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Three Structures of a Multilayer Artificial Neural Network for Predicting the Solar Radiation of Baghdad City- Iraq

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Abstract

In this study, a multilayer neural network with three structures (4-4-4-1), (4-8-8-1) and (4-9-9-1) is investigated to predict the average daily solar radiation in the capital city of Iraq. A MATLAB algorithm is used to implement these structures with totally dataset of 2604 hourly points for each January and August in three years 2014, 2015 and 2016. The database was recorded in the Energy and Environment Research Center Station of Al-Jadriyah-Baghdad as 14 hour in day and then the average value were taken for one day as maximum daily ambient temperature, sunshine duration, relative humidity and wind speed as input parameters and average daily solar radiation as output parameter. The algorithm is trained through the back propagation technique with traingdm, learngdm, MSE, and tansig as the training, learning, performance, and transfer functions, respectively. The results show that the optimum testing structure for solar radiation in January was the 4-9-9-1 structure with coefficient of determination (R^2 = 0.925) and Mean square error (MSE=6.5), while in August the structure 4-8-8-1 was the best with coefficient of determination (R^2 = 0.934) and Mean square error (MSE=5.4).

Keywords: Solar radiation, neural network, MATLAB.

Nomenclature

E	Sum of square error
W	Weight matrix
wj	Synaptic weights

Greek symbols

υ	Neuron
$\varphi(\upsilon)$	Sigmoid function
θ	Bias

Subscripts

ANN	Artificial neural network
learngdm	Learning gradient descent with momentum weight/bias learning function
MSE	Mean square error
Tansig	Tan-sigmoid transfer function
traingdm	Training gradient descent with momentum

INTRODUCTION

Knowledge about direct and diffuse radiation and their variation over the day and the year is desirable to select a technology for collecting solar energy. Many studies have been carried out on predicting global solar radiation (GSR) based on the artificial neural network (ANN) models. As reported in Seyed et al. [1] study, a multi-layer perceptron (MLP) neural networks was used to predict daily global solar radiation based on meteorological variables between 2002 and 2006 for Dezful city in Iran (32° 16' N, 48° 25' E). The results of MLP structure indicate that using soil temperature, daily mean air temperature, relative humidity, sunshine hours, evaporation, and wind speed had acceptable accuracy to GSR modeling. Lopez et al. [2] used a novel technique by employing automatic relevance determination method (ARD) to obtain the relative relevance of a large set of atmospheric and radiometric variables for estimating hourly direct solar irradiance.

Wang et al.[3] proposed a novel Artificial Neural Network using statistical feature parameters for short-term solar irradiance forecasting. Cross-validation and Levenberg-Marquardt algorithm were used to determine the model structure and the network training, respectively. The results show that the forecast accuracy is obviously improved under variable weather conditions. An artificial neural network was used by Maamar et al. [4] to predict the daily global solar radiation on horizontal surface for north Algeria. Six parameters that measured from the meteorological station located inside the University of Blida were used to train the network. The results show that the mean absolute error less than 20% for both training and validation step. Rasheed et al. [5], AbdulAzeez [6] and Emad A. et al.[7] employed an ANN model to estimate monthly GSR. In their studies, the results of model show that the ANN can successfully be used for the estimation of monthly mean daily GSR and its ability to produce accurate estimates. Razafiarison et al. [8] and Krishnaiah et al. [9] trained multilayered neural networks by gradient back-propagation to determine numeric values of monthly means and hourly variations of the global solar radiation upon a titled surface per time. The main objective of the current study is to investigate a multilayer neural network with three structures (4-4-4-1), (4-8-8-1) and (4-9-9-1) to predict the average daily solar radiation in the capital city of Iraq.

METHODOLOGYOF SOLAR RADIATION

The daily radiation is the extra-terrestrial solar radiation on a horizontal surface at the top of the earth's atmosphere and can be expressed as [10]:

$$G_0 = 24 * \frac{I_{SC}}{\pi}\left[1 + 0.033\cos\frac{360\,n}{365}\right]\left[\cos\phi\cos\delta\sin\omega_s + \frac{\pi\omega_s}{180}\sin\phi\sin\delta\right] \quad (1)$$

Where: I_{sc} = 1367 Wm^{-2} is the solar constant, n is the day of the year, ϕ and δ are the latitude and declination angles and ω_s is the sunset hour.

The latitude and declination angles are given by:

$$\delta = 23.45\sin\left(360\frac{284+n}{365}\right) \quad (2)$$

$$\omega_s = \cos^{-1}[-\tan\varphi\tan\delta] \quad (3)$$

ANN MODEL AND ARCHITECTURE

Neural Network model

A neural network consists of a neurons connected to each other by directed communication links which are associated with weights [11]. As shown in Figure 1, there are three basic elements of the neural model; a set of synapses, an adder for summing up the input signals and an activation function for limiting the amplitude of the output of a neuron Haykin [12].

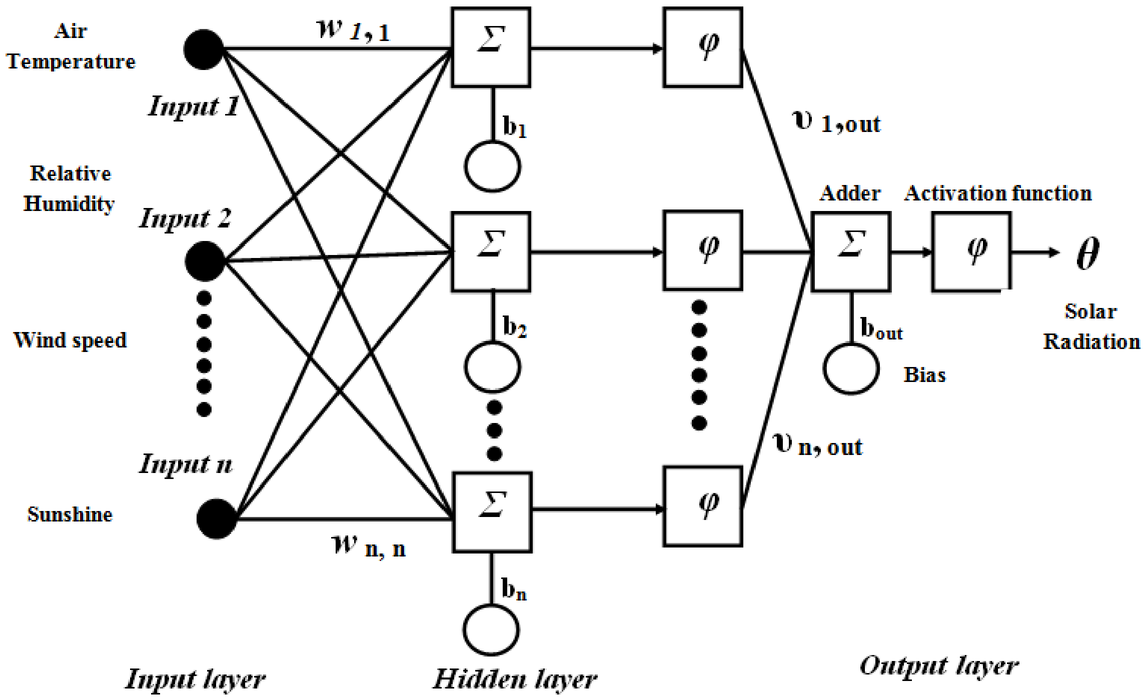


Figure 1. General diagram of neural network system

Activation function

The neural model consists of a set neurons; each neuron consists of the net function and the activation function. The activation function determines how the network inputs $\{y_j; 1 \le j \le n\}$ are combined inside the neuron. The ANN includes also an externally applied bias b, which increases or decreases the net input of the activation function, depending on whether its value, is positive, or negative. A neuron can be described in a mathematical model as:

$$\upsilon = \sum_{j=1}^{m} w_j y_j + b \quad (4)$$

Where $\{w_j; 1 \le j \le n\}$ is the synaptic weights and b is the bias, which is used to model the threshold. The threshold is a factor used to calculate the activation of the given neural network.

$$y = \varphi(\upsilon) \quad (5)$$

The logistic function is the most popular activation function used in the concentration of neural networks, and is defined as follows:

$$\varphi(\upsilon) = {}^{1}\!/_{1+\exp^{(-\upsilon)}} \quad (6)$$

Normalization process

The main task of normalization process is to normalize the quantitative variable to some standard range such as [0 1] or [-1 1]. Equation 7 was used by Sanjay et al. [13] to normalize the input and output data.

$$x_i = \frac{0.8}{d_{\max} - d_{\min}}(d_i - d_{\min}) + 0.1 \qquad (7)$$

Where: d_{min}, d_{max}, and d_i are the minimum, maximum and ith values of the input/output data.

Error Back-Propagation Training of Neural Network

A key step in applying ANN model is to choose the weight matrices. The values of these weights are determined using the error back-propagation training method. Given a set of training samples {(x(k)); 1 ≤ k ≤ K}, error back-propagation training begins by feeding all k input through the neural network and the corresponding output {z(k); 1≤ k ≤ K} is computed [14]. The sum of the square error is represented as follows:

$$E = \sum_{k=1}^{K}\left[e(k)\right]^2 \qquad (8)$$

$$= \sum_{k=1}^{K}\left[d(k) - z(k)\right]^2 = \sum_{k=1}^{K}\left[d(k) - f(W_x(k))\right]^2$$

Where W is the weight matrix $= [W_0 W_1 W_2 \ldots\ldots W_k]$, x is the input vectors $= [x_0 x_1 x_2 \ldots\ldots x_k]$ and d is the desired target value. The objective is to adjust the weight matrix W to minimize error E. However, the aforementioned calculations cause a nonlinear least square optimization problem. There are numerous nonlinear optimization algorithms available to solve this problem. Basically, these algorithms adopt a similar iterative formulation:

$$W(t+1) = W(t) + \Delta W(t) \qquad (9)$$

Where $\Delta W(t)$ is the correction made to the current weights $W(t)$.

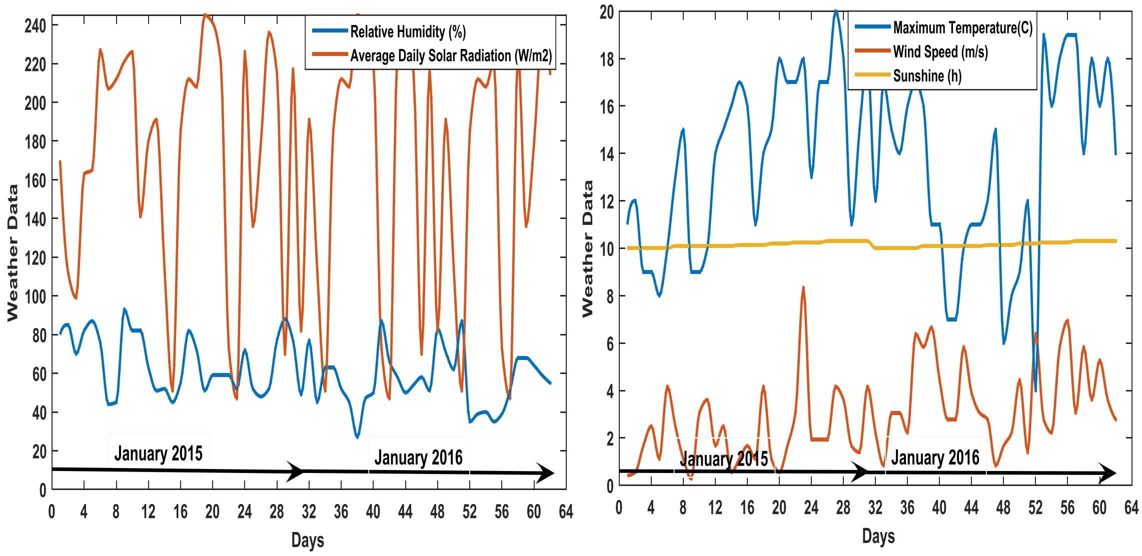
ANN performance

The prediction performance of the neural networks was evaluated based on the mean square error (MSE) in percentage between the predicted and the measured values according to the following expression:

$$MSE = \frac{\sum_{i=1}^{N}\left|X_{predicted} - X_{measured}\right|^2}{N} \qquad (10)$$

MATERIALS AND DATA SET PREPARATION

In this study, a dataset of 2604 hourly points for each January and August in three years 2014, 2015 and 2016 was collected from the Energy and Environment Research Center Station of Al-Jadriyah-Baghdad to investigate the structure of ANN model. The data was recorded for 14 hour in day and then the average value were taken for one day as maximum daily ambient temperature, sunshine duration, relative humidity and wind speed as input parameters and average daily solar radiation as output parameter. Fig.2 represents weather data of January and August in years 2015 and 2016. As shown in figure, the solar radiation ranges as minimum value of 47 W/m^2 in January to maximum value 430 W/m^2 in August, the average air temperature ranges from 4 °C in January to 45 °C in August and the sunshine from 10:50 hrs/day in January to 13:50 hrs/day in August. The relative humidity ranges from 9% in August to 85 % in January while, the wind speed changes between 0.4 m/s in January to 10.2 m/s in August. The minimum and maximum of the database are represented in Table 1 as normalization values. The input vectors and target vectors were scaled between [0 1] to fast the training phase in normalization process.



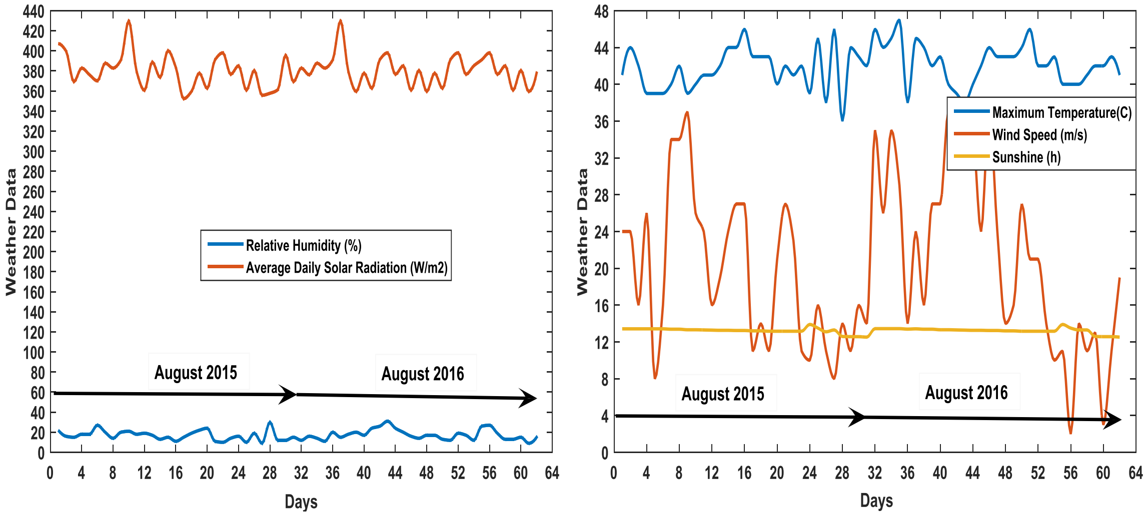


Figure 2. Weather data of January and August

Table 1: The values in term of normalization process

Parameters	January month				August month			
	Minimum value	Normalization process value	maximum value	Normalization process value	Minimum value	Normalization process value	maximum value	Normalization process value
Average daily Solar radiation W/m^2	47	0	245	1	352	0	430	1
Maximum Air temperature °C	4	0	20	1	36	0	45	1
Sunshine hrs/day	10	0	10:30	1	12:50	0	13:50	1
Relative humidity %	27	0	85	1	9	0	27	1
Wind speed m/s	0.4	0	6.9	1	0.8	0	10.2	1

RESULTS AND DISCUSSION

The total of database was divided into 70% about (65 data) for training the network and 30% about (28 data) for testing and validating the network. The number of hidden layer (j) is a function of the number of input nodes (n). According to the Zhang et al. [15], the number of j= n/2, 1*n, 2*n, 2*n+1. Therefore, multiple hidden layers with three structures (4-4-4-1, 4-8-8-1, 4-9-9-1) was selected in ANN architecture. The activation functions 'tansig' and 'purelin' were used in hidden layer and output layer respectively. Some of parameters values that used in MATLAB algorithm to create a fully connected feed-forward neural network were (Learning rate = 0.005, Error goal = 1×10^{-8}, Number of training epochs = 15000, and Momentum factor = 0.1). Mean square error (MSE) and the coefficient of determination (R^2) were selected as indicators to evaluate the performance and accuracy of the three structures of ANNs.

Table 2 represents the values of the ANN structures in the training, validation, testing phases and in the total process with MSE. As shown in Table l, the 4-9-9-1 structure was investigated the best model for predicting the solar radiation in January with the best (MSE=6.5) and with value of R^2 about (0.941 for training phase, 0.744 for validation phase, 0.925 for testing phase and 0.896 for the total process. While in the August, the 4-8-8-1 structure investigated the best model for the prediction the solar radiation with the with the best (MSE=5.4) and value of R^2 about (0.959 for training phase, 0.846 for validation phase, 0.934 for testing phase and 0.945 for the total process.

Table 2. Values of the ANN structures in the training, validation, testing phases and the all with MSE

Structure No.	Phases Training	Validation	Testing R^2	All	MSE
January					
4- 4 -4 - 1	0.725	0.864	0.858	0.755	8.2
4 -8 -8 -1	0.724	0.829	0.847	0.755	11.3
4 -9 -9 -1	0.941	0.744	0.925	0.896	6.5
August					
4- 4 -4 - 1	0.848	0.733	0.895	0.853	14.3
4 -8 -8 -1	0.959	0.846	0.934	0.945	5.4
4 -9 -9 -1	0.935	0.991	0.895	0.945	8.5

The results of comparing between the measured and predicated values of solar radiation in January and August for the total process in 4-9-9-1 and 4-8-8-1 models respectively are shown in Fig.3 and 4. The testing pattern of the structure generated a line similar to the measuring line. The disparity is probably a result of the accuracy of the ANN model and experimental error.

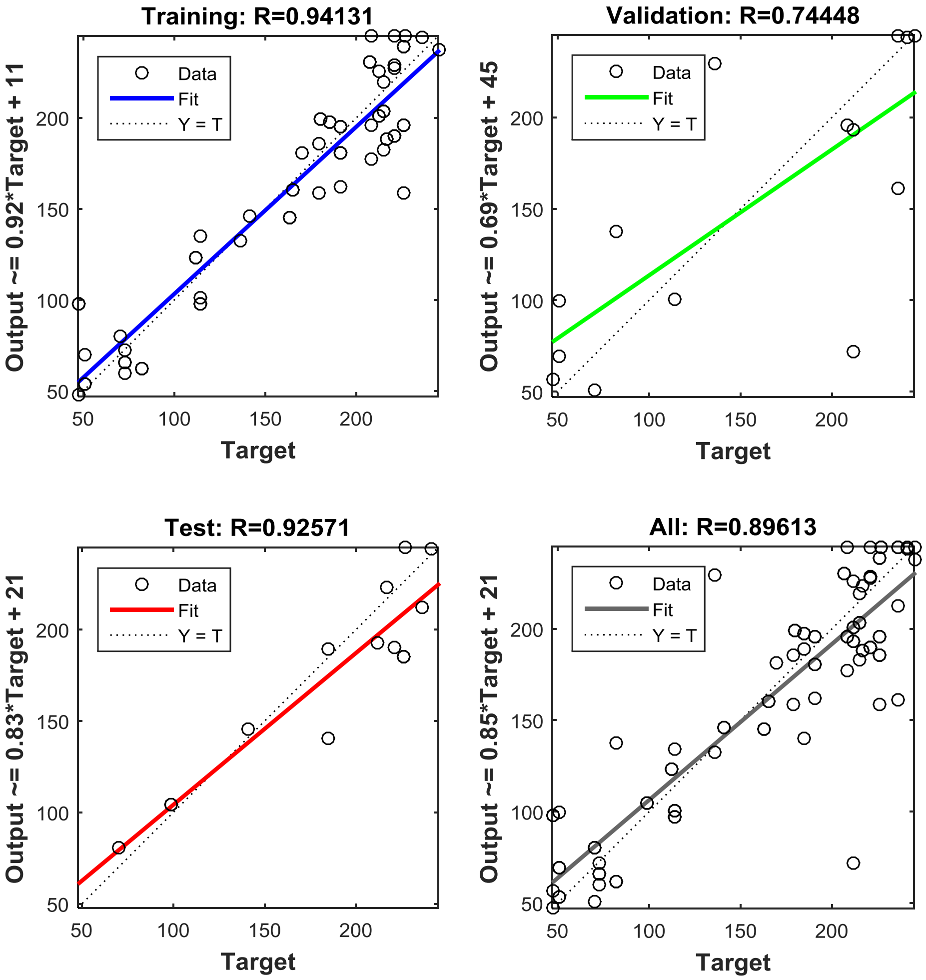


Figure 3. Comparing between the measured and predicated values of best structure in January

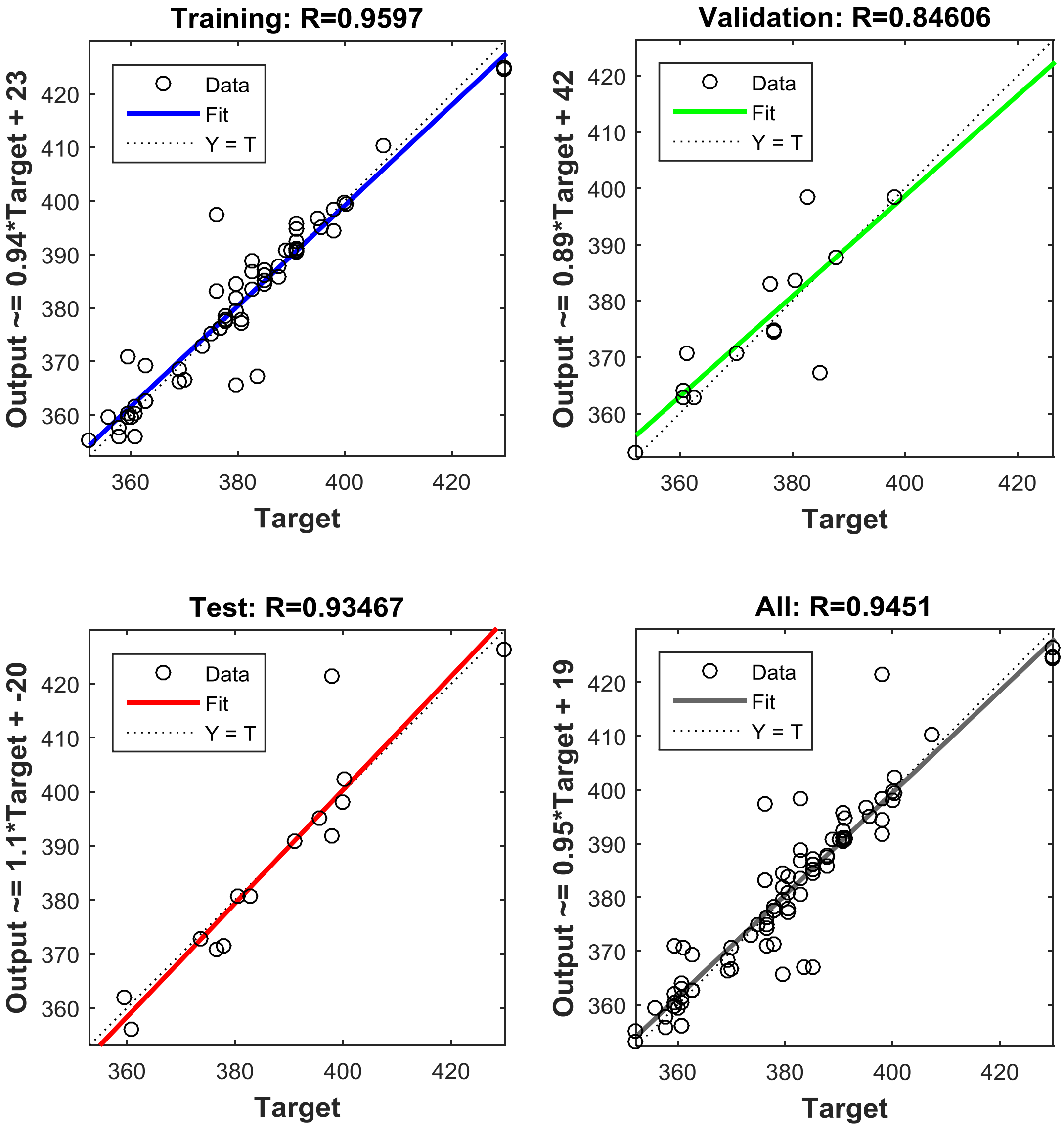


Figure 4. Comparing between the measured and predicated values of best structure in August

The predicted values of the three structures are represented in Figs. 5 and 6 with the number of testing points. We can see that the predicted values of the two months in January and August are very close and have good agreement with the measured values. The difference between the predicted values of ANN model and the measured values were reliable and more effective especially in 4-9-9-1 model for January and 4-8-8-1 for August. The difference and relative error between the predicted and measured values were represented in Table3. As shown in table, the maximum solar radiation differences were quite small in two cases and not exceed 31 W/m^2 in structure 4-4-4-1 of January and 30 W/m^2 in the same structure of August. While, the maximum relative error was increased from 8.6% to 27% in January structures and from 2.22% to 7.5 % in August structures.

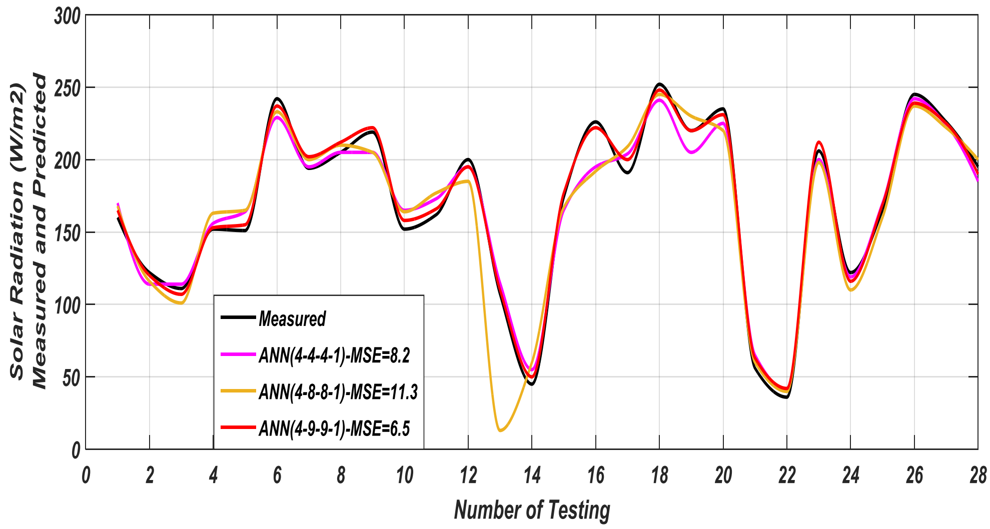


Figure 5. ANNs and measured of solar radiation in January with number of testing

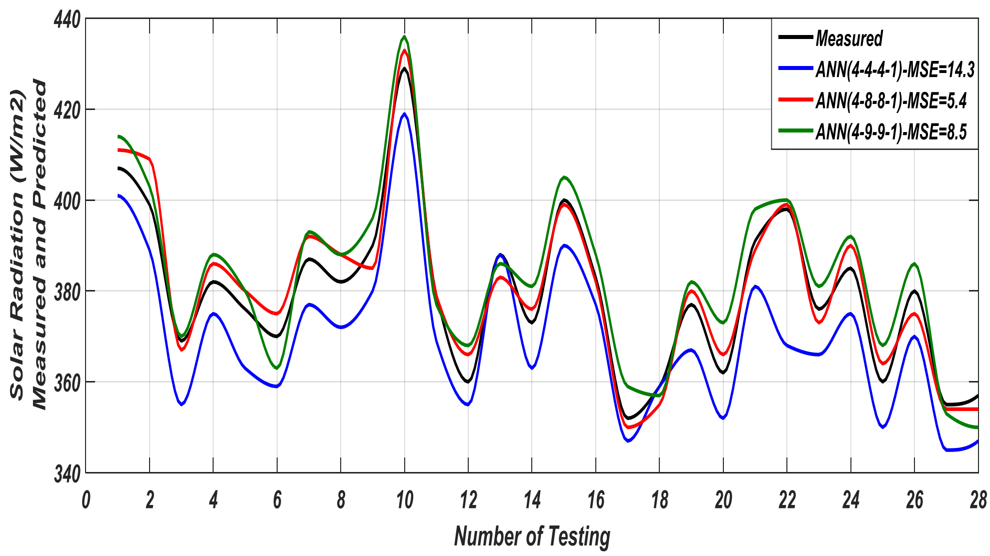


Figure 6. ANNs and measured of solar radiation in August with number of testing

Table 3. Statistical analysis of ANN structures

Structures	Solar radiation difference (W/m^2) Min	Max	Relative error (%) Min	Max
January				
4-4-4-1	0	31	0	8.6
4-8-8-1	4	24	1.7	27
4-9-9-1	1	9	0	14.2
August				
4-4-4-1	0	30	0	7.5
4-8-8-1	1	10	0	2.5
4-9-9-1	1	11	0.2	2.22

CONCLUSIONS

A multilayer neural network with three structures was investigated to predict the average daily solar radiation in the capital city of Iraq. Based on measured and ANN results, the following conclusions can be drawn:

- The difference between the predicted values of ANN model and the measured values were reliable and more effective.
- The maximum difference in solar radiation was found to be 31 W/m^2. These results indicate that the accuracy of the ANN model was satisfactory and coincided with the measured data.

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