Modeling and Prediction of Photovoltaic Power Output Using Artificial Neural Networks Considering Ambient Conditions

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Abstract:- The forecasting of photovoltaic power output with a reliable predictive tools considering ambient conditions is very important in order to dissemination the technologies of the PV system, as well , to improve the performance of the photovoltaic systems in the planning. The aim of this work is present a solar power modeling method using artificial neural networks (ANNs). Two neural network structures, namely, general regression neural network (GRNN) feed-forward back propagation (FFBP), have been used to model a photovoltaic output power and approximate the generated power. Both neural networks have five inputs and one output. The inputs are ambient temperature, cell temperature, wind speed, humidity, and irradiance; the output is the power. The data used in this paper taken from the experimental work which has been conducted in the energy laboratory of energy engineering department, Baghdad city, started from January, 2017 to May, 2017. The five months of data was used for training and testing the neural networks. The results show that, the solar irradiance has the greatest effect on the estimation of the photovoltaic power output with ratio (33.7%) then the cell temperature, and ambient temperature with ratios (28.5%, 25.3%), respectively, while humidity has medium effects with ratio (12.4%). Wind speed has the least effect with ratio (0.1%). The results of simulation indicate that the two models were accurate and can be effectively used for prediction of photovoltaic power output. However, it was demonstrated that the GRNN network model gave more accurate results when compared with those obtained using FFBP network model. As well, GRNN network proved its ability to predict in less time than FFBP network.

Keywords: Artificial neural network; PV; Power prediction; Ambient conditions; Baghdad

1. Introduction

Solar energy is the most important renewable energy sources at all. It is well located in all parts of the world and environmentally friendly. In addition, it is help to mitigate greenhouse gas emissions and thermal damage. Where, it can be converted directly into electricity using photovoltaic system (PV devices) [9]. The electrical power generated by the photovoltaic solar cell depends mostly on the ambient conditions such as: solar radiation, ambient temperature, humidity, wind speed and dust [10]. As well, the work discussed by [1] illustrated that these ambient conditions have an effect on the performance of photovoltaic solar cell in Baghdad city, Iraq. Therefore, it is important to provide a reliable predictive tool to predict the PV output power in order to dissemination the technologies of the PV system, as well, to improve the performance of the PV systems in the planning.

Artificial neural network (ANN) is one of the most important artificial intelligence techniques; the working principle depends in general on the artificial neurons which are the processing elements [12]. Where, it has the ability to deal with noisy data or partial information and can be very efficient especially in the situations where it is not probable to describe the steps or rules which lead to the clarification of the problem [16] and can model the system via samples only, therefore, it can be used to predict the PV output power with reliable and fast process [7].

In the last few years, modeling of PV plant has become an active research field using new models based on artificial intelligence methods, especially ANN technique. So, there have been many studies in order to establish the effect of weather factors on the performance of photovoltaic cells and modeling the result using ANN technique. A.Al-Amoudi and L.Zhang, 2000 used an ANN for the solar array modeling and maximum-point prediction using two architectures of radial basis function networks concluded that this model is satisfactorily accurate in the representing of I/V and P/V characteristics of the PV arrays [2]. The work discussed by Ashraf and Chandra, 2004 used three models of ANN to forecast the performance of electrical output energy generated from a working grids connected solar PV system with 25-kWp and 100-kWp installed at Minicoy Island, India [3]. Taherbaneh and Faez, 2007 estimated the maximum power point (Pmax) of silicon solar panels using two types of ANNs; Back Propagation and radial basis function with different environmental factors [14]. In another work, Mekki et al., 2007, have been modeled and simulated photovoltaic panel using artificial neural network and VHDL language in BLIDA, Algeria [11]. Brano et al., 2014 used three types of artificial neural networks: Recursive Neural Network (RNN), one hidden layer Multilayer Perceptron (MLP) and Gamma Memory (GM) trained using back propagation method to predict output power of the photovoltaic (PV) modules where, the results of modeling show that the adaptive techniques of ANNs were capable to forecast the power output of the PV panel with a large accuracy and small computational time errors [4].Teo et al., 2015used artificial neural network to forecast the photovoltaic output power, Extreme Learning Machine was the training algorithm. The simulation results show that the proposed model forecasts PV power with high accuracy by using bigger training dataset. Also, it showed that the sequences of the input variables have an impact on the performance of the ANN model [15]. Also, the work discussed by Shekher and Khanna, 2016 used feed forward back propagation (FFBP) neural network to model and approximates the generated power of 150KW PV array system in northern India. The input data were (temperature and irradiance) while PV power was the output, the simulation results showed good modeling performance since the regression error of real and predicted data was very low [13]. In another work, Cancro1 et al., 2016used artificial neural network (ANN) for predicting the back - plate temperature (working temperature) of a concentrator PV module (CPV) in Italy, the results show that the proposed model forecasts the PV power with high accuracy, where the mean value of RMSE was 2.67°C [5].

In this research, two neural network structures, namely, general regression neural network (GRNN) and feed-forward back propagation (FFBP) have been used to model a photovoltaic output power and approximate the generated power considering ambient conditions. Where, the FFBP neural network is the simplest and first type of artificial neural network architecture. The information of signals flow is only in the forward direction from the input layer, through the hidden layer and to the output layer. Each layer includes a transfer function to converts the net input value to the node's output value. The connections between neurons are called weights [16].Artificial neural network can realize the input data, understands how the system works and can forecasted new data that didn't offer through the training process [6]. The training process is used to get the relationship between the values of input and output data of any model using an algorithm, which is a list of rules or equations used to solve a specific problem [8]. However, there are many types of training algorithms which can be used for the neural networks training, but in this work Levenberg-Marquardt algorithm will be used to train the feed forward back propagation neural network (FFBP).

While, GRNN is an approximation function and can be forecast the output values of a known input data using training data. Therefore, it will predict the output depending on the average weighted that is provided by the output of the training dataset. It is architecture includes two layers; radial basis layer with radial basis function and special linear layer with linear transfer function. In GRNN the only value of spread constant (σ) is unknown, which can be adjusted with range from 0 to 1by the training process to reduce the error between the network outputs and targets to get the best fit. The major benefit of GRNN is to speed up the training process which can helps the neural network to be taught earlier unlike typical feed forward neural networks [17].

4. Methodology

4.1Experimental Work

In this research the database was taken from the experimental work which has been conducted in the energy laboratory of energy engineering department, Baghdad city from January, 2017 to May, 2017. All readings during this work recorded with period time started from 8:00 AM to 2:00 PM. The experimental work focused on the clarification the effect of weather factors on the performance of a single monocrystalline PV solar module, with maximum power: 30W, cell area: $0.282m^2$, open circuit voltage: 22V, short circuit current: 1.9Amp, voltage at maximum power: 17V, current at maximum power: 1.76Amp.Where, a standard calibration procedure has been made to the monocrystalline PV solar cells according to standard procedure supplied by the manufacture. Solar analyzer prova 200 used to measure PV power and other electrical parameters will be automatically calculated and then transferred the information to be store in work sheet of Excel program. As well, weather station vantage pro2 has been used to measure the weather factors such as wind speed, ambient temperature and humidity. In addition, the temperature of PV solar module has been measured using temperature sensor while, solar power meter “Data Logging Solar Power Meter TES-1333R” has been used to measure the solar radiation intensity in W/m^2.**Fig.1** shows the devices of the experimental work.

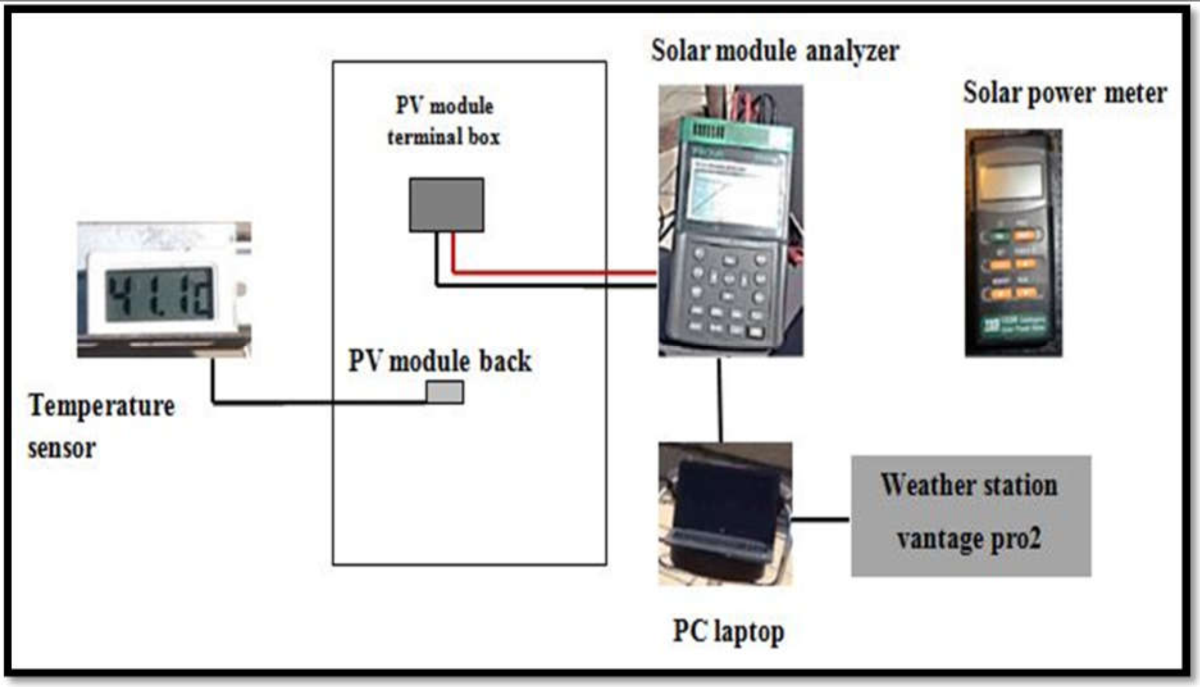

Fig.1 Setup of the experiment.

4.2 ANN Models

In this study, two models for ANNs are proposed to estimate the generated PV power system considering ambient conditions, these models will be based on two neural network structures, namely, general regression neural network (GRNN) and feed-forward back propagation (FFBP),and propose when the input variables (ambient temperature, cell temperature, wind speed, humidity, and irradiance) are known.**Fig.2** illustrated the basic flow to construct the artificial neural networks models.

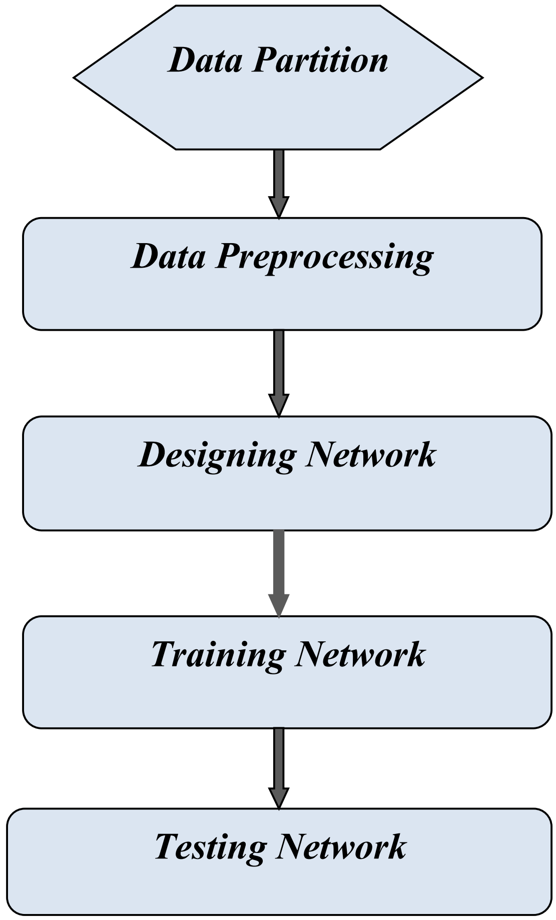

Fig.2 Basic flow for construction ANN models.

In the FFBP case, the number of hidden layer and number of neurons in each layer was chosen using trial-and-error procedure, and the best number of hidden layer was found to be two while, the best number of hidden nodes in the first and second hidden layers was found to be 32-16, respectively. A model of this network is shown in **fig.3**.

Fig.3 FFBP ANN model.

In the GRNN case, the first layer has as many neurons as there are inputs/targets vectors in the input vectors with radial basis function. The number of neurons in the second layer is set to the target vectors with linear transfer function. After several attempts to determine the best value of spread constant with range from 0 to 1, the value of 0.6 was selected as the best number in the range and showed good performance indication. A model of this network is shown in **fig.4**.

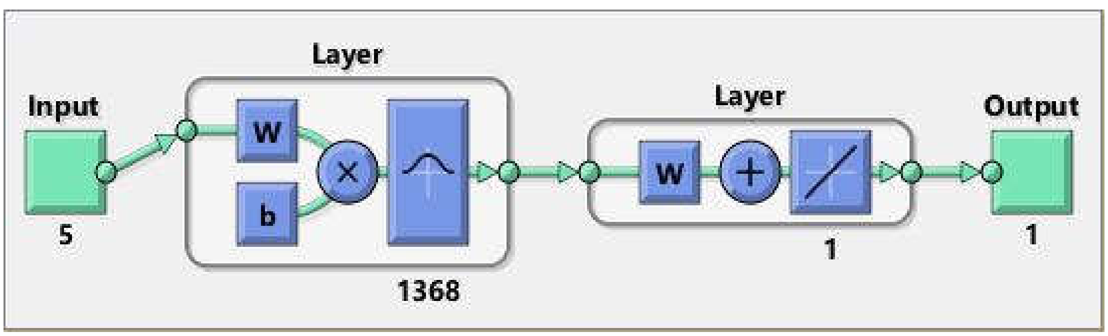

Fig.4 GRNN ANN model.

The performance of the developed ANNs models was evaluated with (mean squared error (MSE), root mean square error (RMSE), correlation and coefficient of determination (R-Squared)).The MSE and RMSE can be calculated from equations(1) and (2) as follows:

$$MSE=\frac{1}{N}\sum_{t=1}^{N}\left(Zt-\overline{Zt}\right)^2 \quad (1)$$

Where, N=number of predication values, $\overline{Zt}$ = the vector of the Nprediction values, and Zt = the vector of the real values [12].

$$RMSE=\sqrt{\frac{1}{N}\sum_{t=1}^{N}(y_i-x_i)^2} \quad (2)$$

Where, y_i = the predicted value, x_i = the actual value, N= the number of observation, Ashraf and Chandra, 2004.

5. Results and Discussion

5.1 ANN models

Tables 1and 2 shows the training time that the neural networks required, magnitude of the mean squared error (MSE), root mean square error (RMSE), correlation and coefficient of determination (R-Squared) between the targets (PV power in Watt using the experimental work results) and outputs (PV power in Watt using the neural networks models) for the training and testing process based on the FFBP and GRNN ANN models, respectively. **Fig.5** shows the error performance of the training FFBP ANN model. **Figs.6, 7** show the output (photovoltaic power output using the proposed model) versus the target (photovoltaic power output using the experimental work results) for the FFBP and GRNN ANN models, respectively. While **figs.8** and **9** shows the scatter plot of the target and network output for the FFBP and GRNN ANN models, respectively, for the testing results.

Table.1 FFBP ANN model results.

Process	Training time (sec)	MSE	RMSE	Correlation	R-Squared
Training Process	846	0.000533	0.023065	0.998902	0.99781
Testing Process	_	0.004929	0.0699	0.989879	0.97986

Table.2 GRNN ANN model results.

Process	Training time (sec)	MSE	RMSE	Correlation	R-Squared
Training Process	552	0.000254	0.015876	0.999479	0.99896
Testing Process	_	0.003588	0.05935	0.992640	0.98533

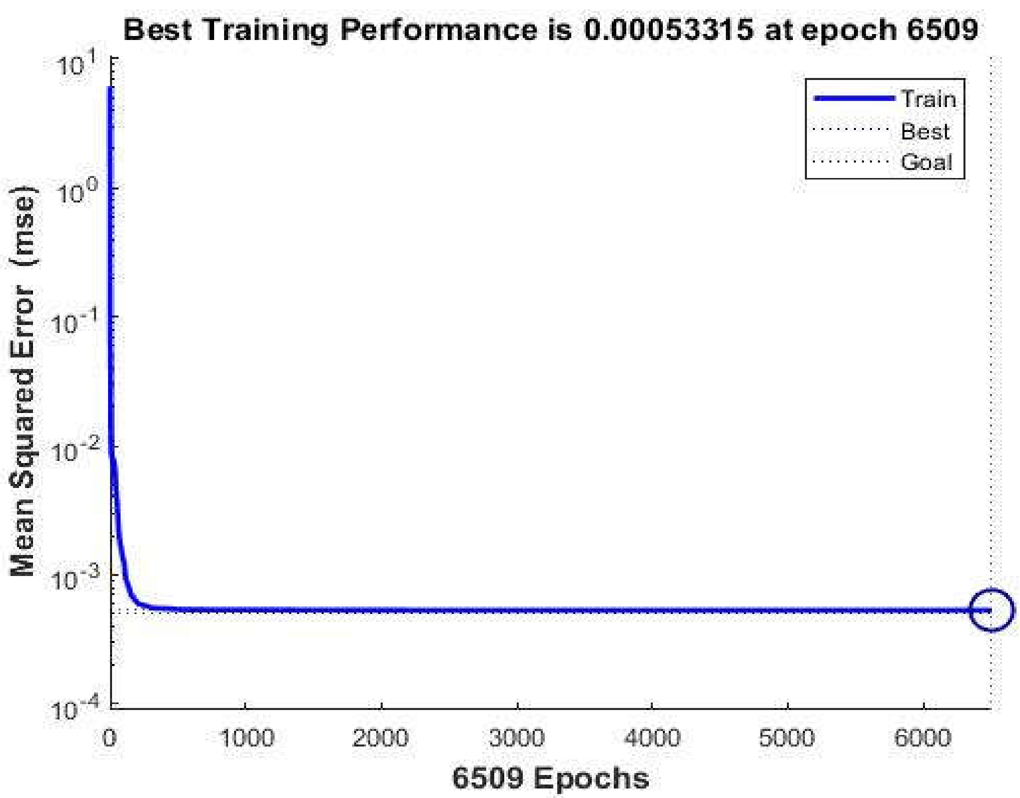

Fig.5 Error performance for the training FFBP ANN model.

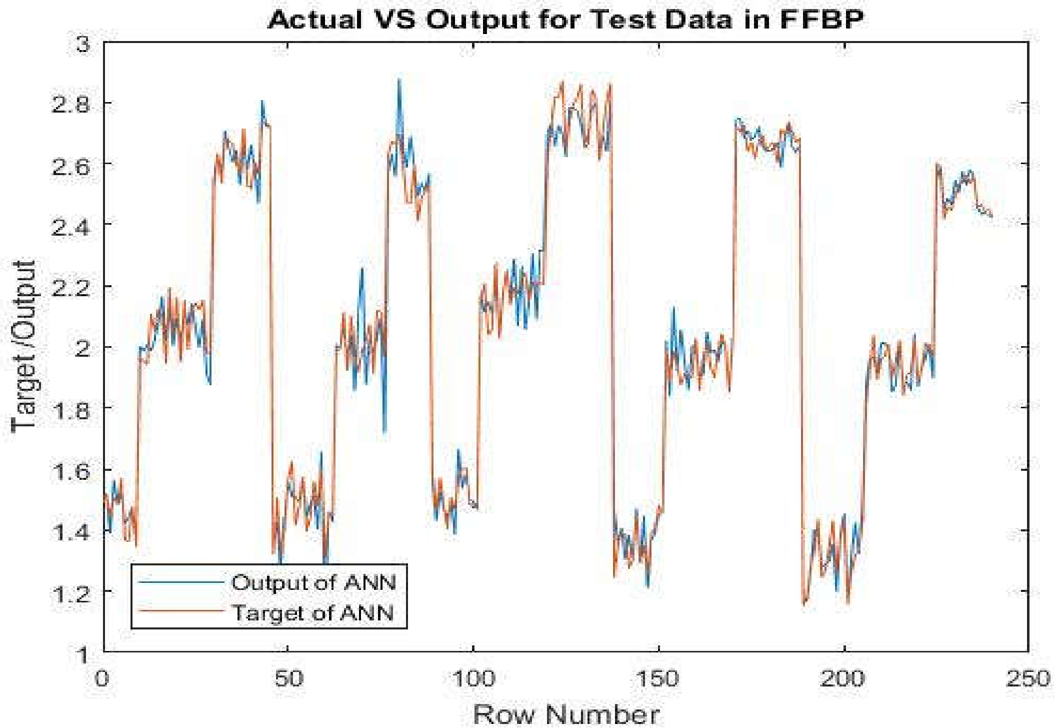

Fig.6 Photovoltaic power output using the proposed neural network model vs. the target.

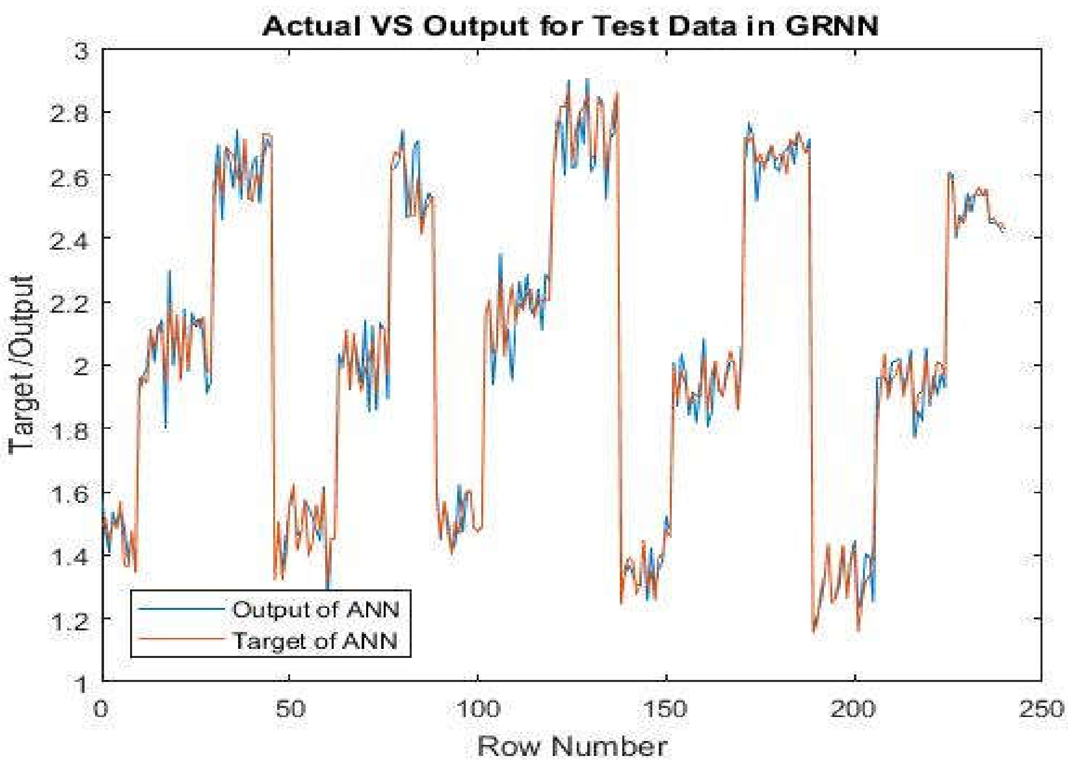

Fig.7 Photovoltaic power output using the proposed neural network model vs. the target.

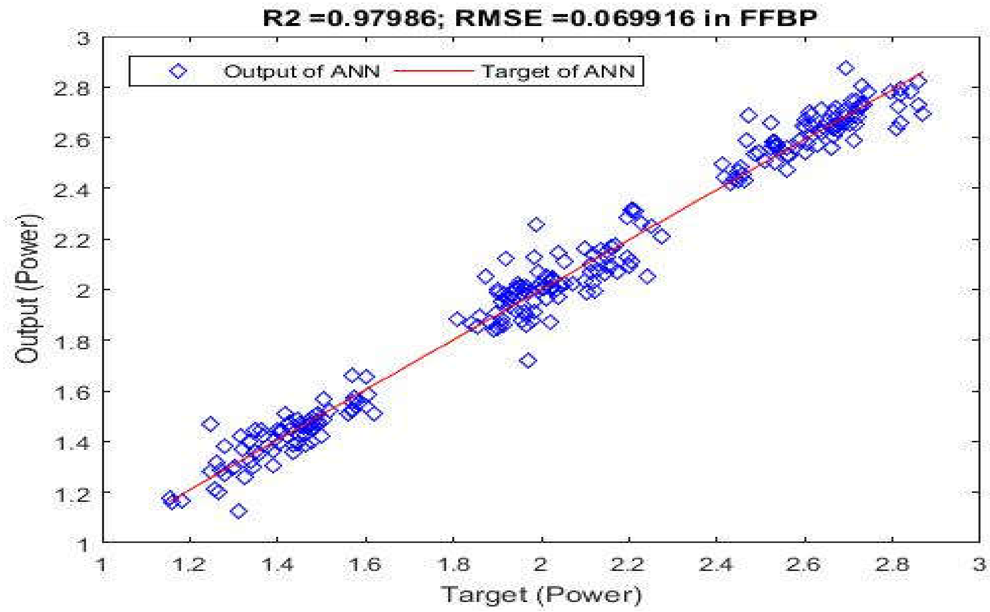

Fig.8 The scatter plot of target and network output of photovoltaic power output.

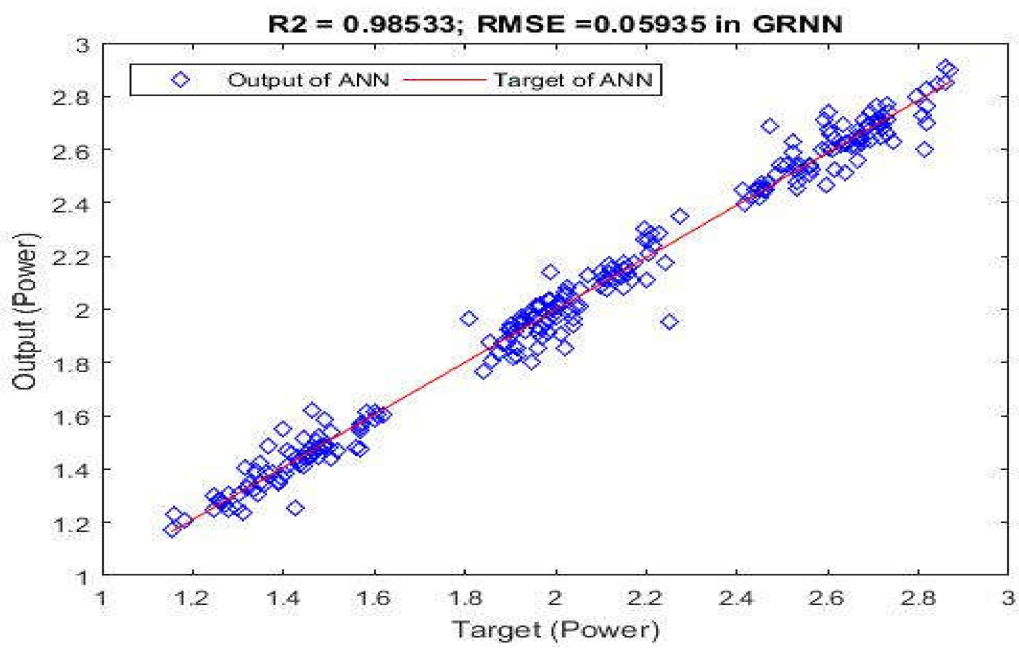

Fig.9 The scatter plot of target and network output of photovoltaic power output.

As noted from the FFBP and GRNN ANN models results for the training and testing process, that the error between the target (PV power in Watt using the experimental work results) and the networks output (PV power in Watt using the neural networks models) was small, which indicates a good performance for the training and testing process. However, it was demonstrated that the GRNN network model gave more accurate results when compared with those obtained using FFBP network model, as can be seen in **fig.10**. Also, noted that the two models have a strong relationship between the targets and outputs with satisfactory and highly positive values of correlation coefficient and R-Squared which indicates that, there is a good fit between the predicted and actual data. These results validate the two proposed models, indicates that the initial training was a success and suggesting that the estimation models were feasible and can be used for the forecasting of PV power output with new cases.

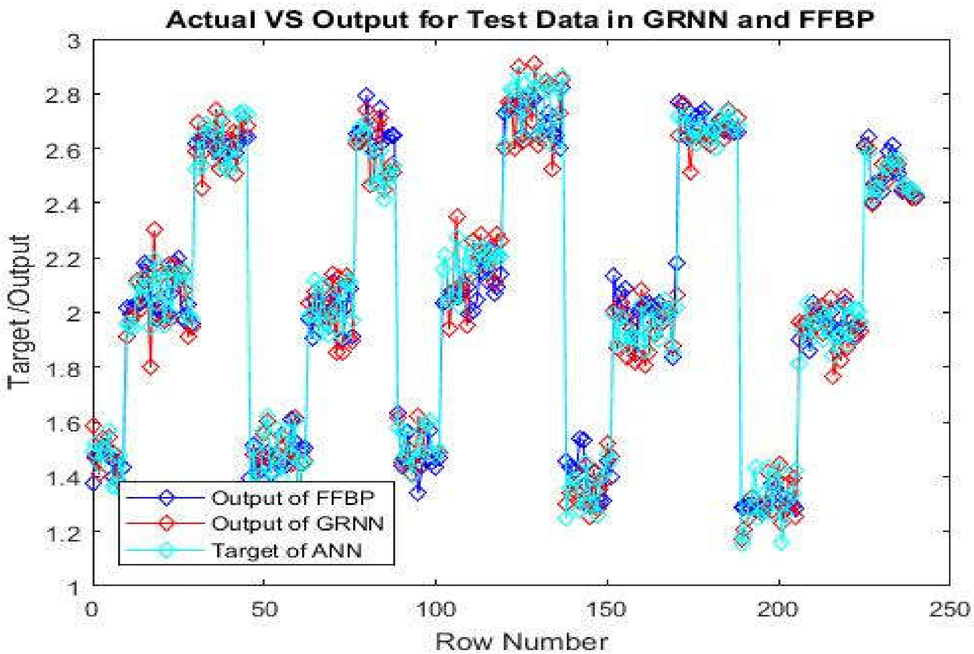

Fig.10 Comparison between the photovoltaic power output using the ANNs models vs. the target.

5.2 Effect of Input Parameters on Photovoltaic Power Output

Each input parameter (ambient temperature, cell temperature, wind speed, humidity, and irradiance) that was used in this research has a notable effect on the estimation of the photovoltaic power output. So, Alyuda Neuro Intelligence Software, which is neural network software designed to assist experts in solving real-world problems, can give indication about the importance and effect of each input parameter. So, **table.3** shows these effects in percentage ratio. This table can help us to understand the most important inputs that had the biggest influence on the estimation of the photovoltaic power output.

Table. 3 Effect of input parameters on the estimation of PV power output.

Input Parameter	Importance, %
Irradiance	33.7
Cell Temperature	28.5
Ambient Temperature	25.3
Humidity	12.4
Wind Speed	0.1

6. Conclusions

The photovoltaic power output was predicted using the FFBP and GRNN networks. The inputs to the ANNs were: ambient temperature, cell temperature, wind speed, humidity, and irradiance. The output is the power of the PV panel. Therefore, from the results obtained we can conclude the followings:

- A neural network model based on feed forward back propagation (FFBP)showed good performance results for estimating the photovoltaic power output with correlation coefficient (0.989879) and R-Squared (0.97986) that make the ANN model with the developed structure reliable for new operating conditionswith least error.
- A second neural network model based on general regression neural network (GRNN) showed good performance results for estimating the photovoltaic power output with correlation coefficient (0.992640) and R-squared (0.98533) that make the ANN model with the developed structure reliable for new operating conditionswith least error.
- The solar irradiance has the greatest effect on the estimation of the photovoltaic power output with ratio (33.7%) then the cell temperature, and ambient temperature with ratios (28.5%, 25.3%), respectively, while humidity has medium effects with ratio (12.4%). Wind speed has the least effect with ratio (0.1%).
- It was demonstrated that the GRNN network model gave more accurate results when compared with those obtained using FFBP network model. As well, GRNN network proved its ability to predict in less time than FFBP network.

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نمذجة وتنبؤ الطاقة الناتجة من الخلايا الضوئية باستخدام الشبكات العصبية الاصطناعية أخذين بالأعتبار الظروف المحيطة

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الخلاصة:-إن التنبؤ بإنتاج الطاقة الكهروضوئية مع أدوات تنبؤية موثوقة في ضوء الظروف المحيطة مهم جدا من أجل نشر تكنولوجيات النظام الكهروضوئي، وكذلك لتحسين أداء الأنظمة الكهروضوئية في التخطيط.الهدف من هذا العمل هو تقديم طريقة لنمذجة الطاقة الشمسية بأستخدام الشبكات العصبية الاصطناعية. اثنين من هياكل الشبكة العصبية وهي, شبكة الانحدار العصبية المعممة (GRNN) و شبكة الانتشار العكسي (FFBP), تم استخدامهما لنمذجة وتنبؤ الطاقة الناتجة من الخلايا الكهروضوئية. الشبكتين الاصطناعية تحتوي على خمسة مدخلات واخراج واحد. المدخلات هي درجة الحرارة المحيطة, درجة حرارة الخلية, سرعة الرياح, الرطوبة, و الاشعاع الشمسي؛ الاخراج هو الطاقة. البيانات المستخدمة في هذا البحث اخذت من العمل التجريبي الذي أجري في مختبر الطاقة فيقسم هندسة الطاقة, مدينة بغداد, والذي بدأ من يناير2017 حتى مايو 2017. وقد استخدمت بيانات الخمسة اشهر لتدريب واختبار الشبكات العصبية.بينت النتائج أن الاشعاع الشمسي له التأثير الاكبر على تقدير انتاج الطاقة الكهروضوئية بنسبة (33.7%) ثم درجة حرارة الخلية ودرجة الحرارة المحيطة بنسب (25.3%, 28.5%) على التوالي, في حين أن الرطوبة لها تأثير متوسط بنسبة (12.4%). سرعة الرياح لها التأثير الاقل بنسبة (0.1%).أشارت نتائج المحاكاة إلى أن النموذجين للشبكات العصبية كانا دقيقين ويمكن استخدامهما بشكل فعال للتنبؤ بإنتاج الطاقة الكهروضوئية,ومع ذلك، فقد تبين أن نموذج الشبكة العصبية (GRNN) اعطى نتائج أكثر دقة بالمقارنة مع تلك التي تم الحصول عليها باستخدام نموذج الشبكة العصبية (FFBP). كذلك، أثبتت شبكة (GRNN) قدرتها على التنبؤ في وقت أقل من شبكة (FFBP).

الكلمات المفتاحية: الشبكة العصبية الاصطناعية؛ الخلايا الضوئية؛ التنبؤ بالطاقة؛ الظروف المحيطة؛ بغداد