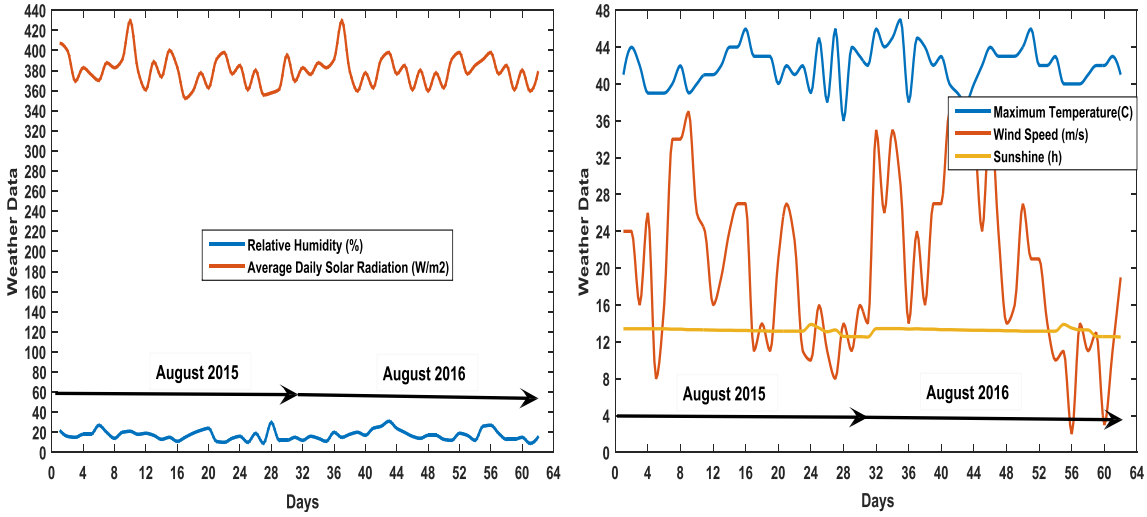

Figure 2. Weather data of January and August

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	All	MSE
			R^2		
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.

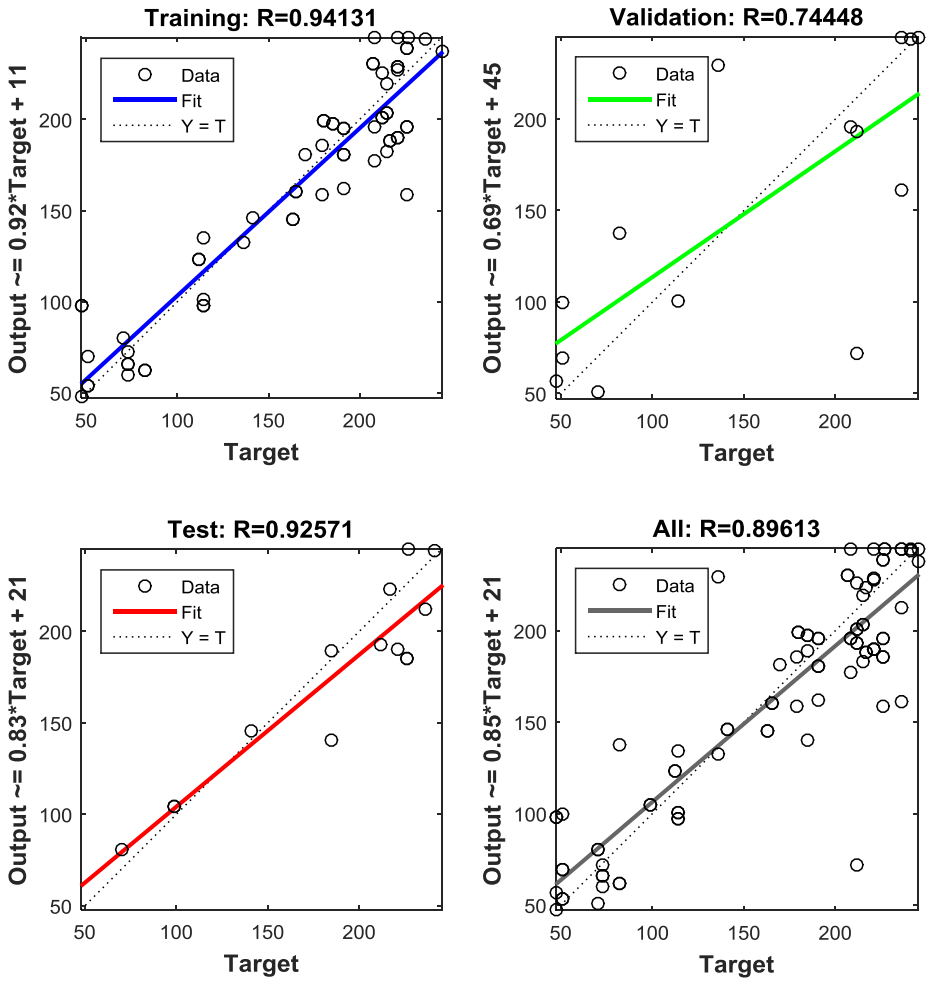

Figure 3. Comparing between the measured and predicated values of best structure in January

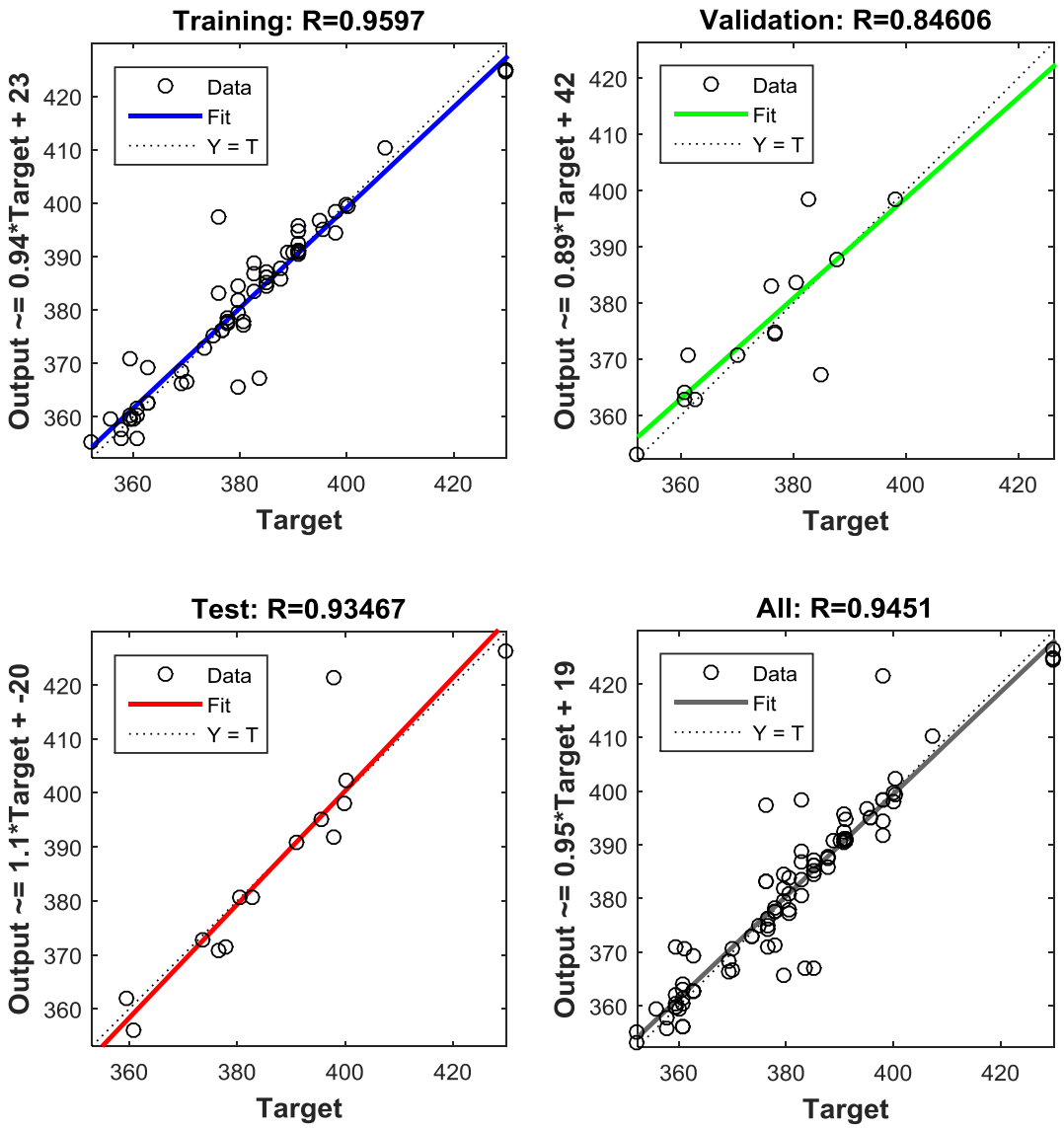

Figure 4. Comparing between the measured and predicated values of best structure in August

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.

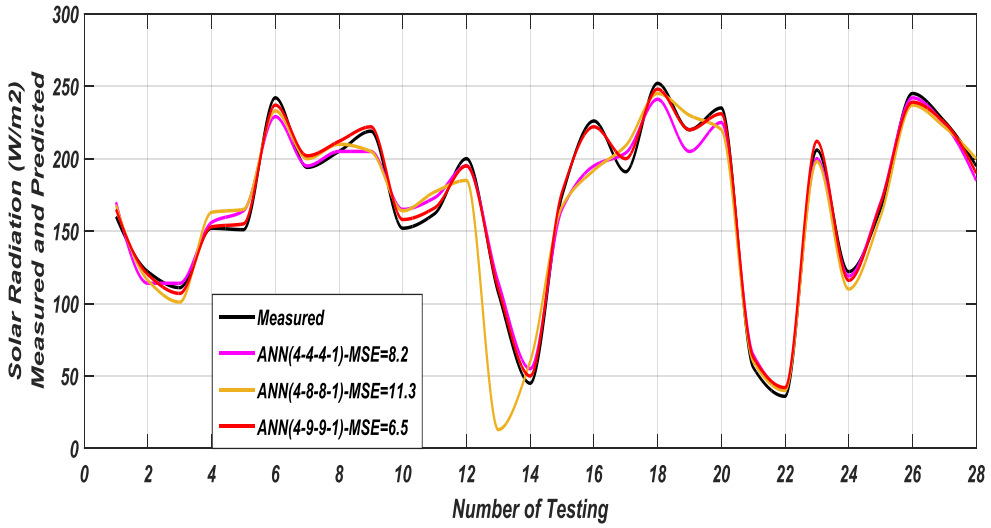

Figure 5. ANNs and measured of solar radiation in January with number of testing

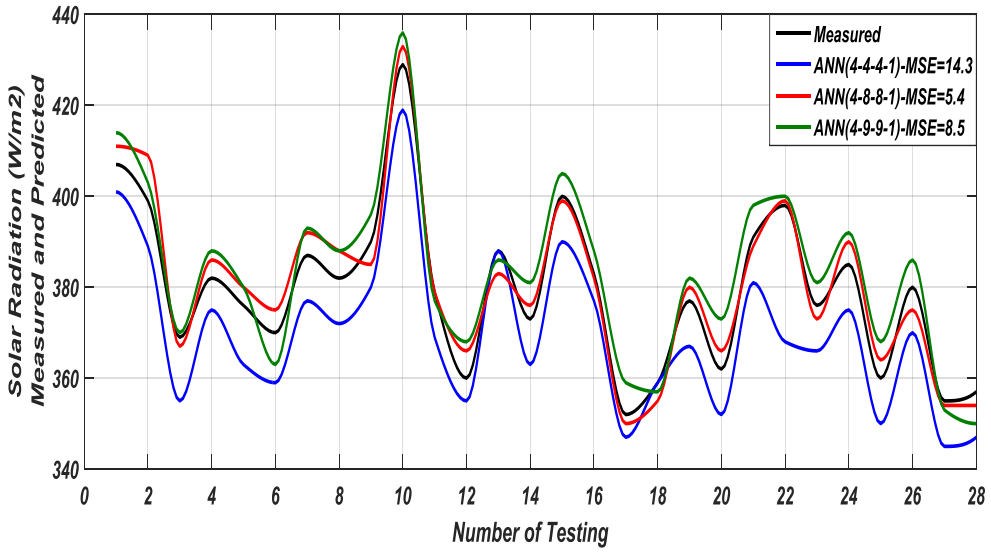

Figure 6. ANNs and measured of solar radiation in August with number of testing

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.

ACKNOWLEDGEMENT

The authors are grateful to the staff of Baqubah Technical Institute/Middle Technical University for their help.

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