PREDICTION OF DAILY SOLAR RADIATION USING ANNS FOR SELECTED PROVINCES IN TURKEY

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Abstract:
In this study, hourly solar radiation was predicted using ANNs. Standard backpropagation and backpropagation with momentum were used for training neural network. In order to train the neural network, meteorological data along the years (1998–2008) belonging to the six cities (Antalya, Konya, Mersin, Mugla, Sanliurfa and Sivas) in Turkey were used as training (five stations) and testing (one station) data. Input parameters are chosen as latitude, longitude, altitude, day of the year and mean temperature while the output parameter is the solar radiation. The various networks designs were tested and then the most successful network was found as tree layer network with 10 neurons in hidden layer. The logistic sigmoid activation function was used for both hidden and output layers. To estimate difference between measured and estimating values, mean absolute error (MAE), root mean square error (RMSE) and coefficient of determination, R^2 were determined. The iteration numbers for the standard backpropagation and backpropagation algorithm with momentum were respectively obtained as 15000 and 7500. The RMSE, MAE and R^2 results for the standard backpropagation are respectively calculated as 0.0663, 0.0570 and 0.9870 while those for the backpropagation algorithm with momentum are computed as 0.0765, 0.0650 and 0.9821, respectively. As a conclusion, the standard backpropagation provides better approach with slower calculation speed than the backpropagation algorithm with momentum.

Keywords: Solar radiation, Artificial neural networks, Standard backpropagation, Backpropagation with momentum

INTRODUCTION

The growing population and the fast depleting reserves of fossil fuels have lead to researchers in the fields of engineering, hydrology, meteorology, economy, and industry to pursue the development and use of renewable energy resources like solar energy. A reasonably accurate knowledge of the availability of the solar resource at any place is required by solar engineers, architects, agriculturists and hydrologists in many applications of solar energy. Solar energy is being seriously considered for satisfying part of the energy demand in Turkey, as in the world. Meteorological data has been carried out in accordance with the standards by Turkish State Meteorological Service since 1935. According to meteorological data, the distribution of solar energy potential based on regional in Turkey was determined with Solar Energy Potential Atlas (SEPA). In Turkey, the maximum sunshine-duration appears in July while minimum sunshine-duration appears is in December. Turkey has sufficient solar radiation intensities and radiation durations for solar thermal applications since Turkey lies in a sunny belt, between 36° and 42° N latitudes. The yearly average solar-radiation is 3.6 kWh/m^{2}day, and the total yearly radiation period is 2610 h [1].

The most important parameter which is often needed is the long-term average daily global irradiation. However, the measurements of this parameter can only be determined in a few places. For places where no measured values are available, a common practice has been to assess this parameter using appropriate correlations which are empirically established

by using measured data at some selected places. These correlations estimate the values of horizontal radiation from more readily available meteorological, climatological and geographical parameters, such as sunshine duration, temperature and latitude.[3]

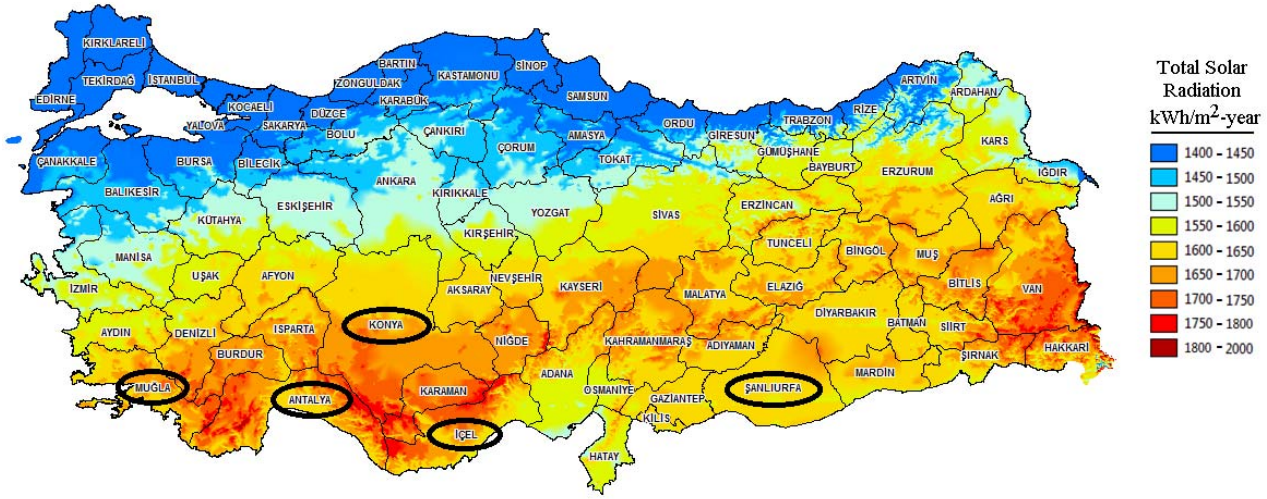


Figure 1. *Solar Energy Potential Atlas for Turkey [2]*

Several studies for the prediction of solar radiation in a few cities in Turkey have ensued [4].Togrul et al.(1999) were investigated the effect of geographical and meteorological parameters on the monthly mean global solar radiation in Elazig. A multiple linear regression was applied to six geographical and meteorological data sets, which were monthly mean extraterrestrial radiation, the ratio of `bright sunshine hours to day length, ambient and soil temperatures, humidity and sine of declination angle. The global solar radiation estimated from the models was compared with the values measured by the Kipp-Zonen pyranometer between April 1994 and March 1995. It has been determined that these equations which express the 99th percentile of the incident solar radiation, have a -9% deviation from our measured values [3].

Dombaycı and Gölcü [5] developed an artificial neural network (ANN) model which can be used to predict daily mean ambient temperatures in Denizli, south-western Turkey. In order to train the model, temperature values measured by The Turkish State Meteorological Service over three years (2003–2005) were used as training data and the values of 2006 were used as testing data. Their selected ANN model of a multi-layer consists of 3 inputs, 6 hidden neurons and 1 output. They performed training of the network by using Levenberg–Marquardt(LM) feed-forward backpropagation algorithms. They used a computer program under Matlab 6.5 software. For each network, coefficient of determination, (R^2) and root-mean squared error (RMSE) values were calculated and compared. Their results showed that the ANN approach was a reliable model for ambient temperature prediction [5]. Sözen et al. has done some studies on solar energy potential of Turkey by using ANN methods [1-4-6-7-8-9]. In one of them, the main focus of their study was to put forward the solar energy potential in Turkey using artificial neural networks (ANNs). Secondly, in their study, the best approach was investigated for each station by using different learning algorithms and a logistic sigmoid transfer function in the neural network with developed software. In order to train the neural network, meteorological data for three years (2000–2002) from 17 stations spread over Turkey were used as training (11 stations) and testing (6 stations) data. They used meteorological and geographical data (latitude, longitude, altitude, month, mean sunshine duration and mean temperature) in the input layer of the network. They predicted solar radiation as output layer. The predicted solar potential values from the ANN were given in the form of monthly maps by them.

Some researchers have predicted solar energy potential using different ANN methods and learning algorithms for their own country [10,11,12,13]. Reddy and Ranjan presented Artificial Neural Network (ANN) based models for estimation of monthly mean daily and hourly values of solar global radiation. Their results indicated that the ANN model

shows promise for evaluating of solar global radiation possibilities at the places where monitoring stations are not established [14].

In this study, hourly solar radiation is predicted using ANNs. Classical backpropagation called model 1 and backpropagation with momentum called model 2 has been used for training neural network. In order to train the neural network, meteorological data along years (1998–2008) from six cities (Antalya, Konya, Mersin, Mugla, Sanliurfa and Sivas) spread over Turkey were used as training (five stations) and testing (one station) data. Selected provinces of Turkey are the most promising from the point of the solar energy potential as seen Figure 1. In addition, the best approach with minimum error for selected station has also been determined by a in-house developed software. Thus, the decision about the quality of each approach (model) may be given using some numeric criterion like R^2.

BACKGROUND THEORIES

The human brain is central element of human nervous system, which composed of billions of neurons. These neurons communicate through specialized connections called synapses.

Each neuron of brain has a body, an axon, and dendrites. The role of dendrites in the brain is receiving signals from other neurons. The axon generates synaptic connections with other neurons. The cell body sums incoming signals from dendrites and synapses. The neuron will send a signal to its axon. The biological neuron model shown in Figure 2.

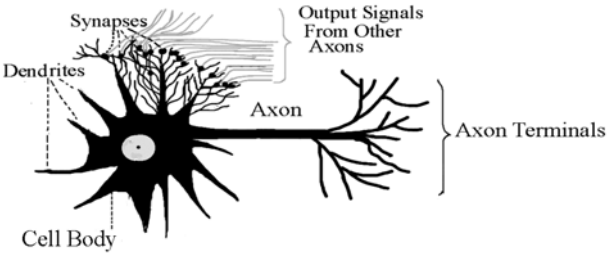


Figure 2. *The biological Neuron [15].*

An Artificial Neural Network (ANN) is inspired from biological nervous systems. An artificial neuron consists of five elements that inputs, weights, summary function, activation function and outputs. An artificial neuron is shown in Figure 3. The values $w_1, w_2, ..., w_n$ are weights, $x_1, x_2, ...x_n$ are inputs. Each input is multiplied by the relevant weight. Obtaining products and bias are summarized. By applying activation function to the result of summary the output of neuron is obtained.

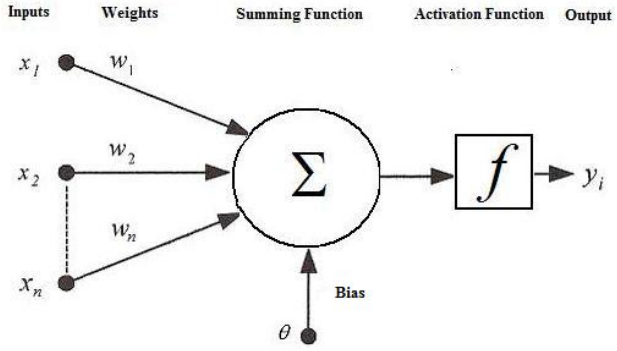


Figure 3. *An artificial neuron.*

Backpropagation

ANN's have always been regarded as the most powerful and universal predictor of all of the various kinds [16]. Typical artificial neural network used for the prediction of solar radiation is shown in Figure 4. These kinds of networks consist of input, hidden and output layers. Considering a typical backpropagation network, there are three layers namely input, output and at least one hidden layer. Each neuron in a layer is connected with all the neurons of consecutive layer. There is no connection between the neurons in the same layer or like a type of feedback. Backpropagation is a technique based on supervised learning and is used for training artificial neural networks. Its first description was by P. Werbos in 1974, and later development of it by D. E. Rumelhart, G. E. Hinton and R. J. Williams in 1986. The way of backpropagation to learn is to process a set of training samples iteratively, to compare the network's prediction for each sample with the actual known class label. In order to minimize the mean squared error between the network's prediction and the actual class, the weights are modified for each training sample [17]. The input to the j neuron of hidden layer is calculated as follow:

$$I_j = \sum_i w_{ij} x_i + \theta_j \qquad (1)$$

where w_{ij} is the weight of the connection from neuron i in the input layer to neuron j of the hidden layer; x_i is the i neuron of input layer; and θ_j is the bias. The output of j neuron of

hidden layer is calculated by using activation function as follow:

$$O_j = f\left(I_j\right) \tag{2}$$

The input to the j neuron of the output layer is calculated as follow:

$$IO_j = \sum_i v_{ij} O_i + \xi_j \tag{3}$$

where v_{ij} is the weight of the connection from i neuron in the hidden layer to j neuron of the output layer ; O_i is the output of neuron i from the hidden layer; and ξ_j is the bias. The output of j neuron of the output layer is calculated by using activation function as follow:

$$Y_j = f\left(IO_j\right) \tag{4}$$

The error of j neuron of output layer is calculated as follows:

$$E_j = \frac{1}{2}\left(D_j - Y_j\right)^2 \tag{5}$$

where, D_j is the desired output. The error gradient for output layer calculated as follow:

$$\delta_j = (D_j - Y_j) f^{'}(IO_j) \tag{6}$$

Δv_{ij} and $\Delta\xi_j$ are calculated as follows:

$$\Delta v_{ij} = l\delta_j O_i \tag{7}$$

$$\Delta\xi_j = l\delta_j \tag{8}$$

where, l is the learning rate. The error gradient for hidden layer calculated as follow:

$$\sigma_j = f^{'}(I_j)\sum_{i=1}^{k}\delta_i w_{ji} \tag{9}$$

where k is the number of neurons in the output layer and δ_i is computed using equation (6). The Δv_{ij} and $\Delta\theta_j$ are calculated as follows:

$$\Delta w_{ij} = l\sigma_j x_i \tag{10}$$

$$\Delta\theta_j = l\sigma_j \tag{11}$$

Weights and biases are updated by the following equation:

$$v_{ij}(new) = v_{ij}(old) + \Delta v_{ij} \tag{12}$$

$$\xi_j(new) = \xi_j(old) + \Delta\xi_j \tag{13}$$

$$w_{ij}(new) = w_{ij}(old) + \Delta w_{ij} \tag{14}$$

$$\theta_j(new) = \theta_j(old) + \Delta\theta_j \tag{15}$$

Algorithm works as follows :

- Initialize the weights to small random values.
- Present a training pattern to the network and calculate the response.
- Compare a desired and calculated response for each output neuron and calculate errors.
- Calculate the new weights using formulas (12) - (15).
- Repeat steps 2-4 for each pattern in the training set until the calculated error is acceptable.

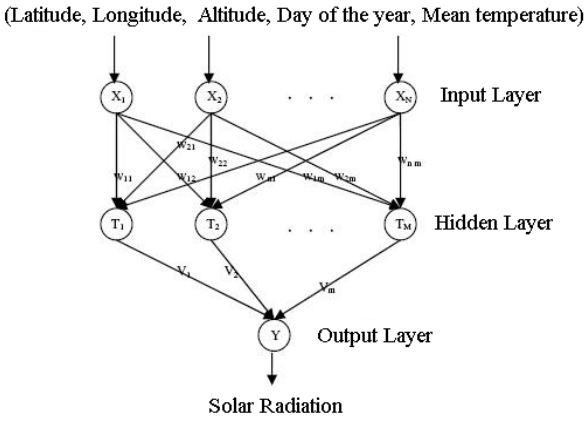


Figure 4. *Typical artificial neural network used for the prediction of solar radiation.*

Backpropagation algorithm with momentum

The difference between the standard backpropagation and backpropagation with momentum is in the updates of weights. In this method for updating of weights, following formulas are used:

$$v_{ij}(m) = v_{ij}(m-1) + \Delta v_{ij} + \alpha\left[v_{ij}(m-1) - v_{ij}(m-2)\right] \tag{16}$$

$$\xi_j(m) = \xi_j(m-1) + \Delta\xi_j + \alpha\left[\xi_j(m-1) - \xi_j(m-2)\right] \tag{17}$$

$$w_{ij}(m) = w_{ij}(m-1) + \Delta w_{ij} + \alpha\left[w_{ij}(m-1) - w_{ij}(m-2)\right] \tag{18}$$

$$\theta_j(m) = \theta_j(m-1) + \Delta\theta_j + \alpha\left[\theta_j(m-1) - \theta_j(m-2)\right] \tag{19}$$

where $\alpha \in (0,1)$ is the random constant.

RESULTS AND DISCUSSION

Data from six stations averaged over ten years (1998-2008) were used to train and test the networks. The data from five stations, namely from Antalya, Mersin, Mugla, Urfa, and Sivas were used for training and the data from remain station, namely from Konya were used for testing the models. Geographical parameters for these cities are given table 1 and location of the cities on map is shown in Figure 5. Input parameters were latitude, longitude, altitude, day of the year, mean temperature. The output parameter is the solar radiation. Typical artificial neural network

used for the prediction of solar radiation is shown in Figure 4. The various networks designs were used. It is found that the most successful network was tree layer network with 10 neurons in hidden layer.

Table 1. Geographical parameters for these cities

Data	City	Latitude	Longitude	Altitude
Training	Antalya	36.70	30.73	63.57
	Mersin	36.80	34.63	3.40
	Mugla	37.22	28.37	646.07
	Urfa	37.15	38.78	547.19
	Sivas	39.75	37.01	1285.00
Testing	Konya	37.98	32.55	1030.61



Figure. 5. *Solar radiation stations in the Turkey (●, stations used for training; ○, stations used for testing)*

The logistic sigmoid activation function has been used both for hidden and output layer, namely

$$f(t) = \frac{1}{1+e^{-t}} \tag{20}$$

where t is the weighted sum of the inputs.

It is easy to estimate that it may be some difference between measured and estimating values. This difference can be quantified by statistical measurements. For this aim in this study mean absolute error (MAE), root mean square error (RMSE) and coefficient of determination, R^2 have been used. The formula for the calculation of MAE, RMSE and R^2 are:

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|a_i - p_i| \tag{21}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(a_i - p_i)^2} \tag{22}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(a_i - p_i)^2}{\sum_{i=1}^{n}(p_i)^2} \tag{23}$$

where a_i is the actual value and p_i is the predicted value. Input and output values are normalized in the ranges of 0 to1 respectively as follows.

$$x_n = \frac{x_r - x_{\min}}{x_{\max} - x_{\min}} \tag{24}$$

Using standard backpropagation network (Model 1) after 15000 iteration, RMSE=0.0663, MAE=0.0570 and R^2=0.9870 has been founded. Figure 6 shows the measured and estimated solar radiation using standard backpropagation.

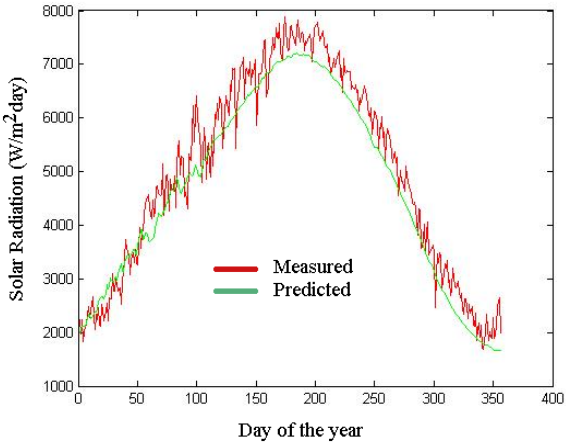


Figure 6. *Solar radiation as measured and estimated using standard backpropagation algorithm (Model 1)*

Using backpropagation algorithm with momentum (Model 2) after 7500 iterations, the results for RMSE=0.0765, MAE=0.0650 and R^2=0.9821 have been found. Figure 7 shows the measured and estimated solar radiation using backpropagation with momentum.

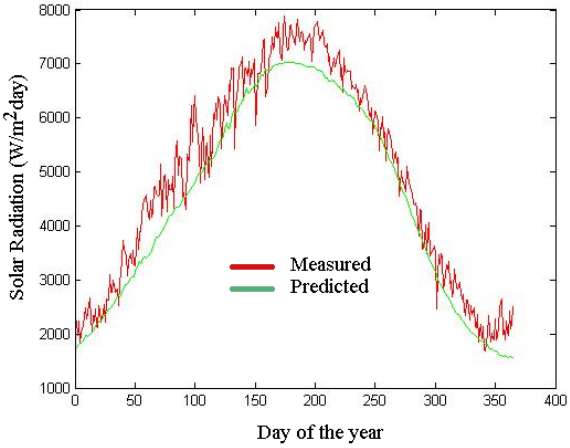


Figure 7. *Solar radiation as measured and estimated using backpropagation algorithm with momentum (Model 2)*

Mean absolute error (MAE), root mean square error (RMSE) and coefficient of determination, R^2 of estimated data for each month of year are given in table 2. The

standard backpropagation is better approach than the backpropagation algorithm with momentum.

Table 2. Comparison of the statistical errors in both models for the daily global solar radiaton

Months	Predicted Model 1			Predicted Model 2		
	RMSE	MAE	R^2	RMSE	MAE	R^2
Jan.	0.040	0.033	0.966	0.045	0.038	0.918
Feb.	0.050	0.038	0.980	0.085	0.073	0.913
March	0.071	0.062	0.979	0.114	0.106	0.930
April	0.090	0.077	0.978	0.112	0.096	0.962
May	0.079	0.070	0.989	0.079	0.069	0.989
June	0.064	0.056	0.995	0.069	0.061	0.994
July	0.065	0.059	0.995	0.087	0.083	0.990
Aug.	0.061	0.055	0.994	0.054	0.049	0.995
Sept.	0.067	0.061	0.988	0.041	0.036	0.996
Oct.	0.059	0.053	0.978	0.056	0.050	0.981
Nov.	0.067	0.061	0.883	0.065	0.059	0.891
Dec.	0.069	0.058	0.486	0.071	0.060	0.440

Figure 8 shows the comparison between the measured and predicted daily global solar radiation for the two models. It can be seen that, in general, there is good agreement between the measurements and predictions. Also, it can be seen that the standard backpropagation is better approach than the backpropagation algorithm with momentum. However, backpropagation algorithm with momentum has needed less computation time than other model.

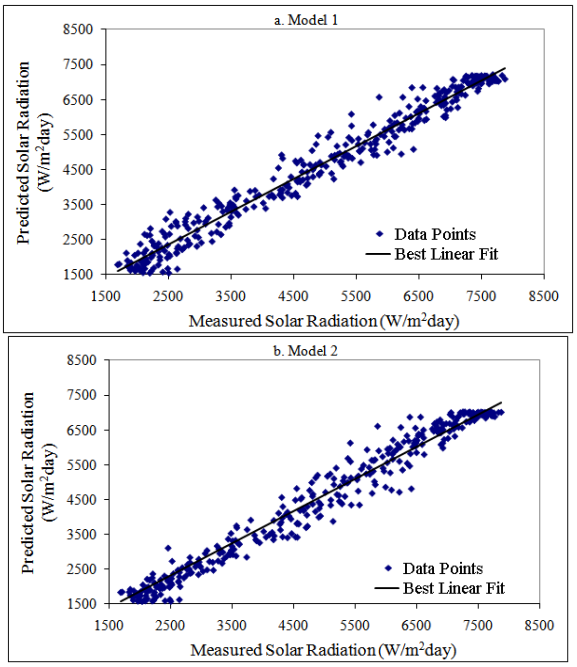


Figure 8. *Performance of the artificial neural network models for prediction of global solar radiation in Turkey (a. Model 1, b. Model 2)*

Relative error (RE) variation between the measured and predicted global solar radiation is calculated as follows;

$$RE = \frac{|Measured - \Pr edicted|}{Measured} * 100 \qquad (25)$$

Relative error variations between the measured and predicted global solar radiation according to the model 1 and 2 along the year is displayed in Figure 9. Most of the relative error values are less than around 10%, which is an acceptable level for engineering approach. Mean values of the relative errors for model 1 and 2 are respectively calculated as 8.96% and 10.12%.

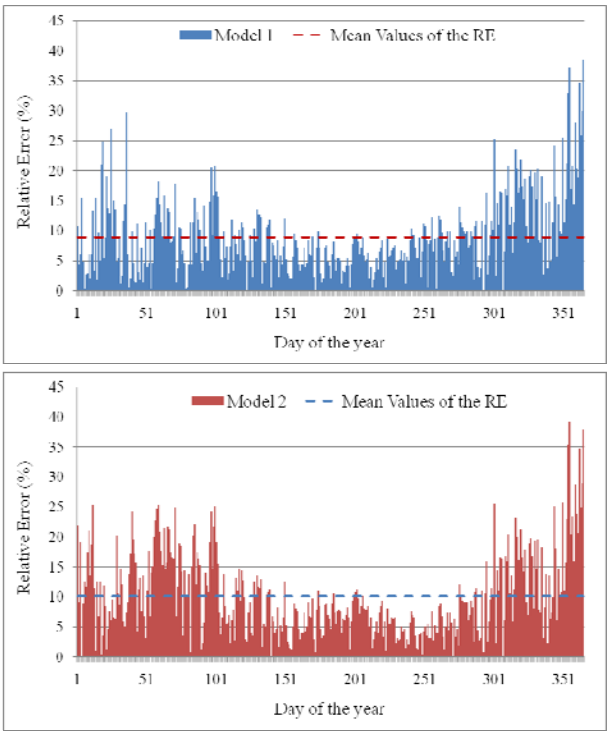


Figure 9. *Relative error of the artificial neural network models for prediction of global solar radiation in Turkey (a. Model 1, b. Model 2)*

CONCLUSIONS

The results of validation and comparative study indicate that the ANN based estimation technique for solar radiation can be used to predict solar radiation as alternative models to the classical regression models proposed by other researchers for Turkey and other countries. This study confirms the ability of the ANN to predict solar radiation values precisely. Mean the relative errors between the measured and predicted global solar radiation along the year for model 1 and 2 are

respectively calculated as 8.96% and 10.12%. The comparison results indicate that the ANN model is promising for evaluating the global solar radiation resource potential at the places where there are no monitoring stations in Turkey.

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