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OUTPUT POWER ESTIMATION OF A PHOTOVOLTAIC PANEL BY EXTREME LEARNING MACHINE

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Abstract

Original scientific paper

In this study, the output power of a photovoltaic (PV) panel under different operating conditions was estimated with the help of an extreme learning algorithm (ELM). For this purpose, a PV panel with a power of 180W was installed, and the open circuit voltage, short circuit current, panel temperature, and solar radiation of this panel were measured and recorded at regular intervals. A total of 75 measurement data were obtained. The maximum power of the panel was calculated using the open circuit voltage and short circuit current information. While panel temperature and solar radiation were given as inputs to the regression model of the PV panel based on ELM, the output of the regression model was taken as the maximum power of the PV panel. To improve the prediction accuracy of ELM, the number of input neurons of ELM and the type of activation function used in the hidden layer were determined by trial and error method. The generated PV data set is separated into training and testing sets. The performance of the method was examined with the 5-fold cross-validation method. For this purpose, the dataset was divided into 5 equal parts. One of these parts was used for testing the ELM and the remaining four sets were used for training the ELM, and this was done by changing the test set each time. Thus, the network was trained and tested 5 times with different sets, and the test result of the network was obtained by averaging the sum of the performances of all test functions. Regression results obtained from ELM are given for different numbers of hidden layer neurons and different types of activation functions in the hidden layer. The best prediction result of ELM was obtained for the case where the hidden layer activation function was tangent sigmoid and the number of hidden layer neurons was 20. The R-values were found to be 1 when the number of hidden layer neurons was 20 and tangent and radial basis activation functions were used. From the results obtained, it has been seen that ELM predicts the output power of the PV panel with very high accuracy. It is concluded that ELM is a useful tool for estimating the PV panel output power.

Keywords: *Extreme learning algorithm, regression, PV panel.*

ÇIKIŞ GÜCÜ UÇ ÖĞRENME ALGORİTMASI İLE BIR FOTOVOLTAİK PANELİN ÇIKIŞ GÜCÜ TAHMİNİ

Özet

Orijinal bilimsel makale

Bu çalışmada, farklı çalışma şartları altında bir PV panelin çıkış gücü uç öğrenme algoritması (UÖA) yardımı ile tahmin edilmiştir. Bu amaçla, 180 W gücünde bir PV panel kurulmuş, bu panelin açık devre gerilimi, kısa devre akımı, panel sıcaklığı ve güneş ışınımı belirli aralıklarla ölçülerek kaydedilmiştir. Toplam 75 adet ölçüm verisi elde edilmiştir. Açık devre gerilimi ve kısa devre akımı bilgileri kullanılarak panelin maksimum gücü hesaplanmıştır. UÖA kullanılarak oluşturulan PV panelin regresyon modeline giriş olarak panel sıcaklığı ve güneş ışınımı verilirken, regresyon modelinin çıkışı PV panelin maksimum gücü olarak alınmıştır. ÜOA'nın tahmin doğruluğunu iyileştirmek için UÖA'nın giriş nöron sayısı ve ara katmanda kullanılan aktivasyon fonksiyonu tipi deneme yanılma yöntemi belirlenmiştir. Oluşturulan veri kümesi eğitim ve test kümesi olarak ayrılmıştır. Yöntemin başarımı 5-katlamalı çapraz doğrulama yöntemi ile incelenmiştir. Bu amaçla, veri kümesi 5 eşit parçaya bölünmüştür. Bu parçalardan biri test için ayrılıp geri kalan dördü ağın eğitim için kullanılmış ve bu işlem her defasında test kümesi değiştirilerek gerçekleştirilmiştir. Böylece 5 defa ağ farklı kümelerle eğitilip test edilmiş ve ağın test sonucu bütün test fonksiyonlarının performanslarının toplamının ortalaması alınarak elde edilmiştir. UÖA'dan elde edilen regresyon sonuçları farklı ara katman nöron sayısı ve farklı tip aktivasyon fonksiyonları için verilmiştir. ÜOA'nın en iyi tahmin sonucu ara katman aktivasyon fonksiyonu tipinin tanjant sigmoid ve ara katman nöron sayısının 20 olduğu durum için elde edilmiştir. Elde edilen sonuçlardan UÖA'nın PV panelin çıkış gücünü çok yüksek doğrulukta tahmin ettiği görülmüş ve UÖA'nın PV panellerin çıkış gücünün tahmininde etkin bir araç olarak kullanılabileceğini göstermiştir.

Anahtar Kelimeler: *Uç öğrenme algoritması, regresyon, PV Panel.*

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1 Introduction

Solar energy is an environmentally friendly energy source. However, clouds and weather conditions can affect the availability of solar energy. Therefore, the electrical energy produced from solar energy may vary depending on different parameters. For these reasons, responding to load demand with solar power plants is a very difficult task. One way to prevent this situation is to estimate the output power of photovoltaic (PV) systems [1]. Different forecasting methods can be used to estimate solar energy. This forecast will help power plant operators monitor solar conditions and prepare for any rapid fluctuations in power output. Additionally, energy storage systems can be considered as one of the possible solutions that can help in dealing with changes in solar energy. In addition, energy storage systems bring high and maintenance costs to the system.

However, the power obtained from PV systems varies due to reasons such as solar radiation, shading, and panel protection. One approach to changing variability is to estimate PV output power as accurately as possible. Using such visions, the energy storage efficiency capacity of off-grid PV users can be optimized [2]. Similarly, grid-connected distributed PV energy usage schedules can be optimized, and grid-connected PV systems can use these forecasts to develop their strategies using electricity market offers, allowing system operators to better organize their reserves. The output power of a single PV system is highly affected by local weather changes. Photovoltaics has its disadvantages. Unpredictable weather conditions have a major impact on the electricity generation of solar power plant when connected to the electricity supply and distribution grids. For this reaosn, precise and reliable estimation of solar system output power are crucial for the safe and cost-efficient operation of the PV power system and forecasting [3].

If there are PV electricity generation plants with high power in the interconnected system, serious disruptions may occur in the network in case of cloudiness. In this case, the power at the PV output will show a rather large and sudden change. When this change in irradiance occurs during a sudden change in load, the situation will worsen [4]. Therefore, it is clear that reliable estimation tools are crucial for PV technologies, optimizing the performance of solar power plants in the planning and operating stages, and ultimately accurately assessing the economic return. Accurate estimation of solar power output is crucial to evaluate the actual performance of PV panels.

In literature, some methods have been proposed for the prediction of the solar panel’s output power. In [5], an improved feedforward neural network model was proposed for power output prediction of solar panel. The neural network model was optimized using the particle swarm optimization algorithm. Two hidden layers were used in the neural network model and the inputs to this network are day, time, cloudiness index, air temperature, wind speed, air humidity, radiation, precipitation, and air pressure. In [6], a neural fuzzy network is proposed for the prediction of daily energy production. Day, irradiance, air temperature, wind speed, air humidity, and air pressure are given as input to the neuro-fuzzy network. The prediction accuracy of this model was evaluated with data obtained from three PV plants and the average prediction error was found to be 5%. In [7], a hybrid model was proposed for the output power estimation of a solar power plant. The training set was divided into four groups according to the weather conditions, and each training set was used to train four support vector machine models. According to the weather types of the predicted day, the appropriate support vector machine model is selected. Data taken at 15-minute intervals yielded predictions for one day ahead with a mean square error of 10.5%. The mean square error for each support vector machine was 9.12% for the cloudy model, 12.6% for the foggy model, 12.4% for the rainy model, and 7.85% for the sunny model. In [8], a hybrid model combining a power support vector machine and a similar day method was used to predict power output for 50 days. In [9], a new method for PV power estimation based on machine learning, image processing, and acoustic classification techniques is proposed. In [10], a deep learning-based neural network is proposed to estimate solar irradiance. The results of the proposed method are compared with the results obtained from support vector machines and feedforward neural network methods. In [11], a residential distribution network is proposed for output power estimation of PV. In [12], compared the performance of four artificial neural networks (ANNs) models for predicting the PV solar power. They utilized four PV data sets and online weather data. The obtained results provide high accuracy in analysing weather data, which is suitable and useful for planning the PV plant. In Ref. [13], authors investigated the performance of deep learning methods and created models ANNs and recurrent neural networks to forecast solar radiation. Both hidden layers were included in the ANN model. In Ref. [14], to determine the PV modules' performance, an ANN model was developed. They used temperature and irradiance parameters as inputs and current and voltage parameters as outputs for their feed-forward artificial neural network model. Levenberg-Marquardt and robust back propagation are the two training algorithms the authors experimented with throughout training. An ANN technique was developed by Ref. [15] to investigate and model the fouling effect on solar PV glass. The network input variables were six meteorological data sets. There are 35 neurons in the single layer of this artificial neural network design. In order to forecast PV power output, Ref. [16] developed a model based on ANN and an adaptive neuro-fuzzy inference system. Horizontal and global diffused irradiances, air pressure and temperature outside, precipitation, wind speed, length of daylight, relative humidity, and panel surface temperature were chosen as network input parameters. This study’s training algorithm was Levenberg-Marquardt. ANN-based artificial intelligence methods have widely used in estimating PV panel output power. However, ANN has some disadvantages such as low learning speed and local minima. There are two primary causes for this behavior. One of them is the use of slow gradient-based learning algorithms in neural network training, and the other is the learning algorithms iteratively adjustment of the networks' parameters [17]. Recently, a new learning algorithm called extreme learning machine (ELM) has been proposed to eliminate the drawbacks of the ANN. The studies on ELM showed that ELM is feasible and promising in real-time applications [18].

In this study, the output power of a PV panel under different operating conditions was tried to be estimated with the help of an Extreme Learning Machine (ELM). For this purpose, a PV panel with a power of 180 W was installed and the open circuit voltage and short circuit current of this panel, panel temperature, and solar radiation were measured and recorded at regular intervals. A total of 75 measurement data were obtained. The maximum power of the panel was calculated from the open circuit voltage and short circuit current. While panel temperature and solar radiation were given as inputs to the regression model of the PV panel based on ELM, the output of this regression model was taken as the maximum power of the PV panel. Some parameters of ELM (number of input neurons, type of activation function) were adjusted to give the best results by trial and error method. The dataset is separated into training and test sets. The performance of the proposed method was examined with the 5-fold cross-validation method. For this purpose, the dataset was divided into 5 equal parts. One of these parts is reserved for testing the network whereas the remaining four sets are used for training the network, and this is done by changing the test set each time. The network is trained and tested 5 times in total with different sets. The test result of the network is the average of the sum of the performances of all test functions. The ELM was implemented using MATLAB software. From the regression results obtained, it was seen that ELM predicted the output power of the PV panel with very high accuracy. In addition, results show that ELM can be a reliable tool for estimating the output power of solar panels.

2 The Mathematical Model of Photovoltaic

It is essential for a PV model to make precise predictions of dependable current-voltage (I-V) and power-voltage (P-V) curves in actual operating situations. The most common equivalent circuit that describes well the electrical behaviour of a PV system is the five-parameter circuit model, shown in Figure 1 [19]. This equivalent circuit model shown consists of the photo-current source I_L, the shunt resistor R_{sh}, a diode parallel to this resistor, and the series resistor R_s. When the amount of radiation falling on the cell increases, the electric current produced also increases. The voltage obtained from the solar cell is shown as V. The resistance value R_s shown in the series connection to the output end is equal to the semiconductor material's total resistance forming the cell and the contact resistances formed at the connection points of the cells. Parallel (shunt) resistance R_{sh} is taken as the sum of the resistances occurring between the layers and around the cell in materials with a thin film structure consisting of very thin layers. It is determined that the series resistance value is very small compared to the parallel resistance and could be neglected [19], [20], [21]. The actual resistance of the circuit can be considered as series resistance. In the ideal case, R_s is zero and R_{sh} is infinite. Although the perfect conditions are unattainable, manufacturers work towards minimizing the influence of both resistances to enhance their products [20].

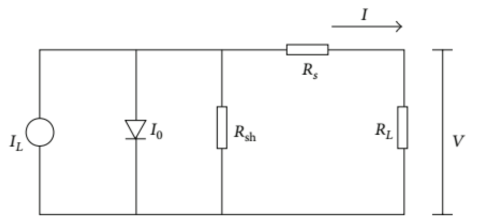


Figure 1. Single diode equivalent circuit for a solar cell.

From Figure 1, the output current of the cell is I_L can be written by using Kirchhoff's law as follows:

$$I = I_L - I_D - I_{sh}, \tag{1}$$

Diode current I_D can be written as follows:

$$I_D = I_o\left[\exp\left(\frac{q(V+R_sI)}{nkT}\right)-1\right], \tag{2}$$

In Eq. 2, k; Boltzmann constant, q; unit electron charge amount, T; It shows the absolute temperature of the cell in Kelvin. If Eq.1 is substituted into Eq.2, Eq.3 is obtained as follows:

$$I = I_L - I_o\left[\exp\left(\frac{q(V+R_sI)}{nkT}\right)-1\right]-\frac{V+IR_s}{R_{sh}}, \tag{3}$$

3 Extreme Learning Machine

The fact that the learning rate of feedforward neural networks is generally much slower than necessary is a major problem in practice. There are two reasons:
1) These networks are typically trained using slow gradient-based learning algorithms.
2) The network's parameters are iteratively adjusted by this learning algorithm.

G. B. Huang suggested a unique learning strategy for the single hidden layer neural network (SLFN) that differs from these conventional training procedures. The extreme learning machine (ELM) is the name given to this learning method. In this learning algorithm, the input weights are selected randomly and the single hidden layer neural network's (SLFN) output weights are computed analytically. Theoretically, this learning method offers a fast learning rate with strong generalization performance. [22], [17].

Figure 2 shows the structure of a SLFN. In this figure, l, w, f present input weights, output weights, and activation function (AF) in the hidden layer, respectively [22].

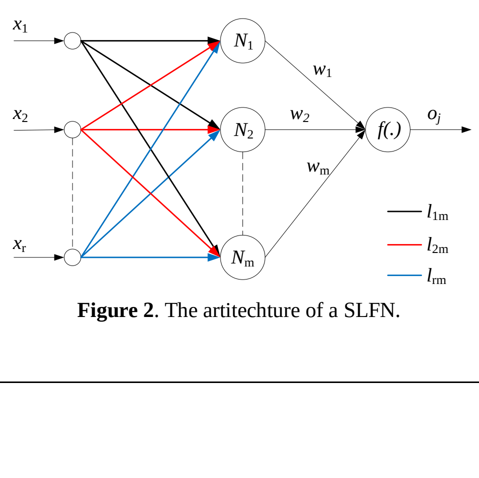


Figure 2. The artitechture of a SLFN.

The SLFN’s output can be obtained as follows:

$$o_j = \sum_{i=1}^{m} w_i f(l_i x_r + b_i) \tag{4}$$

In Eq.4; x is inputs; b is bias value. The standard SLFN can approximate the samples without error and there are values of w, l and b that will make the error zero [11], [20]. The following equation shows one way to write the m set of equations.

$$H \times w = T \tag{5}$$

In Eq. 5; H is known as output matrix of the hidden layer and it can be obtained as follows:

$$H(l_1,...,l_m,b_1,...,b_m,x_1,...,x_m) = \begin{bmatrix} f(l_1x_1+b_1) & \dots & f(l_mx_1+b_m) \\ \vdots & \dots & \vdots \\ f(l_1x_m+b_1) & \dots & f(l_mx_m+b_m) \end{bmatrix}$$

A quick explanation of ELM for SLFNs are given as follows:

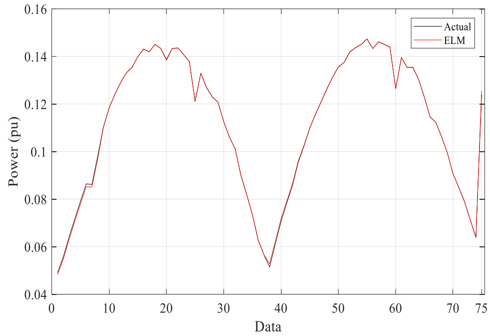
a) Random assignments are made for the input weight and bias.
b) For the hidden layer, the output matrix H is acquired.
c) The output weight w is calculated [22].

Although ELM has many advantages, it may not be effective in estimating the output power of solar power plants where big data is available. In the current big data age, it is essential for creating an ELM algorithm that can train massive data sets. But when it comes to training massive data, the ELM has several drawbacks such as memory residency, difficulty with solving the matrix and online training [23].

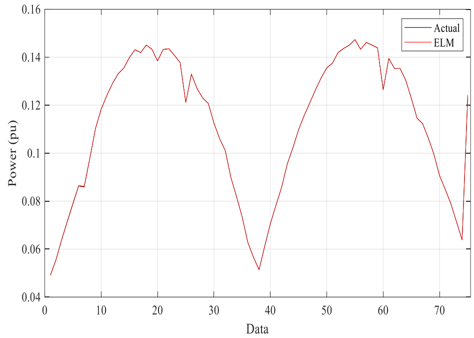
4 Simulations and Results

In this study, the power of a 180 W PV panel was tried to be estimated using ELM. For this purpose, solar radiation, panel temperature, open circuit voltage, and short circuit current of the PV panel were measured at 15-minute intervals. The maximum power of the panel was calculated using the open circuit voltage and short circuit current of the PV panel. The inputs of ELM are selected as panel temperature and solar radiation, and the output of ELM is the power of the panel. Additionally, input and output values to ELM were normalized and the results were given using 5-cross validation. The most important parameters affecting the performance of ELM are the number of hidden layer neurons and the type of *AF* in this layer. The regression performance of the ELM is given for different numbers of the hidden layer neurons and different types of *AF*.

Figure 3 shows the prediction results of ELM and actual results. The results are presented for tangent sigmoid activation function (TSAF) and hidden layer neurons (NHLN) with 10 and 20.



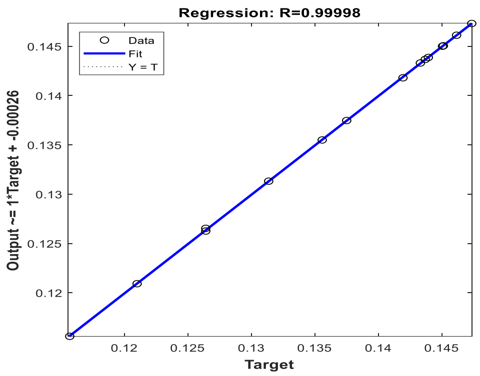
(a) NHLN: 10



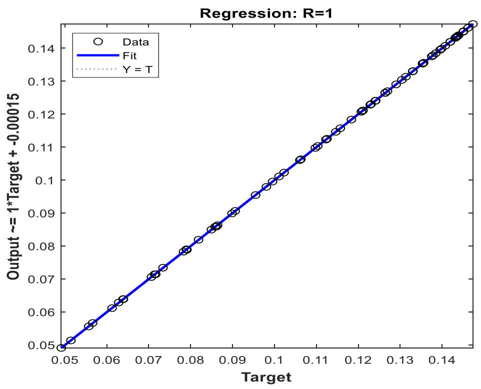
(b) NHLN: 20

Figure 3. The actual results and prediction results of ELM for TSAF.

The regression results are given in Figure 4. When the number of hidden layer neurons is increased from 10 to 20, the R-value increases from 0.99998 to 1. When Figure 4(a) and (b) are examined, it is seen that the prediction performance of ELM increases as the number of hidden layer neurons increases.



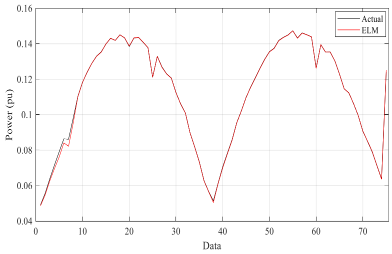
(a) NHLN: 10



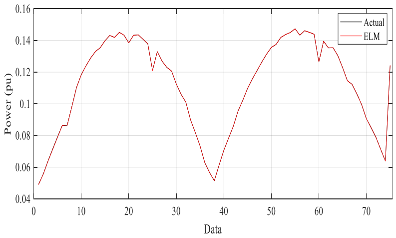
(b) NHLN: 20

Figure 4. Regression curves for TSAF.

The prediction results of ELM, which uses a radial basis activation function (RBAF), and actual results are given in Figure 5 for the number of hidden layer cells, 10 and 20, respectively.



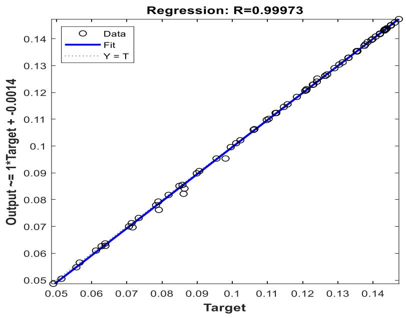
(a) The number of hidden neurons: 10



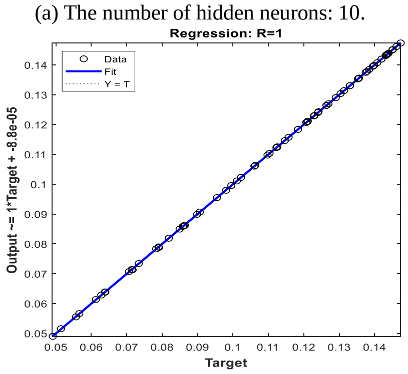
(b) The number of hidden neurons: 20

Figure 5. The actual results and prediction results of ELM for RBAF.

The regression results are given in Figure 6. When the number of hidden layer neurons is increased from 10 to 20, the R value increases from 0. 99973 to 1. When Figure 6(a) and (b) are examined, it is seen that the prediction performance of ELM increases as the number of hidden layer neurons increases.



(a) The number of hidden neurons: 10.



(b) The number of hidden neurons: 20.

Figure 6. Regression curves for RBAF.

The regression performance of the ELM for different types of activation functions and different numbers of hidden layer neurons is shown in Table 1. As can be seen from the table, the lowest root mean square error (RMSE) was obtained by using TSAF and 20 hidden layer neurons.

Table 1. The regression performance of the ELM for different types of activation functions and different numbers of hidden layer neurons.

AF	NHLN	RMSE	Training time (s)
TSAF	10	3.9646×10^{-4}	0.0136
	20	4.5486×10^{-5}	0.0156
RBAF	10	5.2283×10^{-4}	0.0156
	20	4.8058×10^{-5}	0.0156

To better validate the performance of the proposed method, the comparison studies were conducted. In the comparison studies, neural network, linear regression and quadratic Gauss regression models were used. The regression result obtained from neural network is given in Figure 7. Tangent activation function and the number of hidden layer neurons are used in the neural network structure. R-value was obtained the 0.91598.

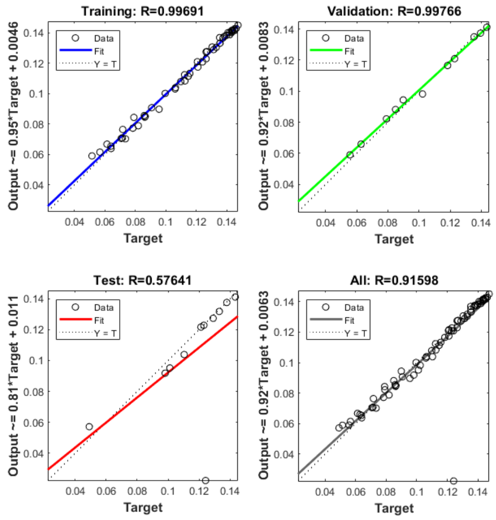


Figure 7. Regression curves for neural network.

Figure 8 and 9 show estimation results of linear regression and quadratic Gauss regression models. It is seen from these figures that linear regression model has better estimation performance than quadratic regression model.

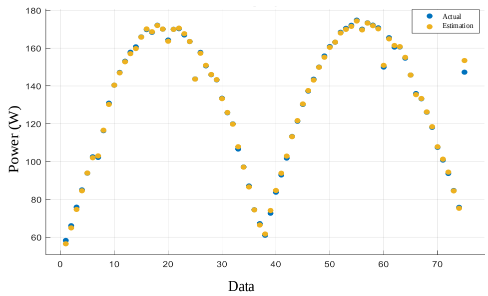


Figure 8. Estimation results of linear regression model.

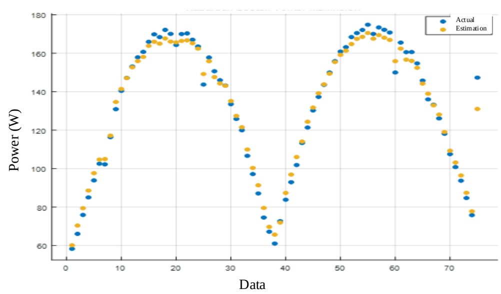


Figure 9. Estimation results of linear regression model.

5 Conclusion

This study presents an ELM based regression model for the estimation of PV panel output power. Training and test data for ELM was obtained from an experimentally established PV panel. PV panel has a power of 180 W. The irradiation on the panel, panel temperature, open-circuit voltage of the PV panel and short-circuit current of the PV panel, were recorded at 15-minute intervals. A total of 75 measurement data were obtained by measurements. Panel temperature and irradiation were applied to inputs of ELM whereas panel output power to output of the ELM. The ELM algorithm was carried out using MATLAB software. The optimal values of some parameters of the ELM such as input neurons, activation function are found by trial and error method to improve its regression performance. The regression performance of the ELM was evaluated by a 5-k fold. The ELM gives the best regression result for the case where the hidden layer activation function was tangent sigmoid and the number of hidden layer neurons was 20. The comparison studies were given to validate the regression performance of the ELM. The regression results show that the ELM predicts the output power of the PV panel with very high sensitivity.

Some factors such as the type of PV material, cloud and other shading effects, dust, module orientation and different weather conditions.

Declaration

The authors declare that the ethics committee approval is not required for this study.

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