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Neural network based global solar radiation estimation using limited meteorological data for Baghdad, Iraq

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Abstract
In present paper, an artificial neural network (ANN) model is developed for estimating monthly mean daily global solar radiation of Baghdad city, Iraq. The results of the ANN models have been compared with measured data on the basis of root mean square error (RMSE), mean absolute error (MAE) and determination coefficient (R^2). It is found that the solar radiation estimations by ANN are in good agreement with the measured values .Results obtained indicate that the ANN model can successfully be used for the estimation of monthly mean daily global solar radiation for Baghdad city. These results testify the generalization capability of the ANN model and its ability to produce accurate estimates in Baghdad.

Keywords: Neural network; Solar radiation; Baghdad; Iraq.

1. Introduction

Solar energy is the most ancient source of energy; it is the basic element for almost all fossil and renewable types. Solar energy is freely available and could be easily harnessed to reduce our reliance on hydrocarbon-based energy by both, passive and active designs. Precise solar radiation estimation tools are critical in the design of solar systems [1]. Solar radiation data is always a necessary basis for the design of any solar energy conversion device and for a feasibility study of the possible use of solar energy [2]. There is no doubt that the measured data are the best but cannot always be available, in addition to the cost of equipment, maintenance and calibration. Theoretical and empirical models have been postulated to compute the components of the solar radiation [3-9]. Some of these models are theoretical, dealing with the solution of the radiative transfer equation, while others are simply regression models. Angstrom (1924) presented the first attempt at estimating global solar radiation was the well-known empirical relation between global solar radiation under clear sky conditions and bright sunshine duration [10].

An artificial neural network (ANN) provides a computationally efficient way of determining an empirical, possibly nonlinear relationship between a number of inputs and one or more outputs. ANN has been applied for modeling, identification, optimization, prediction, forecasting and control of complex systems. ANN models are type of solar prediction models and there have been several articles that have used artificial neural networks for predicting solar radiation [11-17].

The present paper employee Artificial Neural Network (ANN) method to estimate global solar radiation in Baghdad city based mean air temperature, Maximum air temperature, Minimum air temperature, and Relative Humidity and Sunshine duration.

2. Artificial neural network for global solar radiation estimation

A neural network is a massively parallel distributed processor made up of simple processing units that have a natural propensity for storing experiential knowledge and making it available for us. Artificial neural network (ANN) is a branch of artificial intelligence technique that mimics the behavior of the human brain [18-20]. ANN are computing system which attempt to simulate the structure and function of biological neurons .Neural networks generally consist of a number of interconnected processing elements. How the interneuron connections are arranged and the nature of the connection determine the structure of network. Neural networks can be classified according to their strictures into following to type [21].

1- Feed forward network: In a feed for ward network the neurons are generally grouped in to layers. Signals flow always from the input layer through to the output layer via unidirectional connections, the neurons being connected from one layer to the next, but not it in same layer.

2- Recurrent network: In recurrent network, the outputs of some neurons are feed back to the same neurons or to neurons in preceding layers. Therefore, signals can flow in both forward and backward directions.

A multi-layer feed forward neural network is shown in Figure 1.The network consist of three layers: an input layer, hidden layer and output layer. The input layer consist of all the input factors: information from the input layer is then processed in the course of one hidden layer; the output vector is computed in the final (output) layer.

Generally the hidden and output layers have activation functions. The dashed lines in Figure 1 mean that there are more neurons in each layer than represented in this figure. The time series prediction problem using a neural network approach can be separated into three successive steps or sub problem [22].

1. Neural network architecture.
2. The learning or training process.
3. The testing.

In the present study a multi-layer feed forward network based on back propagation learning procedure is designed for estimating the solar radiation time series .This type of neural network is extensively used in the time series estimation.

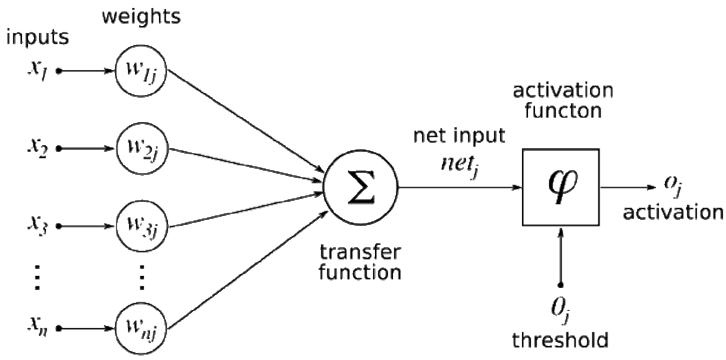

Figure 1. Schematic diagram of neural network

3. Methodology

The Meteorological data set provided by Iraq Meteorological Organization and seismology (IMOS) in Baghdad city for the period between (1971-2000) used was divided into three sets: A training data set having mean air temperature, Maximum air temperature, Minimum air temperature, Relative Humidity, Sunshine duration and Solar Radiation records for each month per the years. From 1971-1997(324 months), testing data set for months of the years 1998 to 1999 (24 months) and estimating data set for the year 2000 (12 month). The training data set has been used for the training of the artificial neural network, while the test data set has been for testing of the build network. Qnet 2000 tool was used for creating, training and testing Artificial Neural models.

In order to get the optimal Artificial Neural Network architecture, various Algorithms with different number of neurons and hidden layers and transfer functions including (Sigmoid, Hyperbolic Tangent, Hyperbolic Secant) were investigated, fifteen training Algorithms were tested in order to determine the most appropriate for the training process.

Many alternate training-processes have different variants are available such as back-propagation. The goal of any training algorithm is to minimize the global error, such as root mean squared error (RMSE), mean absolute error (MAE) and (R^2).The error for the hidden layers is determined by propagation back the error determined for the output layer.

$$RMSE = \frac{1}{n}\sum_{i=1}^{n}\left(\frac{o-t}{t}\right)^2 \tag{1}$$

In addition, Determination Coefficient (R^2) and mean absolute error (MAE) are defined as follows, respectively:

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{o-t}{t}\right| \tag{2}$$

$$R^2 = 1-\left[\frac{\sum(t-o)^2}{\sum(o)^2}\right] \tag{3}$$

where t is measured, o is output and n is number of observations [22].
ANNS have been used in a broad range of applications including pattern classification, function approximation, optimization, prediction, and automatic control [23]. The back-propagation algorithm has been used in feed-forward single hidden layers.

$$f(x) = \mathrm{sech(x)} \tag{4}$$

where X is the weighted sum of inputs.

4. Results and discussion

The performance of the ANN models during training, testing and estimating procedure were evaluated on the basis of the following statistical error tests: Root Mean Square Error (RMSE), Mean Absolute Error (MAE) and coefficient of determination (R^2) as shown in Tables 1, 2 and 3 respectively. ANN model 5 is superior to other ANN models because it has the smallest errors. The MAE are 0.0924, 0.0502, 0.0541, the RMSE 0.145, 0.0340, 0.035021. The coefficient of determination (R^2 value) of ANN model 5 are found to be 0.9943 , 0.987719, 0.960908 for training, testing and estimating procedure respectively which implies that ANN model 5 provides an accurate estimation of monthly mean daily global solar radiation of Baghdad city. Figure 2 compares the estimated values by ANN models against the measured values. The results indicate that most of the points fall along the diagonal line and the degree of the deviation from the diagonal line is small. So comparison results indicate that ANN model provides the best results among the nine models. That is, ANN model 5 is superior to the other ANN models, most of the points fall along the diagonal line. The estimated values have good agreement with the measured values. It can also be seen from the comparison of ANN model (1-9) that the dispersion degree of ANN model 5 is smaller than the other ANN models, which indicate that the ANN model 5 provided the best estimations among all the proposed models. The determination coefficient of ANN model 5 (R^2 value) obtained for the data set is 0.97. In this respect, the closer to unity is the coefficient of determination, the better the prediction accuracy. R^2 approaching 1 means that the solution of the problem gives accurate results. To test the generalization of the ANN model, Tables 1-3 show that ANN has the minimum predictions errors in Baghdad city. Low values of prediction errors for Baghdad city confirm the ability of the ANN models to predict solar radiation values precisely. These results demonstrate the generalization capability of the ANN model and its ability to produce accurate estimates in Baghdad city.

5. Conclusion

The use of ANN approach for monthly mean global solar radiation estimation in Baghdad cities has been investigated. The results of validation and comparative study indicate that the ANN based estimation technique for solar radiation is suitable to estimate the solar radiation than the empirical regression models proposed by other researchers. This study confirms the ability of the ANN to estimate solar radiation values precisely. Therefore, the present ANN model 5 may be suitable for estimating solar radiation at any location in Iraq, employing limited meteorological data.

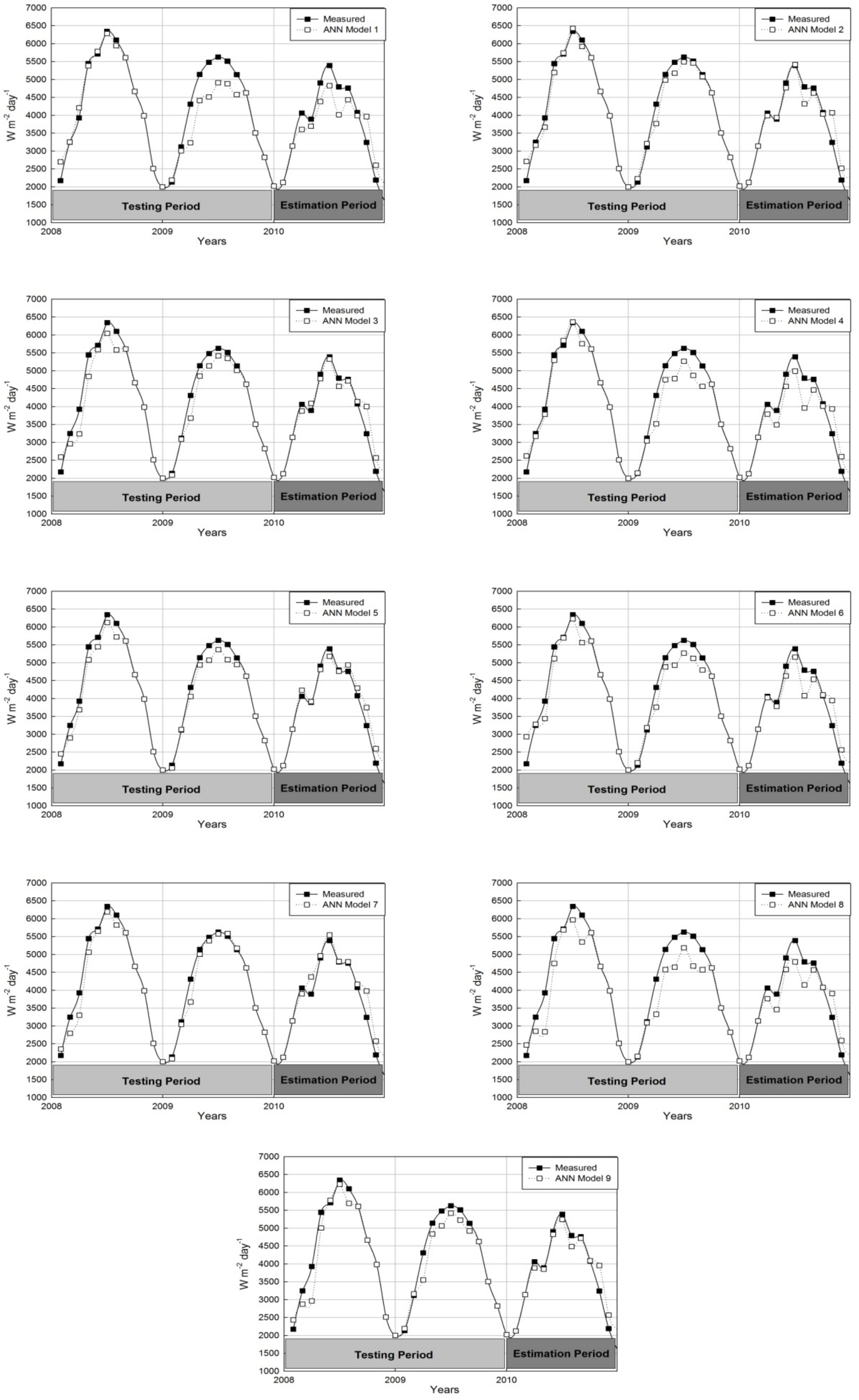

Figure 2. The measured and ANN model (1-9) estimated values of monthly mean global solar radiation

Table 1. Prediction errors for monthly mean daily global solar radiation of nine ANN models for training stage

Model no	Architecture of ANN	Iteration	Activation Function	RMSE	MAE	R^2
1	6,9,1	30000	Sec-e^{-x}	0.160	0.1357	0.9849
2	6,6,1	30000	Sec-e^{-x}	0.172	0.1052	0.9905
3	6,8,1	30000	Sec-e^{-x}	0.150	0.098	0.9926
4	6,5,1	30000	Sec-e^{-x}	0.156	0.1289	0.9967
5	6,6,1	20000	Sec-e^{-x}	0.145	0.0924	0.9943
6	6,7,1	20000	Sec-e^{-x}	0.163	0.1119	0.9896
7	6,6,7,1	30000	Sec- TAN - e^{-x}	0.151	0.1004	0.9920
8	6,9,1	20000	Sec- e^{-x}	0.162	0.1288	0.9871
9	6,10,1	30000	Sec- e^{-x}	0.150	0.0945	0.9929

Table 2. Prediction errors for monthly mean daily global solar radiation of nine ANN models for testing stage

Model no	Architecture of ANN	Iteration	Activation Function	RMSE	MAE	R^2
1	6,9,1	30000	Sec-e^{-x}	0.0552	0.058746	0.968832
2	6,6,1	30000	Sec-e^{-x}	0.0490	0.055144	0.975583
3	6,8,1	30000	Sec-e^{-x}	0.0400	0.053957	0.985869
4	6,5,1	30000	Sec-e^{-x}	0.0418	0.061454	0.981580
5	6,6,1	20000	Sec-e^{-x}	0.0340	0.050200	0.987719
6	6,7,1	20000	Sec-e^{-x}	0.0424	0.052021	0.989598
7	6,6,7,1	30000	Sec- TAN - e^{-x}	0.0424	0.050286	0.986982
8	6,9,1	20000	Sec- e^{-x}	0.0349	0.047507	0.991701
9	6,10,1	30000	Sec- e^{-x}	0.0425	0.049787	0.984777

Table 3. Prediction errors for monthly mean daily global solar radiation of nine ANN models for estimation stage

Model no	Architecture of ANN	Iteration	Activation Function	RMSE	MAE	R^2
1	6,9,1	30000	Sec-e^{-x}	0.035291	0.0540	0.962473
2	6,6,1	30000	Sec-e^{-x}	0.035647	0.0546	0.961714
3	6,8,1	30000	Sec-e^{-x}	0.035735	0.0546	0.961525
4	6,5,1	30000	Sec-e^{-x}	0.035950	0.0551	0.961061
5	6,6,1	20000	Sec-e^{-x}	0.035021	0.0541	0.960908
6	6,7,1	20000	Sec-e^{-x}	0.036080	0.0549	0.960780
7	6,6,7,1	30000	Sec- TAN - e^{-x}	0.036160	0.0549	0.960676
8	6,9,1	20000	Sec- e^{-x}	0.036160	0.0551	0.960606
9	6,10,1	30000	Sec- e^{-x}	0.036170	0.0548	0.960582

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