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The Potential of Artificial Neural Network (ANN) Technique in Photovoltaic Power Output Modeling Based on Meteorological Data

Rusul S. Hadi†, Osamah F. Abdulateef‡*

†College of Engineering, Energy Engineering Department, University of Baghdad, Baghdad, Iraq.

‡AlKhwarizmi College of Engineering, Automated Manufacturing Engineering Department, University of Baghdad, Baghdad, Iraq.

*Corresponding Author email: drosamah@kecbu.uobaghdad.edu.iq; drosamah65@gmail.com

ABSTRACT: It has become critical to estimate the effect of ambient conditions on the photovoltaic power output for optimal designing of the PV systems. For this purpose, several techniques have already been used. In the present study, we have presented a solar power modeling technique using the general regression neural network (GRNN) to model a PV output power and to approximate the generated power on the basis of the ambient conditions such as the ambient and cell temperature, wind speed, humidity, and irradiance. We considered the effect of each climate factor on the PV power output estimation using the feature-selection process with 4 combinations of input variables. All data used in this study was sourced from the experimental research conducted in Baghdad city between January 2018 and May 2018. The data of 5 months were used for training and testing the neural network. The simulation results indicated that the 4 combinations of input variables were valid and showed good modeling performance, albeit the accuracy of the GRNNmodel with the 5 and 4 input factors (ignoring the wind speed factor), achieved maximum performance for the estimation of the PV power output with the coefficients of determination (R-Squared) of 0.98533 and 0.98796, respectively.

KEYWORDS: GRNN model; PV performance; power prediction; forecasting

INTRODUCTION

The tremendous surge in the increased utilization of solar energy in the last 2 decades can be attributed to the rising awareness for the need of green and environmental friendly devices, technical improvements, and improved efficiency. Semiconductors are devices in which the solar energy can be converted directly into electricity using a photovoltaic (PV) device through an electronic process [1]. Several types of PV solar cells are available, but the 2 most common commercial types are those made from crystalline silicon (both monocrystalline and polycrystalline), which obviously has high efficiencies of about 15–20% and a high cost of production and manufacturing [2]. On the other hand, the electrical power generated by PV solar cells can be affected mostly by the ambient conditions such as solar radiation, ambient temperature, humidity, wind speed, and dust [3]. Therefore, it is important to provide a reliable predictive tool to predict the PV output power, considering ambient conditions to dissemination the technologies of the PV system as well to improve the performance of the PV systems in the planning stage. Artificial neural network

(ANN)is one of the most significant artificial intelligence (AI) techniques, whose working principle depends on the artificial neurons that are the processing elements. ANN can deal with noisy data or partial information and can be extremely efficient, especially, in situations where it is improbable to describe the steps or rules that clarify the issues and can model the system via samples only. Thus, ANN can be used to predict the PV output power with a reliable and a fast process [4, 5].

LITERATURE REVIEW

Modeling of the PV plant has become an active research field that uses new models based on AI methods, especially the ANN technique. Several studies have been performed to establish the effect of weather factors on the performance of PV cells and for modeling the result using the ANN technique. Brano et al. used 3 types of

ANNs, namely, Recursive Neural Network (RNN), one hidden layer Multilayer Perceptron (MLP), and Gamma Memory (GM) trained using the backpropagation method to predict the output power of the PV modules, wherein the modeling results depicted that the adaptive techniques of ANNs could forecast the power output of PV panel with a great accuracy and small computational time errors [6]. Teo et al. used an ANN to forecast the PV output power; Extreme Learning Machine was the training algorithm. The simulation results revealed that the proposed model could forecast PV power with a high accuracy with the bigger training dataset. Moreover, the sequences of the input variables affected the performance of the ANN model [7]. Shekher and Khanna reported the use of feed-forward backpropagation (FFBP) neural network to model and approximate the generated power of 150KW PV array system in northern India. The input data included temperature and irradiance, while PV power acted as the output; the simulation results revealed a good modeling performance since the regression error of real and predicted data was extremely low [8]. Cancro et al. used ANN to predictthe back-plate temperature (working temperature) of a concentrator PV module (CPV) in Italy; they found that the proposed model could forecast the PV power with a high accuracy, with the mean RMSE value of 2.67°C [9]. Saberian et al. used ANNs to predict and model the generated power of a PV panel in Malaysia. They have used two ANN structures: feed-forward backpropagation (FFBP) and general regression neural network (GRNN); the results revealed that both the ANNs represented a good modeling performance [10].

Several types of ANNs are currently being used in different applications and researches. Here, the GRNN model was proposed for the estimation of the generated PV power system while considering the ambient conditions. GRNN is an approximation function that is used to forecast the output values of a known input data using the training data. Therefore, it is expected to predict the output depending on the average weighted provided by the output of the training dataset. Architecturally, it 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 in the range of 0 to 1 by the training process in order to reduce the error between the network outputs and the targets to obtain the best fit. The major benefit of GRNN is in speeding up the training process to help the neural network learn earlier unlike in a typical feed-forward neural network. In addition, GRNN evaluation is considered always capable of converging to a global solution and it would not be trapped by a local minimum [11].

Occasionally, the data sets contains more information than is required to build the ANNs models, and these unneeded columns degrade the quality by using additional storage space for the completed ANNs models. The feature selection process must perform to identify the best input columns for achieving the maximum performance with respect to the prediction of the PV power output. Moreover, it can indicate the effect of each input parameter (such as solar irradiance, cell temperature, ambient temperature, humidity, and wind speed) on the estimation of the PV power output.

Research Gaps

PV system output is difficult to control due to the nature resource from the sun and climate conditions which distress the performance of PV panel output itself due to changing climate condition. This could make the PV panel output is incompatible values with the rated value.

Previous studies that have provide a reliable predictive tool to predict the PV output power, considering ambient conditions in many countries rather than Iraq appear to have left significant research gaps as follows:

1- There are many factors in Iraq that could influence the power output of PV panel systems such as ambient temperature, wind speed, relative humidity, dust, solar radiation or other factor relate to ambient factor.

2. This will cause difficult to knowing the power output of PV panel system due to multiplicity amount of solar radiation and the ambient environmental factors in certain location around Iraq.

3. The methodology used in this study can be considered the effect of each climate factor of Iraq on the PV power output estimation using the feature-selection process.

Research Objective

The main purpose of this study is to model a PV output power and to approximate the generated power using GRNN by considering the ambient conditions based on the feature selection process with 4 combinations of input variables, including the PV power output with 5 inputs (using all input factors), PV power output with 4 inputs (ignoring wind speed), PV power output with 3 inputs (ignoring humidity and wind speed), and PV power output with 2 inputs (ignoring ambient temperature, humidity, and wind speed).

METHODOLOGY

According to the purpose of the study, this study will involve two methods of data analysis for the decision making, namely experimental work and GRNN models of the future selection combinations.

Experimental Work

The database used in this study was sourced from the experimental research conducted in Baghdad city between January 2018 and May 2018. All the readings in this work were recorded from 8:00 AM to 2:00 PM. The experimental work focused basically on the clarification of the effect of weather factors on the performance of a single monocrystalline PV solar module with the maximum power of 30W, cell area of 0.282 m^2, open circuit voltage of 22V, short circuit current of 1.9A, voltageat the maximum power of 17V, and current at the maximum power of 1.76A.The standard calibration procedure was followed for the monocrystalline PV solar cells as per the manufacturer's recommendation. The Prova 200 Solar Analyzer was used to measure the PV power, and the other electrical parameters were automatically calculated and then transferred for storage in Excel worksheet. In addition, The Weather Station Vantage Pro2 was used to measure the weather factors such as wind speed, ambient temperature, and humidity [14]. In addition, the temperature of PV solar module was measured using a temperature sensor, while the solar power meter "Data Logging Solar Power Meter TES-1333R"was used to measure the solar radiation intensity (in W/m^2). Fig. (1) shows the devices used in the experimental research [14].

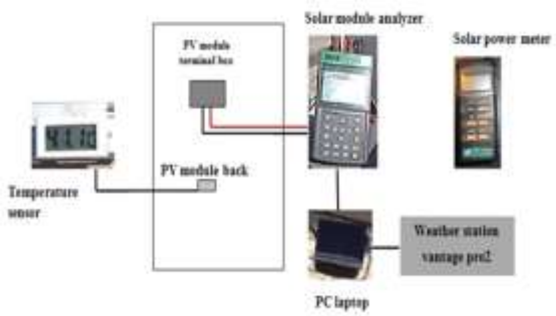


Figure 1. Setup of the experiment [14]

Each parameter of ambient condition (including the ambient temperature, cell temperature, wind speed, humidity, and irradiance) used in this study had a notable effect on the estimation of the PV power output. AlyudaNeuro Intelligence Software, which is a neural network software designed to assist experts in solving real-world problems, can indicate the importance and effect of each parameter [12]. Table (1) shows these effects in percent ratio. From this table, we can understand the most important inputs that had the biggest influence on the estimation of the PV power output. Based on these values and the importance of each input factor, 4 combinations of the input variables were considered.

Table 1. 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

GRNN Models of Feature Selection Combinations

GRNN models were proposed in this study to estimate the generated PV power system based on the feature selection process with 4 combinations of input variables considering the ambient conditions (such as ambient temperature, cell temperature, wind speed, humidity, and irradiance). Fig. (2) Illustrates the basic flow followed to construct the ANN models.

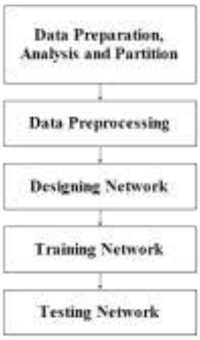
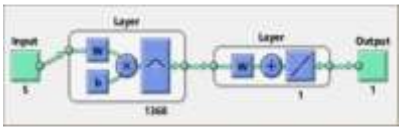
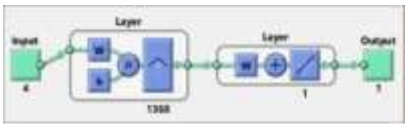


Figure 2. General block diagram of ANN models.

The first layer of the GRNN has as several neurons as there are inputs/targets vectors in the input vectors with radial basis functions. The number of neurons in the second layer was set to the target vectors with a linear transfer function for the 4 combinations of input variables. However, after several attempts to determine the best value of spread constant with a range of 0 to 1, the values of 0.6, 0.5, 0.7, and 0.3 were selected as the best numbers in the range; these numbers showed good performance indications for the 4 combinations, respectively. Models of this network with the 5 inputs (i.e., solar irradiance, cell temperature, ambient temperature, humidity, and wind speed), four inputs (i.e., solar irradiance, cell temperature, ambient temperature, and humidity), three inputs (i.e., solar irradiance, cell temperature, and ambient temperature), and two inputs (i.e., solar irradiance and cell temperature) are shown in Figs. (3) (a, b, c, and d), respectively.



(a)



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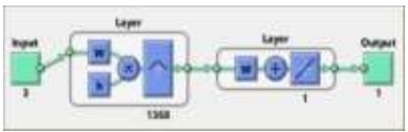

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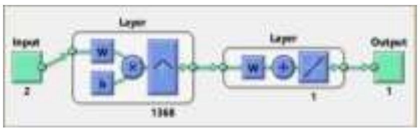


(d)

Figure 3. GRNN models: (a) five inputs (b) four inputs (c) three inputs (d) two inputs.

The performance of the developed ANN 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 [10, 13]:

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

Where, N = number of predication values, $\overline{\text{Zt}}$ = the vector of the N prediction values, and Zt = the vector of the real values.

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

Where, y_i = the predicted value, x_i = the actual value, N = number of observation.

The implementation of GRNN models for the estimation of PV power output for the four combinations of input variables has been summarized in Fig. (4).

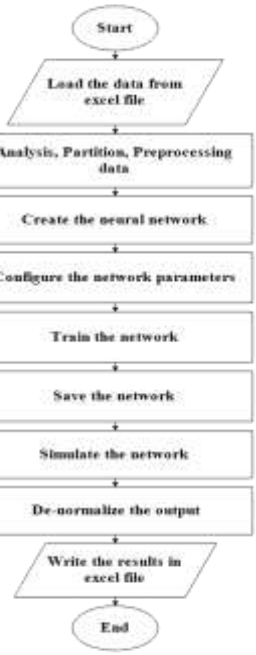
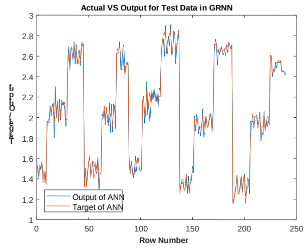


Figure 4. Flowchart for implementation GRNN models.

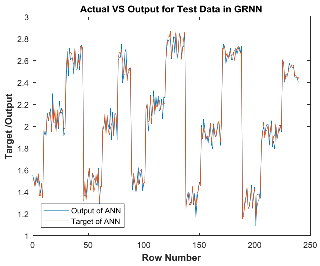
RESULTS AND DISCUSSIONS

Table (2) illustrates the training time that the neural network required, magnitude of the MSE, RMSE, correlation and coefficient of determination (R-Squared) between the target (PV power [in watt] using the experimental work results) and output (PV power [in watt] using the neural network model) for the training and testing process based on the GRNN models for the 4 combinations of input variables, respectively. Figs. (5) and (6) (a, b, c, and d) show the output versus the target and scatter plot of the target and network output for the testing results using the 4 combinations of input variables.

The results of GRNN models with the 4 combinations of input variables indicated that the MSE and RMSE values were between the target (PV power [in watt] using the experimental work results) and the network output (PV power [in watt] using the neural network model) for the training and testing process was small, which indicates a good performance for the two process. Fig.(5) (a, b, c, and d) show that the targets were nearly the same as the outputs and the extent of convergence between the targets with the outputs was located at several locations by convergence results of the target with the output. Moreover, Fig. (6) (a, b, c, and d) show that the models had a good relationship between the outputs and targets with high values of R-Squared, although the accuracy of the ANN models with 2 or 3 inputs was less than for the models that used 4 or 5 inputs, which indicated that 5 or 4 input factors (ignoring wind speed), can be used to achieve the maximum performance on the estimation of PV power output, since the wind speed factor had the least effect in predicting the PV power output with 0.1%.



(a)



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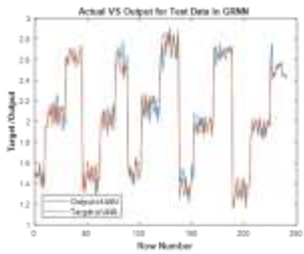

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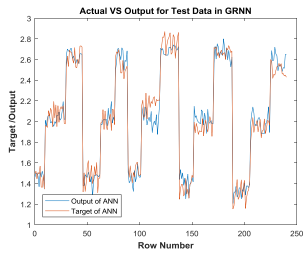
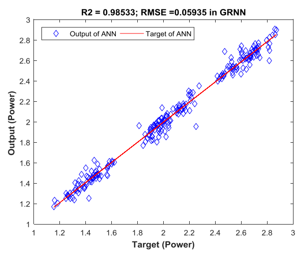
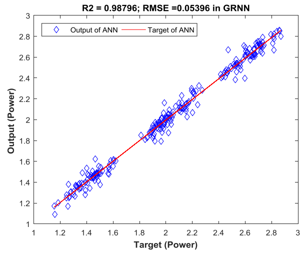


(d)

Figure 5. PV power output using the proposed neural network model: (a) five inputs (b) four inputs (c) three inputs (d) two inputs vs. the target.



(a)



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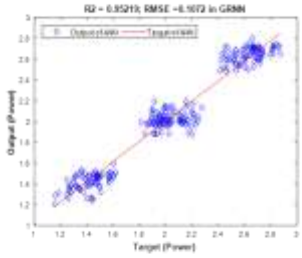

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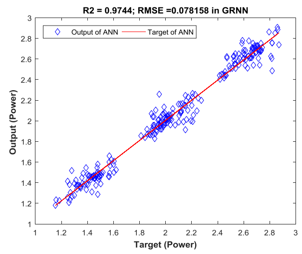

(d)

Figure 6. The scatter plot of target and network output of PV power output: (a) five inputs (b) four inputs (c) three inputs (d) two inputs.

Table 2. GRNN models results

Process		Training time (sec)	MSE	RMSE	Correlation	R-Squared
Five inputs	Training	681	0.000254	0.015876	0.999479	0.99896
	Testing	_	0.003588	0.05935	0.992640	0.98533
Four inputs	Training	407	0.000193	0.013889	0.999602	0.99921
	Testing	_	0.002950	0.05396	0.993961	0.98796
Three inputs	Training	285	0.002528	0.049954	0.994786	0.9896
	Testing	_	0.006264	0.078158	0.987116	0.9744
Two inputs	Training	230	0.008571	0.090863	0.982207	0.96473
	Testing	_	0.011738	0.1072	0.975802	0.95219

CONCLUSIONS AND RECOMMENDATIONS

We predicted the PV power output under the effect of ambient conditions using the GRNN. Ambient temperature, cell temperature, wind speed, humidity, and irradiance were used in this study. Four models with different combinations of input variables, depending on the GRNN, were proposed. From the results obtained, we can conclude the following:

- The solar irradiance has the greatest effect on the estimation of the PV power output with 33.7% more effect than that by the cell temperature, and ambient temperature with percent (28.5%, 25.3%), respectively, while humidity had medium effects with a percent (12.4%). Wind speed had the least effect with 0.1% only.
- The four combinations of input variables models were valid, but the accuracy of the ANN models with 2 or 3 inputs was less than that for the models that used 4 or 5 inputs, indicating that 5or 4 input factors (ignoring wind speed), since that wind speed factor has the least effect in predicting PV power output with just 0.1%, can be used to achieve the maximum performance for the estimation of PV power output with the correlation coefficients0.992640 and0.993961 and R-squared values 0.98533 and0.98796, respectively, that make the ANN models with the developed structure reliable for new operating conditions with least error.

For future works, we recommend Studying other parameters forecasting that has an important feature in the photovoltaic (PV) systems design such as back-plate temperature (working temperature)or dust. Also try to forecast power output with other types of PV solar modules such as polycrystalline PV solar module.

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