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Estimation of Electrical Characteristics and Maximum Power Point of Photovoltaic Panel

This paper proposes to estimate the electrical characteristics and maximum power point of a photovoltaic (PV) panel under variable environmental conditions in Şanlıurfa region (southeast of Turkey). Variable environment conditions cause to change of current, voltage and maximum power point (MPP) of PV panels. Under any environmental conditions there is a unique MPP for PV panels, to increase efficiency and reduce cost of energy systems, it is need to determine the maximum power point and electrical characteristics of PV panels. The Artificial Neural Network (ANN) is an improved structure that neurobiologically inspires brain functioning, to determine the effects of all parameters on system, ANN Cascade-forward backpropagation and feed-forward backpropagation algorithm have been used, the installed system performed in Şanlıurfa region and the detailed performance tests have been performed in MATLAB simulation program. The proposed system is the first study by means of installing in Şanlıurfa region and estimating all variables of a PV panel with Cascade-Forward Backpropagation and Feed-Forward Backpropagation.

Keywords: PV panel; MPP; ANN; Cascade-forward backpropagation; Feed-forward Backpropagation

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1. Introduction

Increased energy needs with technological developments, threatening global warming and the depletion of fossil fuels have led us to use renewable energy sources. Such as wind energy, geothermal energy, solar energy and so forth [1, 2, 3]. Solar energy has some advantages like to be clean energy, Photovoltaic (PV) panels can convert solar energy to electrical energy directly and also they can produce electrical energy everywhere sunlight exist. The other side PV panels have a few drawbacks like that the power, current and voltage of PV panels are nonlinear they depend on environmental conditions so that variable environment conditions affects efficiency of energy system. Determination of the electrical characteristics and MPPs of PV panels under variable environmental conditions is an important step for efficiency of PV panels and saving energy cost [4, 5]. Şanlıurfa is a region in the southeast of Turkey and annual average sunshine duration is 7.8 hour/day and annual average temperature level is about 17ºC [6]. BLUESUN BSM-230M model Photovoltaic (PV) panel is used in the field study. The inputs of ANN are PV temperature, ambient temperature, Irradiance and outputs are Maximum Power Points, Open Circuit Voltages, Short Circuit Currents, Current and Voltages at MPP, Fill Factors, and Eta % ratio. The installed system is shown in the Figure 1.

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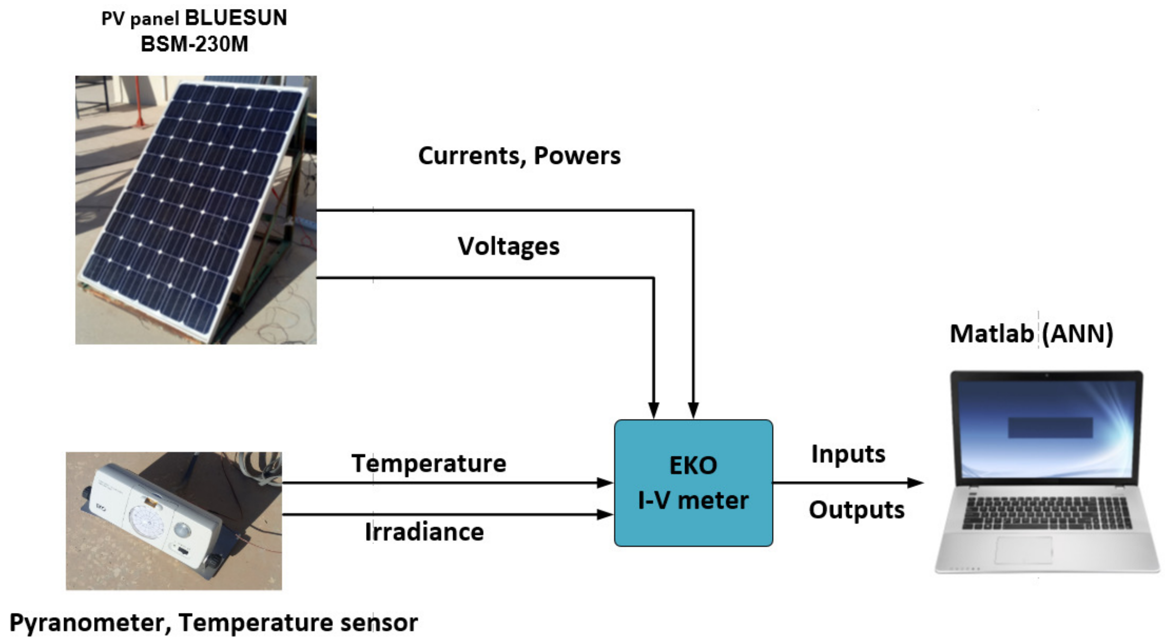


Fig. 1. The view of installed system

In this study, artificial neural network is used to predict the electrical characteristic and maximum power point of system. The most important feature of neural networks is being the nature of adaptations; this property provides some means of solving the relationship between nonlinear structures. Neural network is an alternative tool for modelling and defining complex structures. It is an important structure in determining the relationship between physical or technical parameters and when try to determine the relationship used the appropriate network algorithm [7, 8]. There are many network algorithms in literature and the algorithms are in vary by their speed, precision and cheapness. For this study, cascade-forward and feed-forward back propagation algorithms are used, although the speed of that algorithms are not good but they perform better than some other algorithms. Three training functions which are BFGS quasi-Newton, Levenberg-Marquardt, Gradient descent used for this study to estimate electrical characteristic and MPP of BLUESUN BSM-230M model Photovoltaic panel. The best result has been obtained from Feed forward back propagation Levenberg-Marquardt activation function. 400 observations have been obtained from this system constructed in Figure 1 and % 15 of observation is used for training and 15% for validation.

Engin Karatepe and friends studied neural network based solar cell model in 2006. They used neural network to estimate the equivalent circuit elements of a solar cell by variable temperature and irradiance.

Mellit and friends (2013) studied Artificial Neural Network-Based Model for predicting the power produced by Photovoltaic Module. They developed ANN-models for estimating the power produced with reasonable accuracy. They claim that their model performed better than polynomial and multiple linear regression and also better than analytical and one-diode models.

Lopez and colleagues (2005) used ANN to examine the selection of input parameters to model direct solar radiation. They studied automatic relevance determination method (ARD) to obtain the relative interest of a large set of atmospheric and radiometric variables used in predicting direct solar radiation per hour.

Adel Mellit and Alessandro Massi Pavan have developed new MLP (multi-layer perceptron) algorithm and they predict the best performance to find solar irradiance, the inputs of their algorithm are solar irradiance and temperature. They studied under sunny days and cloudy days in Italy and they have given the correlation results (2010).

To compare the previous studies this study has difference like different installed system and obtained database also used different ANN algorithms than other studies (Cascade forward back propagation and feed forward back propagation). Also for input data ambient temperature, PV panel temperature and Irradiance for Şanlıurfa region. The outputs are short circuit current, open circuit voltage, current and voltage at maximum power point, fill Factor (FF) and % Eta ratio.

$$FF = \frac{P_{\max}}{P_T} = \frac{V_{mpp} * I_{mpp}}{V_{oc} * I_{sc}} \tag{1}$$

$$Eta = FF * V_{oc} * I_{oc} \tag{2}$$

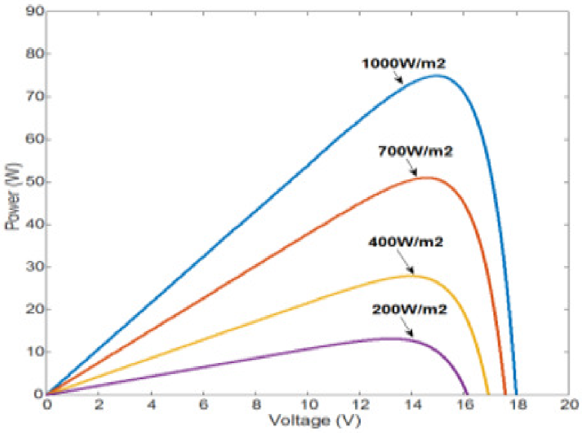
The represents of equations P_{max}=Maximum power of PV panel, V_{mpp}= voltage at maximum power point, I_{mpp}=Current at maximum power point, V_{oc}= Open Circuit voltage, I_{sc}= Short Circuit current.

The main contribution of this study is to estimate the electrical characteristics and maximum power point of PV panel under variable ambient temperature, irradiation and PV panel temperature with ANN models. Input parameters have been obtained from Şanlıurfa region by installed PV panel system shown Fig. 1. It is also purposed to evaluate feed-forward back propagation and cascade-forward back propagation algorithms with three different training function to estimate output parameters of PV panel for different input variations.

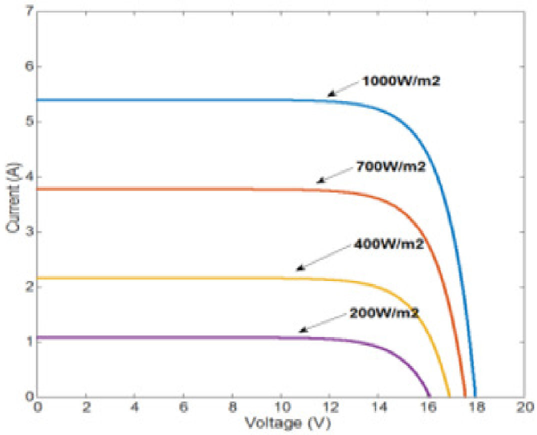
This study is organized as follows. Electrical characteristic of used PV panel and power-voltage, current-voltage characteristic curves are presented in the next section. The structure of proposed ANN is given in Section 3, the test cases of proposed system and statistical comparisons of model performances are presented in Section 4. Finally, the main result report of the article is presented in the conclusion section.

2. PV Panel and Characteristic Curves

Solar cell is a type of semi-conductor device which convert solar energy to electrical energy, the power obtained from a solar cell is so low, to get desired power, solar cells are connected series which named PV panels. Current and voltage of PV panels are nonlinear they depend on temperature and irradiance. Increasing irradiance lead to increase power and current of PV panels, on the other hand increasing temperature cause to decrease the current and power. Under variable irradiance and temperature, the Current-Voltage and Power-Voltage characteristics of PV panel are shown in Figure 2 (a, b, c, d).



(a)



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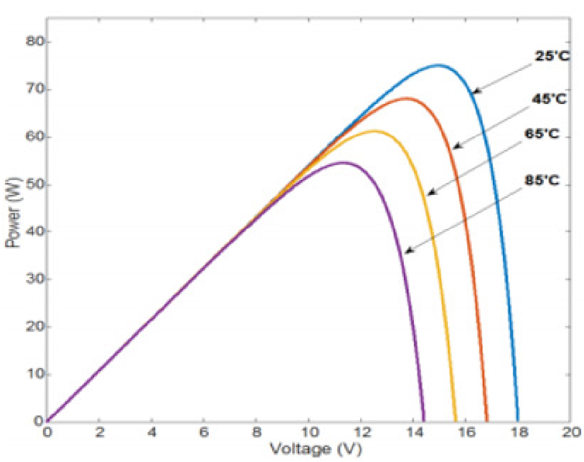

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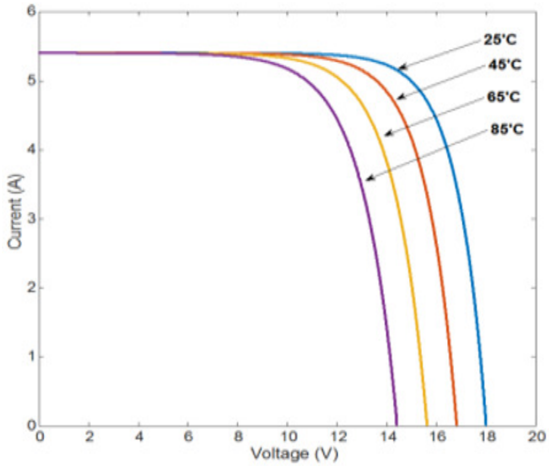

(d)

Fig. 2. (a) Power –Voltage characteristic variable irradiance, (b) Current-Voltage characteristic variable irradiance, (c) Power-Voltage characteristic variable temperature, (d) Current-Voltage characteristic variable temperature

The electrical specifications for BLUESUN BSM-230M model Photovoltaic (PV) panel are shown in Table 1.

Table 1. BLUESUN BSM-230M model Photovoltaic (PV) panel electrical characteristics

P (mpp)	230 W
V (mpp)	29.49 Volt
I (mpp)	7.8 Ampere
V (open circuit)	36.98 Volt
I (open circuit)	8.49 Ampere
Maximum system voltage	1000 V
Maximum fuse rating	10 A
Size	1650*992*45
Weight	21
Output Tolerance	+-%3
Standard test condition	1000W/m2, 25ºC, A.M 1.5
Operating temperature	-40-+85 ºC

3. Structure of Proposed Artificial Neural Network

The ANN is a tool that can be applied in a variety of areas, such as pattern classification, clustering, function approximation, prediction, optimization, where many areas can solve complex problems with high success. An artificial neural network neuron structure consists of input element, weight, summing node, activation function, threshold and output layer.

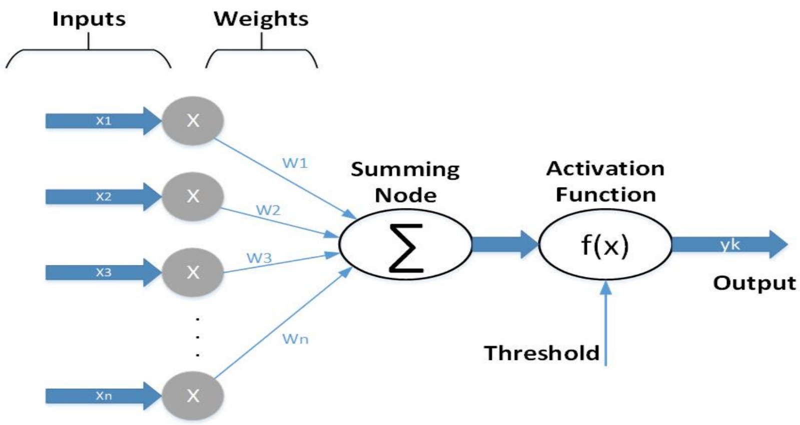

Fig. 3. Structure of Basic Artificial Neural Network Neuron

Artificial neural networks algorithms are based on various roles throughout the process. In the input layer, the inputs are multiplied by the possible weights and process in the activation function. Sometimes a threshold applied to this activation function and it gives the output to the output layer. ANNs have been applied in a many estimation application areas [13, 14]. Cascade-forward back propagation algorithm and feed-forward back propagation algorithm have been used in many applications since these algorithms give better results than other algorithms [8, 15, 16].

The proposed ANN feed-forward back propagation algorithm consists of three input layer, ten hidden layer, and seven output layer. The back propagation algorithm is a learning algorithm that is used to train networks in ANNs. In this network training, all calculations are made from the input layer to the output layer. Then the error value is compared to the tolerance and the error propagates to the previous layer. Feed-forward networks almost has one or more hidden layers [17]. Basic structure of the proposed feed-forward back propagation algorithm is shown in Fig 4.

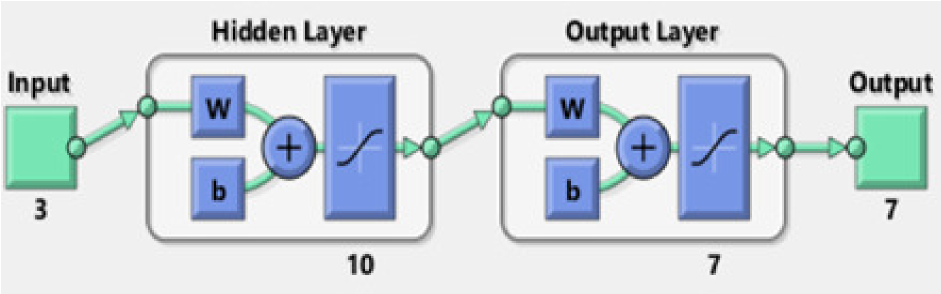

Fig. 4. Basic Structure of a proposed Feed-forward Back Propagation Algorithm

In order to compare the performances of proposed ANN cascade-forward back propagation algorithm and feed-forward back propagation algorithm, the layer size of feed-forward back propagation algorithm has been selected to be the same as feed-forward back propagation. Cascade-forward back propagation and feed-forward back propagation algorithms are similar in shape. However, the cascade-forward back propagation algorithm includes a weight link between the input layer and each layer. The additional link can increase the learning speed of the network's desired relationship. Cascade-forward back propagation and feed-forward back propagation algorithms are both updates weights, but there is a difference which cascade-forward back propagation algorithm's each neuron layer is associated with all prior layer of neurons [17]. The basic structure of the proposed cascade-back propagation algorithm is shown in Fig 5.

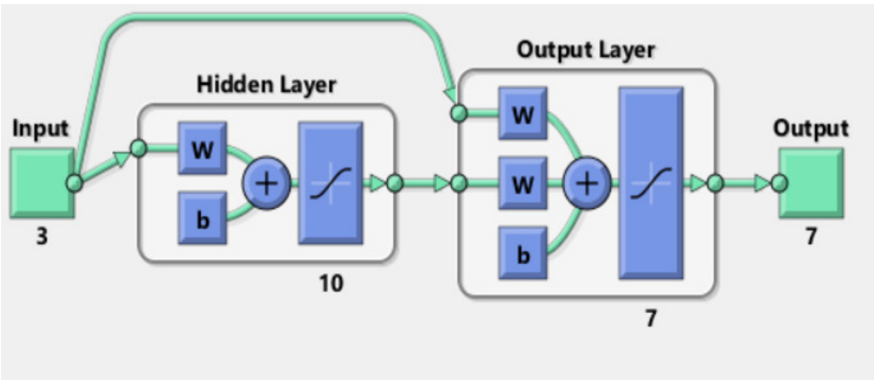

Fig. 5. Basic Structure of the proposed Cascade-forward Back Propagation Algorithm

In the structure of artificial neural networks, a training function is used together with a learning algorithm. There are numerous training functions such as Gradient Descent (GD), Gradient Descent with Momentum (GDM), Levenberg-Marquardt (LM), BFGS Quasi-Newton, Bayesian Regularization (BR), Scaled conjugate gradient (SCG) [15, 18, 19]. Levenberg-Marquardt, Gradient Descent and BFGS Quasi-Newton are often used in many studies because of their faster and better results. Therefore, these training functions, which come to foreground, have also been used in this study to obtain more optimal results.

4. Case study

In this paper, the input and output parameters of proposed ANN are shown in Table 2. This data has been obtained from Şanlıurfa region by installed PV panel system.

Table 2. Measured Data of installed PV panel system

Inputs			Outputs						
Ambient Temperature ('C)	Panel Temperature ('C)	Irradiance (W / m2)	Maximum Power(W)	Voltage at Maximum Power Point(V)	Current at Maximum Power Point(A)	Short Circuit Current(A)	Open Circuit Voltage(V)	Filling Factor(FF%)	Eta Rate (%)
34,687248	43,728157	861,80984	156,231856	26,032717	6,001366	6,64015	34,430152	0,683365	18,128344
35,072102	43,622185	857,94939	154,624577	25,805672	5,991883	6,612495	34,51033	0,677585	18,022576
34,195877	43,675556	854,62139	155,437032	26,101215	5,955165	6,596269	34,468131	0,683657	18,187824
34,966152	43,445797	848,49797	154,8033	26,037766	5,945337	6,547629	34,53565	0,684587	18,244392
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮

Given in Table 2, Ambient temperature (ºC), panel temperature (ºC) and irradiance values are given as input to the artificial neural network and it is aimed to estimate seven different output parameters belonging to PV panel.

Using MATLAB neural network toolbox, artificial neural network is established. Dataset has been introduced to the network. After that, training parameters have been adjusted. Finally, network has been trained for feed-forward back propagation and cascade-forward back propagation algorithms. For these two algorithms have been trained with three different training function. For all different algorithms and training function, regression and mean square error graph have been observed. Weights have been defined randomly and so results in any trial. For 10 training, results are presented in Table 3.

Table 3. Regression results of two different algorithms vs. three different training function

Learning Algorithm	Training function	R Percantage Values for Different Training (%)										
		1st	2nd	3th	4th	5th	6th	7th	8th	9th	10th	Mean Value
Cascade-forward backprop.	Levenberg-Marquardt(LM)	97.505	97.046	96.564	97.617	97.11	97.704	96.004	95.981	99.182	98.47	97,3183
	BFGS quasi-Newton(BFG)	98.338	98.012	96.596	97.801	98.535	98.232	96.697	95.087	96.516	97.257	97.3071
	Gradient Descent(GD)	98.542	97.321	95.71	96.702	98.069	96.701	98.63	97.283	95.879	96.267	97.1104
Feed-forward backprop.	Levenberg-Marquardt(LM)	95.035	98.605	98.597	99.839	98.45	99.842	99.704	99.574	99.684	97.207	**98,6537**
	BFGS quasi-Newton(BFG)	95.536	98.06	98.573	98.569	98.429	98.171	98.243	98.662	97.727	97.795	97,9765
	Gradient Descent(GD)	97.486	96.892	98.185	97.365	97.967	98.121	97.371	97.291	97.624	98.423	97,6725

Table 3 shows the regression results of the trained network using Cascade-forward backpropagation and Feed-forward backpropagation learning algorithms together with three different training functions. The fact that the regression values given in the table are close to 100 percentage indicates that the artificial neural network correctly predicts the output parameters of PV system. The high rate of prediction also depends on the learning algorithm and the training function. The optimal choice of these two parameters is of great importance in terms of estimating studies. The highlight of these elections is clearly seen in the Table 3. The best regression results have been obtained with the combination of the Feed-forward backpropagation learning algorithm and the Levenberg Marquardt training function.

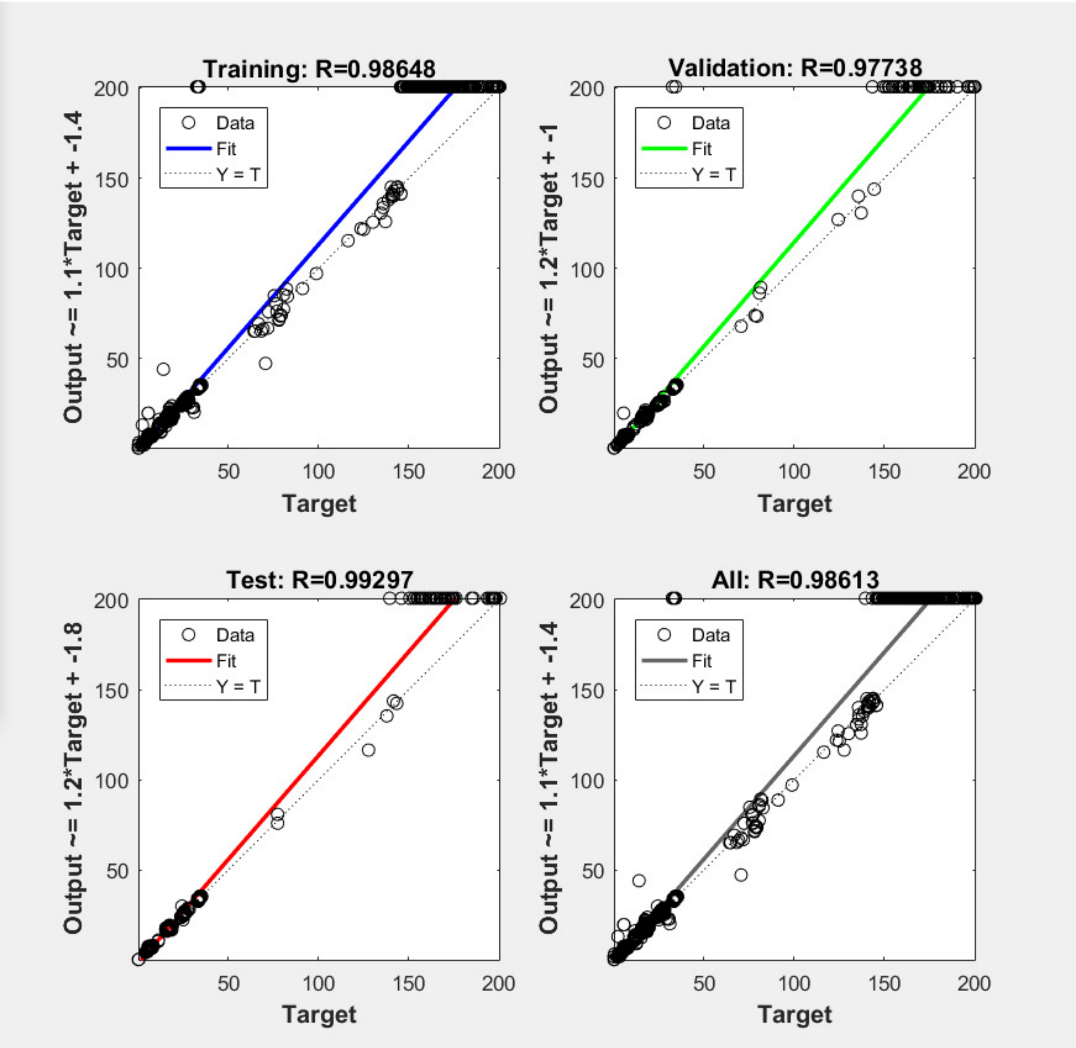

Fig. 6. Best Regression Result for Proposed Feed-forward Back propagation with Levenberg-Marquardt function

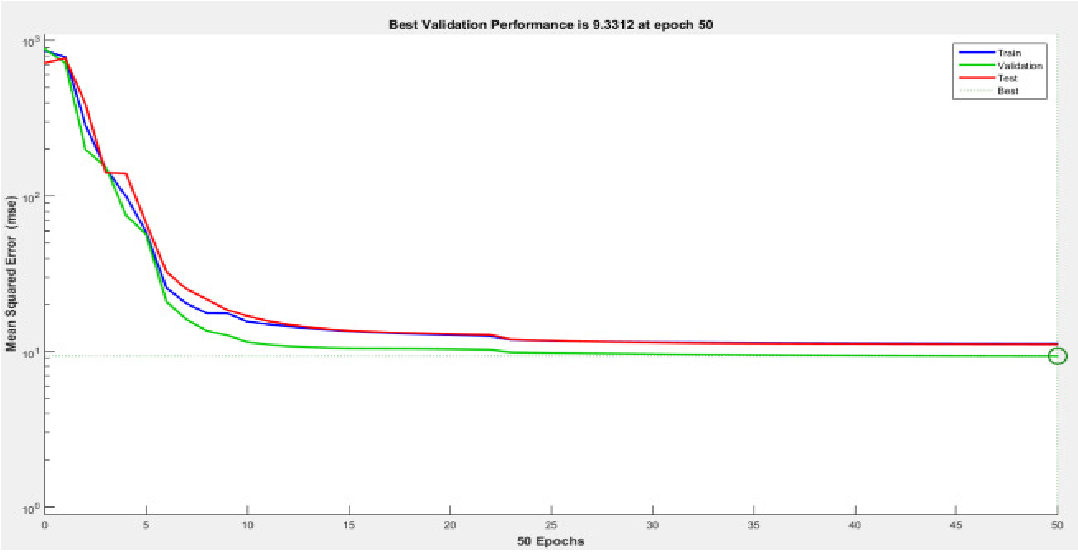

Fig. 7. Mean Square Error of Proposed Feed-forward Back propagation with Levenberg-Marquardt function

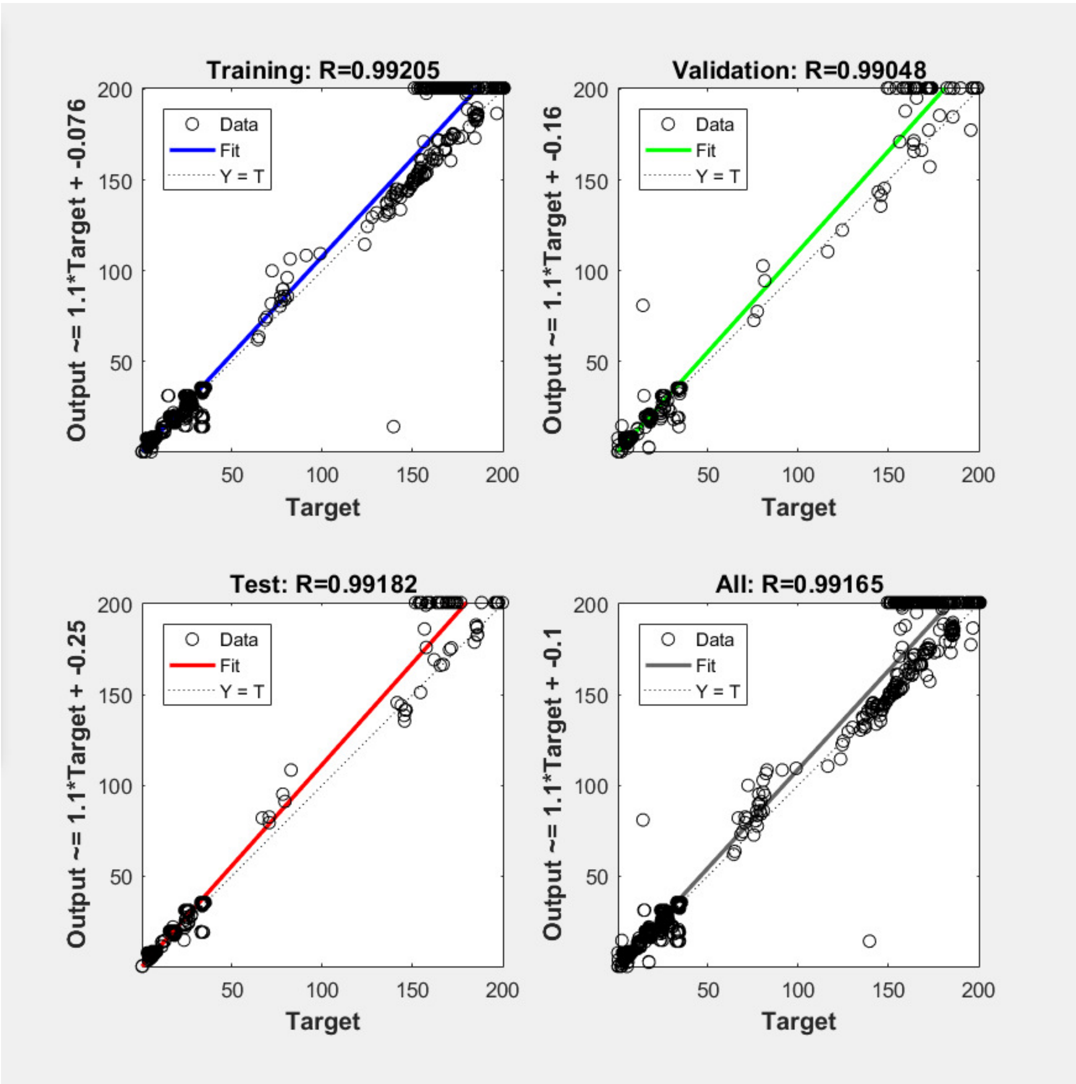

Fig. 8. Best Regression Result for Proposed Cascade-forward Back propagation with Levenberg-Marquardt function

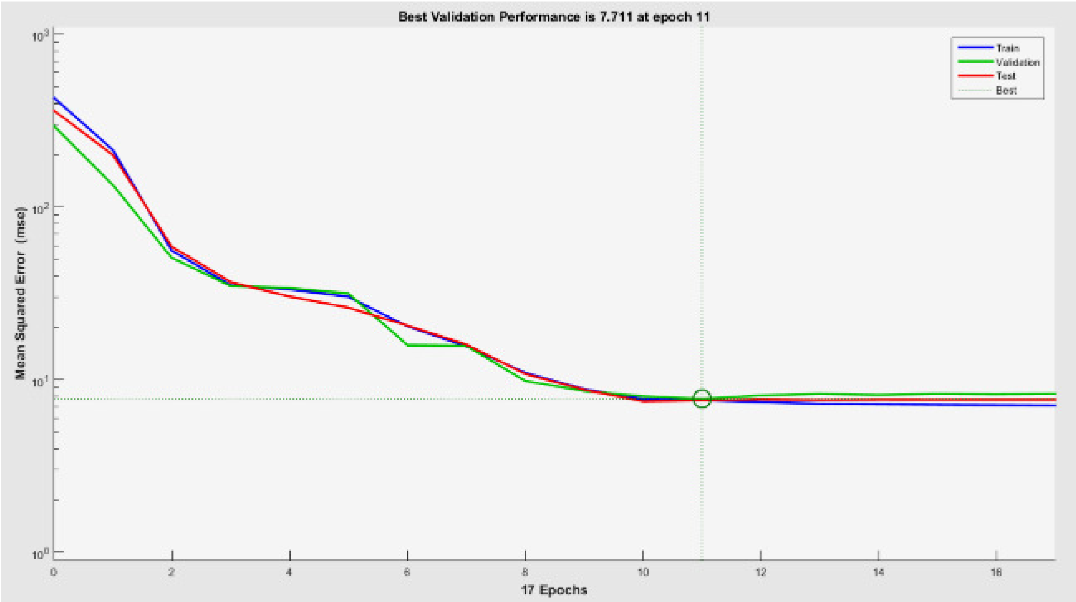

Fig. 9. Mean Square Error of Proposed Cascade-forward Back propagation with Levenberg-Marquardt function

5. Conclusion

In this paper, estimation of electrical characteristics and maximum power point of Photovoltaic (PV) panel under variable environmental conditions in Şanlıurfa region (southeast of Turkey) has been proposed. Hence, two artificial neural network algorithms have been used for estimation of the system's output parameters. Comparing the feed-forward back propagation and cascade-forward back propagation algorithms, feed-forward back propagation algorithm performs better results in all of training attempt. In training functions, Levenberg Marquardt has been seemed to be successful in making the most accurate estimate for output values. All results taking into account, desired results were obtained by feed-forward back propagation algorithm with Levenberg Marquardt training function. The proposed system is the first study by means of installing in Şanlıurfa region and also estimating all variables of a PV panel with Cascade-Forward Backpropagation and Feed-Forward Backpropagation.

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