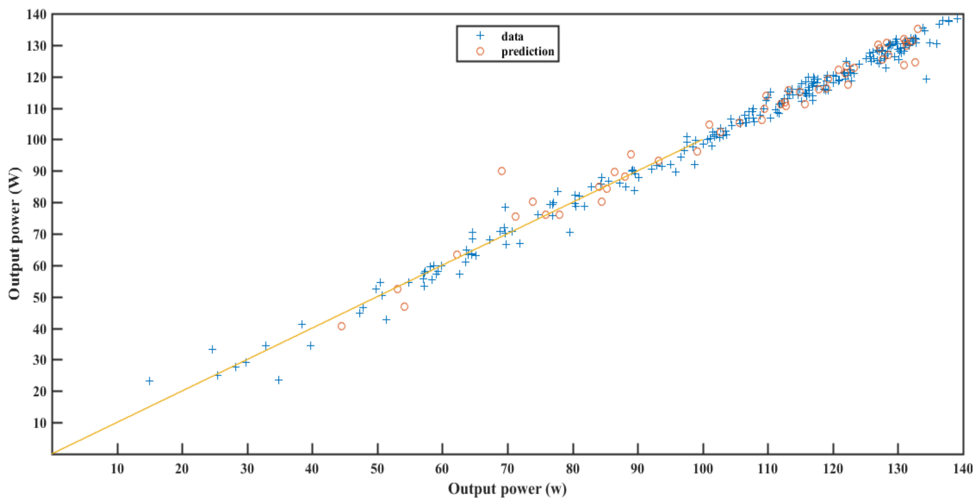

Fig. 9. Visualize the prediction of the proposed model

The predicted results from the ANN model were compared with measured results for the training and validation stages. The number of data points for training was 277 (70% of the data set), and for validation, it was considered to be 49 (15% of the data set). As shown in Fig. 10, the convergence is clear and precise between the predicted and measured output power of the PV module in ANN with a single hidden layer.

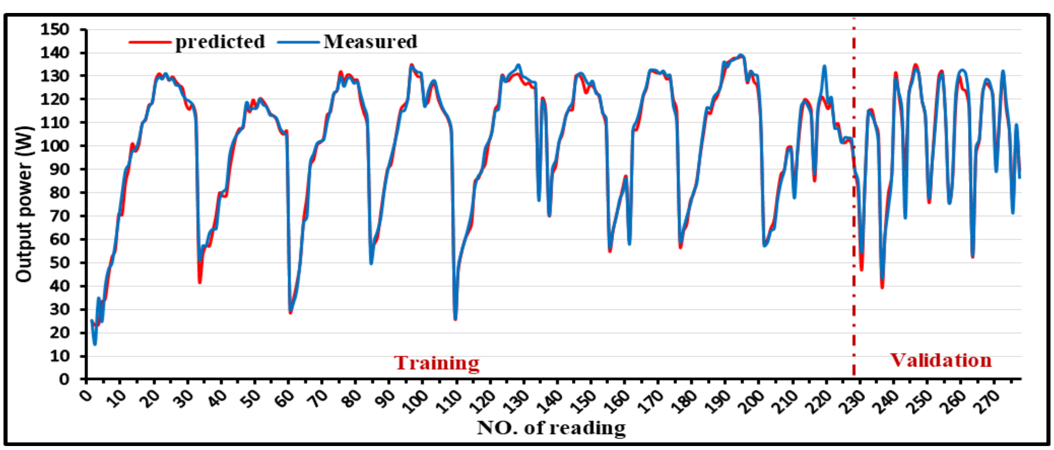

Fig. 10. Comparison between predicted and measured output power of PV module

6. Conclusion

This work deals with using the ANN model to predict the power output of PV modules based on measured data in summer days of Baghdad city-Iraq. According to the analysis of the obtained results, the architecture of ANN is appropriate for predicting power generated from the PV module. The developed ANN models have good accuracy. The MSE is 0.002747 at epoch 9 in the model. Furthermore, the R is recorded as 0.99078, 0.98254, 0.99125, and 0.99005 for training, testing, validation, and all respectively in the proposed model. In addition, the optimization of neurons number in the hidden layer gave sufficient accuracy without referring to the choice of the neurons by trial and error. The better neuron is chosen based on the minimum value of RMSE for the validation process with a minimum difference in RMSE of the training process.

7. Recommendations for the Future Work

The following recommendations may be useful for other subjects in this field:

- Increasing number of input parameters to the ANN model by adding V_{oc}, I_{sc}, humidity, and dust.
- Use the proposed model for other regions in Iraq or other countries.

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