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Global Solar Radiation Forecasting Using Neural Network Based on PV Module Performance

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Abstract: Forecasting of global solar radiation is essential for a design of any solar system, especially for photovoltaic applications. Neural network is the most popular model used for estimating solar radiation due to its nonlinear nature that matches well with the nonlinear prediction of solar radiation. The photovoltaic module output directly depends on both module surface solar radiation and temperature. So, these two parameters can be used in predicting the incident global solar radiation using neural networks. This paper introduces a simple and accurate neural network for estimating instantaneous global solar radiation based photovoltaic module maximum power and surface temperature for Egyptian climates. The proposed neural network consists of three layers (input, output and hidden layers). The input layer has two inputs (photovoltaic module maximum power and surface temperature), the hidden layer has five neurons, while the output layer has only one neuron that estimates the global solar radiation. The results showed that the correlation coefficient for estimating the global solar radiation with the proposed neural network reached more than 97% related to the measured values.

Key words: Solar radiation · PV module · Neural networks · Training algorithm

INTRODUCTION

The dependence on renewable energies, especially solar energy, in recent decades becomes an essential in countries that have considerable solar radiation levels for high sunshine hours [1, 2]. The Photovoltaic (PV) systems are highly used in rural or suburban areas. The performance of the PV system can be affected by the climatic data of the system location such as global solar radiation and ambient temperature [3]. Successful PV system design is highly related to the accurate estimation of the global solar irradiation related to the system site. The over estimations lead to high system cost while the under estimations result in insufficient power output [4]. All PV system traditional models (for estimating the module instantaneous power) depend mainly on the global solar irradiation of the PV module and its surface temperature [5-8].

The global solar radiation can be measured by different types of weather stations (meteorological stations) or detected by different conventional predication models. Weather stations are usually used for direct measurement and storage for instantaneous climatic data, such as global solar irradiation, wind speed, ambient temperature, wind direction and amount of rain water. Unfortunately, there are large areas that still away from installing these weather stations in their sites due to the economical consideration, so there is a lack of the solar radiation data as well as other climatic parameters that are important to facilitate solar system installation [9]. To track the lack of global solar radiation measurements, solar approaches or solar traditional models or recently neural networks have been developed to get the solar radiation under different operating conditions in different sites of the world [10-13]. Global solar radiation estimation models can be classified into liner, non linear and models using neural network (NN). Among the prediction models, NNs are the most accurate ones that estimate the instantaneous global solar radiations [14, 15].

NN deals with systems that have a lot of inputs according to the nature of the system and manipulating these inputs via different stages (layers) until reaching the required predicted variables. It needs variety of inputs and outputs training pairs to adjust the links (weights) between the different layers. The quality of the NN can be strongly affected by its design, training data and algorithm of training [16-18].

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During the last decades, different NNs models were introduced to estimate the hourly, daily and monthly global solar radiation as instantaneous or average values. Maximum and minimum ambient temperatures with the extraterrestrial radiation are used for detecting global solar radiation as daily values using NN in South west of Iran [19]. Monthly solar radiation values were detected in Turkey by NN model using the site parameters, mean duration of sunshine and ambient temperatures [20]. The same data inputs beside the relative humidity were used for estimation of monthly values of radiation levels using NN in Nigeria [21]. In Egypt, diffuse radiation percentage as fraction of the total solar radiation was detected using NN depending on temperature, relative humidity, wind speed and wind direction [22]. Global radiation was estimated by NN using the humidity and temperature values with the day number and evaporation rates in Dezful, Iran [23]. The same data in addition to the cloud cover were used in Uganda to forecast monthly average values of the solar radiation received by a horizontal surface using NN [24]. Global solar radiation based on monthly mean daily values was estimated by NN in Tibetan Plateau using difference of air pressures at sea level to its local value and the temperature difference between the daytime and nighttime at a horizontal surface with local coordinates of geographical location and weather data [25]. In France, meteorological forecasts used to be manipulated by artificial NN to detect the solar irradiation of the horizontal plane [26]. Finally, the solar radiation in monthly global values was estimated using NN based on different inputs as ratio of the sunshine hours, site coordinates, month number of the year and altitude level in Oman [27].

This paper uses the NN to estimate the instantaneous global solar radiation in the test field in Cairo, Egypt (Latitude of 30.033 North and Longitude of 31.233 East) via a measured PV module instantaneous maximum power (MP) and surface temperature. The PV module MP and surface temperatures can be measured instantaneously using a measuring circuit designed especially for these purposes. The NN takes the module MP and surface temperatures as inputs and produces the global solar radiation as output via three linked layers (input, hidden and output layers). The error back propagation method is used for training the NN.

PV Module: A thin film, 64 W, 22 cells PV module (Fig. 1) is used in this work. Table 1 represents the electrical parameters of the PV module, while Fig. 2 shows the two main performance curves of the PV module (voltage values versus corresponding current (I-V) and power (P-V) values) under standard test conditions (STC; 1000 W/m^2 irradiation, 25°C surface temperature and air mass of 1.5). As clear from Fig. 1, the PV module was installed on a metal structure of iron steel rods tilted by 30 deg. (the site latitude angle to get the optimal performance over the year) and facing directly to south direction.

Figs. 3 & 4 show different I-V curves of the PV module under different operating radiation levels and module surface temperatures, respectively. From the figures, it is evident that the performance of the PV module is enhanced as solar irradiation increases. The short circuit current and maximum power can be directly increased proportional to the radiation level (Fig. 3), while the opposite can be seen from the effect of temperatures (Fig. 4). As the temperature increases, both the module maximum power and open circuit voltage decrease. So, it can be concluded that the solar radiation as well as the module temperature can detect the PV module instantaneous maximum power. Solar radiation level can directly affect the PV module MP and surface temperature. Using these two later parameters as inputs to the proposed NN, the global solar radiation can be detected accurately depending on the configuration and training of the NN.

Fig. 1: 64 W PV modules

Table 1: Electrical and mechanical data of the PV module at STC

Item	Value
Rated power	64 W
Voltage at open circuit	21.8 V
Maximum operating voltage	16.5 V
Current at short circuit	4.8 A
Maximum operating current	3.88 A
Dimensions	136.6x74.1x3.2 cm^3
Weight	9.17 Kg

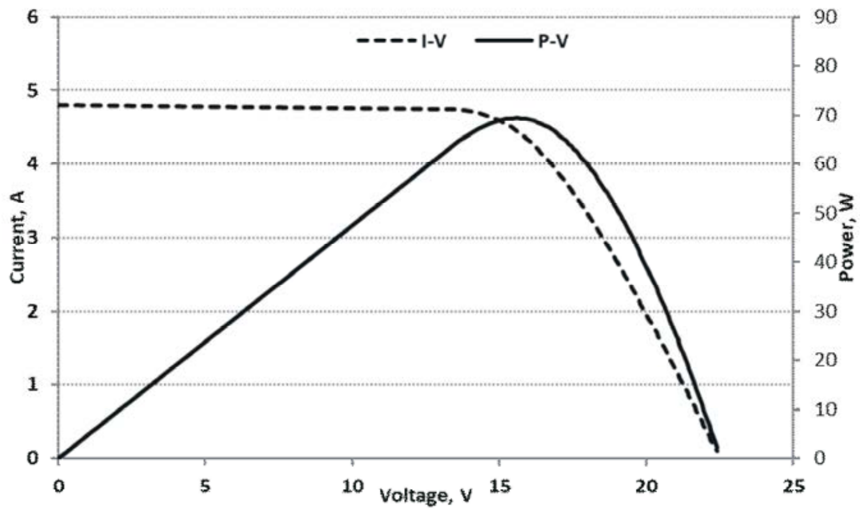

Fig. 2: PV module I-V and P-V characteristics at STC

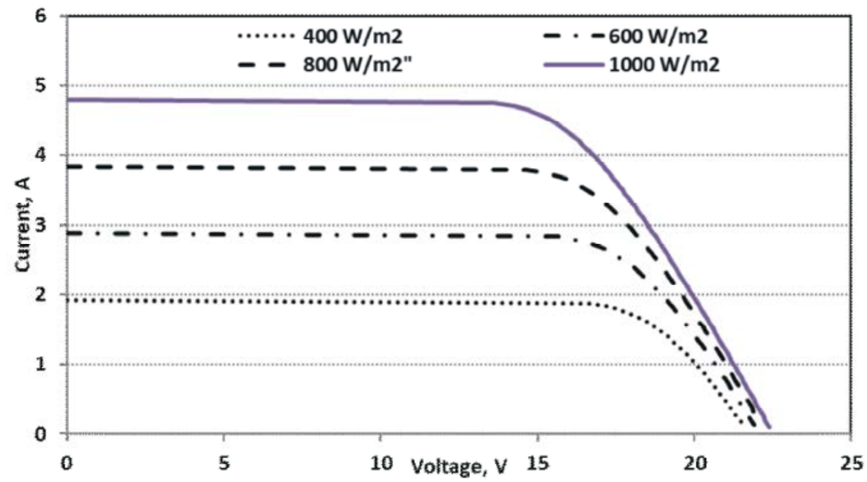

Fig. 3: I-V curves of the PV module under different solar radiation levels at 25°C

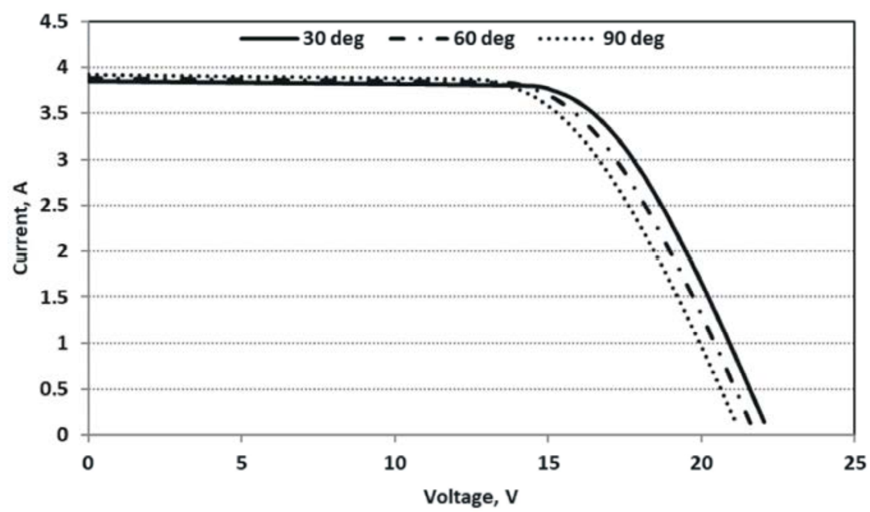

Fig. 4: I-V curves of the PV module under different operating temperatures at solar radiation of 800 W/m^2

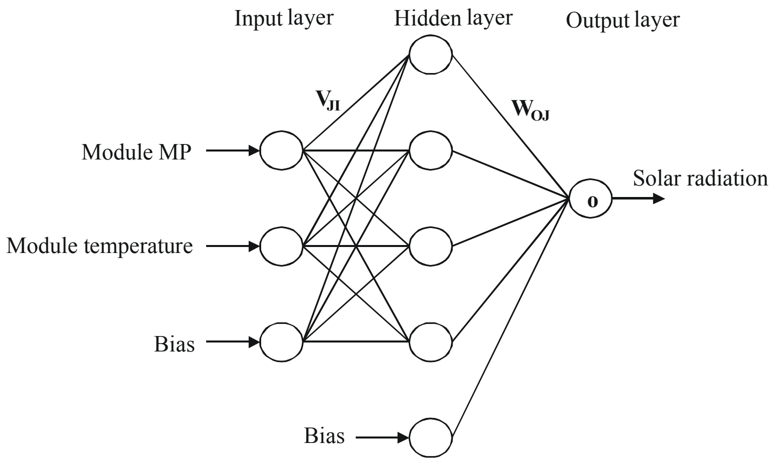

Fig. 5: NN for estimation the global solar radiation using the PV module MP and surface temperature

Neural Network: NNs are tools that have been developed to convert inputs to outputs so as to simulate the process manipulation by the human brain via parallel-distributed configuration consisting of different processing nodes [28]. The structure of the NN is composed of; i) input layer to receive the input data, ii) one output layer to get out the manipulated data and send the computed information and iii) hidden layer to connect between input and output layers. The number of the input, output or hidden layers can be differed according to the nature of the system under process [29]. According to the configuration of the NN, all of the neurons in any layer are directly connected to all of the neurons in the neighbor layers. Fig. 5 shows the proposed NN for estimating the global solar radiation using the PV module MP and surface temperature.

Fig. 5 illustrates the three NN layers as follows; i) input layer consists of three neurons with two inputs; PV module MP and surface temperature with a third bias signal with unity input to improve the learning speed in training process, ii) hidden layer consists of four neurons with one unity bias and iii) output layer with a single neuron to estimate the global solar radiation.

The algorithm of calculation of the NN output using its inputs can be carried out according to the flowchart shown in Fig. 6 as follows [30];

As the input layer sends its inputs directly to the hidden layer via V weights, each node in the hidden layer gets its output as follows;

$$H_j = \frac{1}{1+e^{-net_j}} \quad \text{for 4 hidden nodes} \tag{1}$$

$$net_j = \sum_{i=1}^{3} V_{ji} \cdot X_i \quad \text{for i = 1 to 3} \tag{2}$$

Then, the hidden layer nodes send their outputs to the output layer via W weights and the NN can get its output (global solar radiation) as follows;

$$O = \frac{1}{1+e^{-net_o}} \tag{3}$$

$$net_o = \sum_{j=1}^{5} W_j \cdot Hj \quad \text{for j =1 to 5} \tag{4}$$

The training of the NN is the process that adjusts all connection weights in all layers of the NN using multiples of inputs-outputs called training data (training pairs). The training data of the current NN uses the multiple measured values for PV module MP and surface temperatures as inputs and the corresponding instantaneous global solar radiation as output. To optimize the final estimation accuracy of the NN, the measured set of the training data is covering all possible operating conditions for different module surface temperatures and MP with corresponding to global solar radiation levels. The MP of the PV module was measured using the electronic load and the measuring circuit described in [31]. Based on MOSFET transistor, the measuring circuit used an electronic load to track the I-V characteristics of the PV module. The module surface temperature is measured using a K-type thermocouple connected directly to data acquisition system via an amplification circuit. Also, the global solar radiation measured for training data is measured using a thermopile pyranometer of type Kipp & Zonen located at the same structure with PV module to receive the same solar radiation, as shown in Fig. 1.

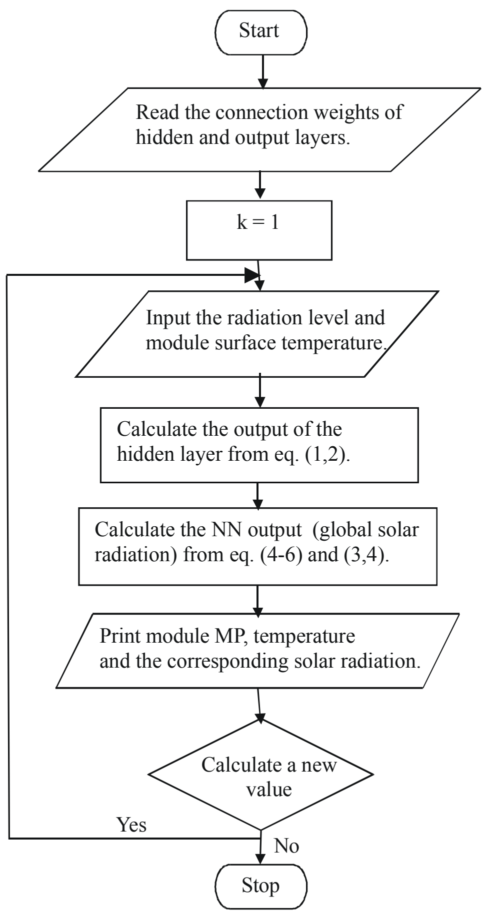

Fig. 6: Flowchart for calculating the global solar radiation using NN

The NN weights between any two layers can be modified or adjusted via training process. There are different training algorithms that can be categorized as supervised or non-supervised. The error back propagation (EPP) is used for adjusting the NN weights due to its simple nature and high accuracy especially in simple NN configurations [30]. In this algorithm, measured input and output (target) training data pairs are manipulated by the NN and the corresponding calculated value is obtained. The calculated output from the NN and the target input can be compared for error detection. This error, according to the algorithm, is essential to update the different weights in the NN. Updating the weights leads to reduce the NN output-target error for the following training pairs until all training data is finished. In this method, the error was propagated in each training pairs backward from the output to the input layer. The following steps summarize the use of the EPP training algorithm for updating the NN different weights [30, 32];

Step 1 (initial weights): Weights of hidden and output layers are initialized at small random values. These values can be modified with the progress of the training process.

Step 2 (first iteration): Using the first training pattern (input – target pair), compute the hidden layer's output and consequently the calculated output from the neural network using eqs. 1-4.

Step 3 (error calculation): Since the first calculated value (in the training process) of the global solar radiation by NN (O in Eq. 3) differs from the measured solar radiation in this training pair (target d), the output layer error signal (used to modify the output layer weights, W) can be calculated as follows;

$$\delta_o = (d - O)(1 - O) \cdot O \tag{5}$$

Also, the hidden layer error signal (used to modify the hidden layer weights, V) can be calculated as follows;

$$\delta_{Hj} = H_j(1 - H_j) \cdot \delta_o W_{oj} \quad \text{for j = 1-4} \tag{6}$$

Step 4 (weights update): Adjust the output (Eq. 7) and hidden (Eq. 8) layers weights using a small learning constant ($\beta = 0.1$) as follows;

$$W_{oj} = W_{oj} + \beta \delta_o H_j \quad \text{for j = 1-5} \tag{7}$$

$$V_{ji} = V_{ji} + \beta \delta_{Hj} X_i \quad \text{for j = 1-4, i = 1-3} \tag{8}$$

Step 5 (repeat training pair): Use the next training pattern to update again the NN weights and repeat step continuously until all patterns are finished. After the training process, the final weight for hidden (Vji) and output (Woj) layers should be updated to the most

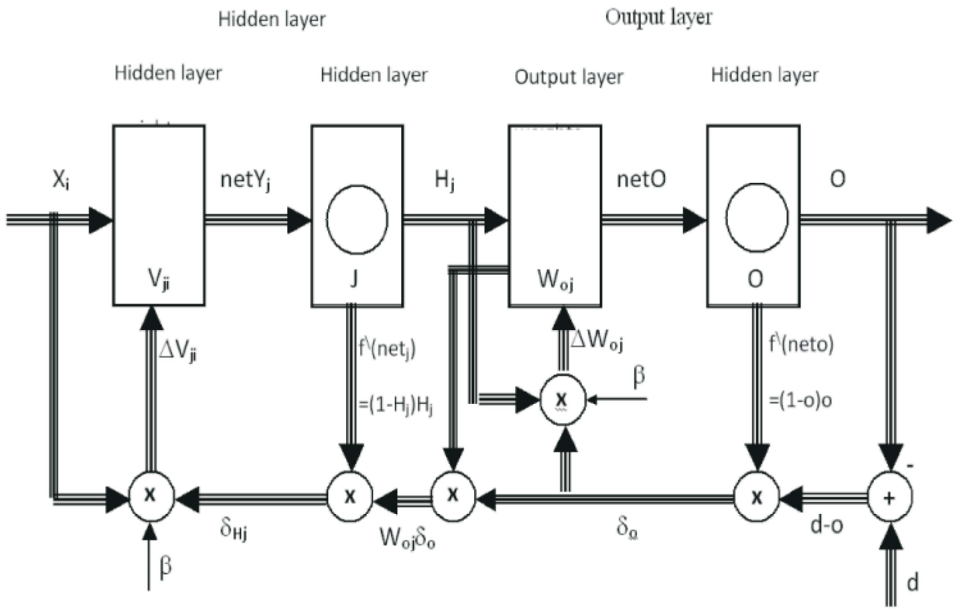

Fig. 7: Shows signal flow in the error back propagation algorithm for training the NN

accurate values, so the NN is now ready to calculate the global solar radiation from the PV module MP and surface temperature. Fig. 7 shows the signal flow in the error back propagation algorithm for training the NN. The figure explains the training process based on Eqs. (1-8) as follows;

- Use the first input training pairs (measured MP and surface temperature, as X_1 and X_2, while X_3=1, bias input) to get hidden layer output (H_j) (Eqs. 1, 2) via input layer initial weights (V_{ji}).
- Use the calculated hidden layer output (H_j) with the initial weights of the output layer (W_{oj}) to get the calculated output (O) (Eqs. 3, 4), which differs from the measured output in the first training pair (target, d).
- Get the difference between the calculated (O) and target (d) values and calculate the output error signal (δ_o) (Eq. 5) and the hidden layer error signal (δ_{Hj}) (Eq. 6).
- Update the output layer weights (W_{oj}) by ΔW_{oj} (Eq. 7) and hidden layer weights (V_{ji}) by ΔV_{ji} (Eq. 8).
- Use the next training pairs and repeat the steps until finish all training pairs, then the hidden and the output layer weights should be updated and the NN becomes ready to estimate its output.

RESULTS

Since the accuracy of the NN for estimating its output mainly depends on the NN architecture, number of hidden layer, training process and training data pairs, the current NN will be verified according to the comparison between the measured and estimated instantaneous global solar radiation. The verification of the current NN used the data measured for both clear and cloudy days. The data used is the measured instantaneous PV module MP, surface temperature and the corresponding instantaneous global solar radiation, for comparison with the calculated by the NN. Fig. 8 shows the measured instantaneous PV module MP and surface temperature during the clear sample day. The corresponding calculated instantaneous global solar radiation for this day compared to the measured values is shown in Fig. 9. Consequently, the corresponding deviation between the measured and calculated solar radiation in W/m^2 is presented in Fig. 10. The figures showed that the NN could be used accurately to estimate the instantaneous global solar radiation incident on the surface of the PV module using its MP and surface temperature. Fig. 11 ensures the same behavior between measured and calculated solar radiation for the cloudy day. The results also showed that the percent of agreement between the current NN and the measured global solar radiation reached more than 97% irrespective to the nature of day.

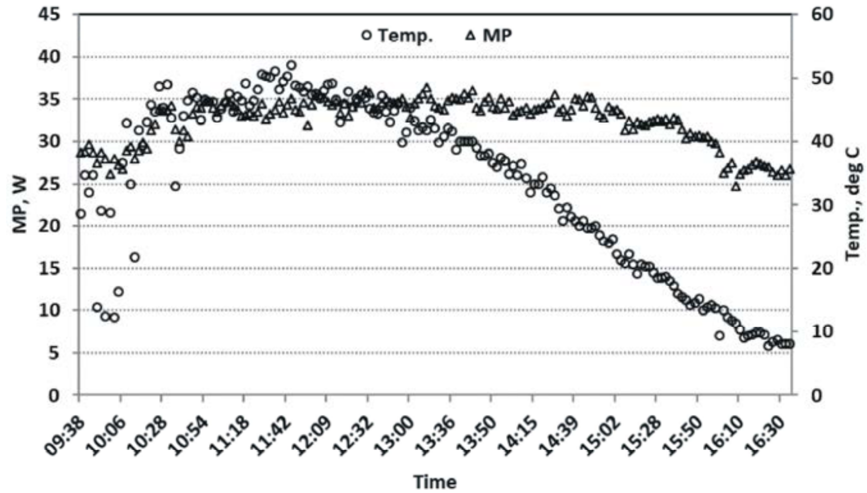

Fig. 8: PV module MP and surface temperature for the clear sample day

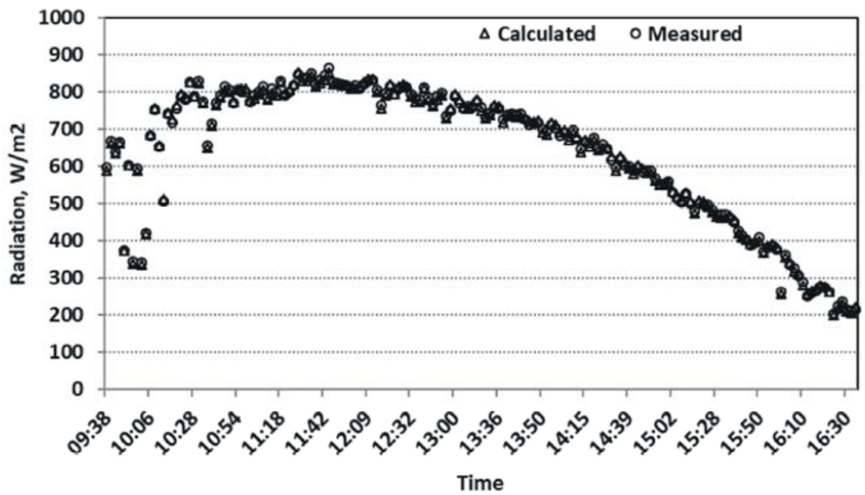

Fig. 9: Calculated and measured global solar radiation for the clear sample day in Fig. 8

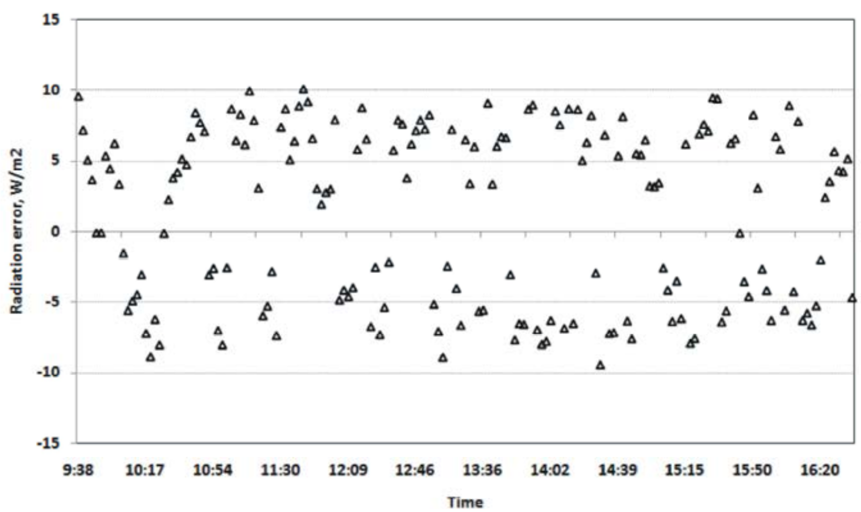

Fig. 10: instantaneous error between measured and calculated global solar radiation for the clear sample day in Fig. 8

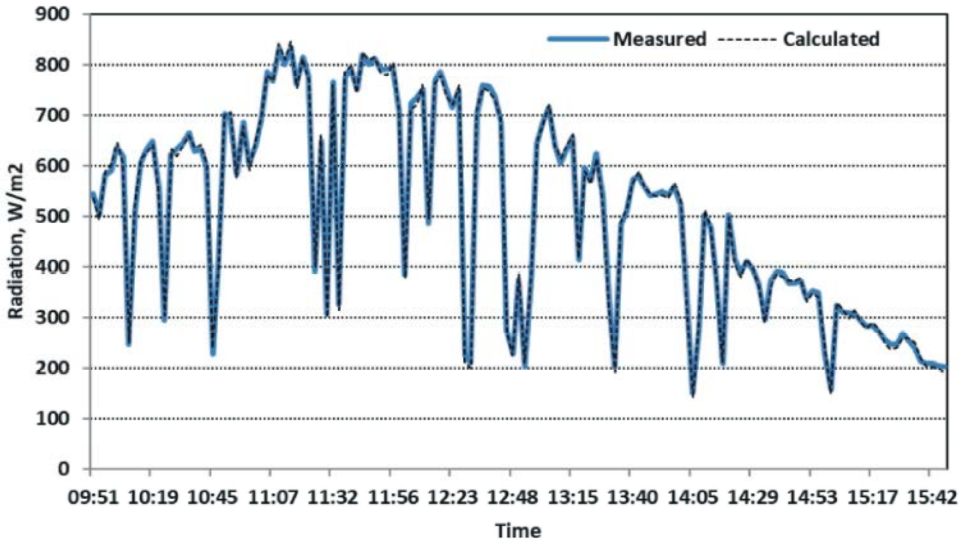

Fig. 11: Calculated and measured global solar radiation for the cloudy sample day

CONCLUSION

This paper presented a simple and accurate NN for estimation of global solar radiation in Cairo, Egypt based on PV module characteristics. The input data to the NN is the measured PV module MP and surface temperature, while the output is the estimated global solar radiation. The NN consisted of three layers. The input layer takes the PV module MP and surface temperatures as well as a unity bias input. The hidden layer consists of 5 nodes which contain one as unity input. The output layer has one node to get the calculated solar radiation. Error back propagation algorithm was used to train the NN and to adjust the weights of the hidden and output layers based on measured data pairs from the PV module. The training data is collected using an accurate measuring circuit with data acquisition system for measuring PV module temperature and measured solar radiation, while the PV module MP was measured using I-V tracker circuit based on MOSFET transistor. The verification of the NN via comparing the calculated and measured global solar radiation showed that the NN estimation reaches about 97% of the actual measured solar radiation value at different clear and cloudy conditions.

Symbols and Abbreviations:

d	Desired global solar radiation (measured) corresponding to the input values.
Hj	The output from any node j(1-4, without the bias node) in the hidden layer.
netj	Some of inputs to any node j in the hidden layer (3 inputs) multiplied by their weights.
net_o	Some of inputs to the output node in the output layer multiplied by their weights.
O	Output from the NN.
Vji	Weight between the input and the hidden layers.
Wj	Weights between the hidden and the output layers.
X_i	NN inputs (PV module MP, surface temperature and unity bias).
β	Learning constant (0.1).
δ_o	Output error signal.

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