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Estimation of solar radiation over Turkey using artificial neural network and satellite data

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ABSTRACT

This study introduces artificial neural networks (ANNs) for the estimation of solar radiation in Turkey (26–45 E and 36–42 N). Resilient propagation (RP), Scale conjugate gradient (SCG) learning algorithms and logistic sigmoid transfer function were used in the network. In order to train the neural network, meteorological data for the period from August 1997 to December 1997 for 12 cities (Antalya, Artvin, Edirne, Kayseri, Kütahya, Van, Adana, Ankara, İstanbul, Samsun, İzmir, Diyarbakır) spread over Turkey were used as training (nine stations) and testing (three stations) data. Meteorological and geographical data (latitude, longitude, altitude, month, mean diffuse radiation and mean beam radiation) are used in the input layer of the network. Solar radiation is the output. However, solar radiation has been estimated as monthly mean daily sum by using Meteosat-6 satellite C3 D data in the visible range over 12 cities in Turkey. Digital counts of satellite data were converted into radiances and these are used to calculate the albedos. Using the albedo, the cloud cover index of each pixel was constructed. Diffuse and direct component of horizontal irradiation were calculated as a function of optical air mass, turbidity factor and Rayleigh optical thickness for clear-sky. Using the relation between clear-sky index and cloud cover index, the solar irradiance for any pixel is calculated for Physical method. RMS between the estimated and ground values for monthly mean daily sum with ANN and Physical method values have been found as 2.32 MJ m^{-2} (54 W/m^2) and 2.75 MJ m^{-2} (64 W/m^2) (training cities), 3.94 MJ m^{-2} (91 W/m^2) and 5.37 MJ m^{-2} (125 W/m^2) (testing cities), respectively.

1. Introduction

Energy is essential to the economic and social development and improved quality of life in Turkey as in other countries. Turkey is an energy importing country. Because of its limited energy resources, more than the half of the energy requirement is supplied by imports [1]. Solar energy is being seriously considered for satisfying a significant part of energy demand in Turkey, as is in the world [2]. Solar energy potential is very high in Turkey. Turkey is located at the Mediterranean at 36 and 42°N latitudes and has a typical Mediterranean climate. The yearly average solar radiation is 3.6 kW h/m^2 day, and the total yearly radiation period is ~2610 h. Solar radiation incident on a horizontal surface and sunshine duration are measured by all recording stations in Turkey [1]. Therefore solar availability in China is excellent with more than two thirds of the areas having 2200 h of sunshine and annual solar radiation in excess of 5860 MJ/m^2 [3,4]. In spite of large area of China has same solar radiation value with Turkey. Although, in recent years, many individual studies have been carried out on this subject for different locations of Turkey [2] (e.g., Saudi Arabia [5,6], Spain [7,8] and Turkey [9,10]), the studies have not been completed yet because of insufficient stations values for large areas [11]. Several studies have individually been presented [12,13] for the prediction of solar radiation in various cities in Turkey. In order to determine the behavior of solar radiation at the site of interest, long-term data from a near by location along with empirical, semi-empirical, physical, neural networks, wavelets, fractals, etc. techniques are used [14]. Comparative studies of ANNs and the traditional regression approaches in modeling global solar radiation have also been conducted, and it has been shown that ANN methodology offers a promising alternative to the traditional approach [15,16]. Artificial neural networks have been used by the author in the field of solar energy; for modeling and design of a solar steam generating plant, for the estimation of a parabolic-trough collector's intercept factor and local concentration ratio and for the modeling and performance prediction of solar water-heating systems [17]. The effect of relative humidity on solar potential is investigated using artificial neural-networks [10]. In this study physical and neural network (ANN) techniques are used for prediction of solar radiation. In solar radiation based studies basically two

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methods were used, namely ANN and Physical methods. Usage of these methods is more suitable especially for large places. Both methods are applicable on any region and everywhere for the very large distances between the stations. So the objective of the present study is to apply the ANN and Physical methods for the prediction of the solar radiation of target station using neighboring measuring stations, in order to show that these methods can be applied to predict the solar radiation for any locations around sampled measuring stations.

According to Sözen et al. few studies have been presented for prediction of solar resource in several cities in Turkey using artificial neural network (ANN) [18,9]. These studies show general perspective of solar radiation in Turkey [19]. In this study, twelve stations (Antalya, Artvin, Edirne, Kayseri, Kütahya, Van, Adana, Ankara, İstanbul, Samsun, İzmir, Diyarbakır) are selected from different regions of Turkey. The geographical locations of these solar radiation stations are shown in Fig. 1. The cities selected can give a general idea about solar radiation values of Turkey. In this study, estimation of solar radiation in Turkey was based on meteorological and geographical data (latitude, longitude, altitude, month, mean diffuse radiation, and mean beam radiation). These selected locations covering Turkey have different values as seen Table 1. Resilient propagation (RP), Scale conjugate gradient (SCG) learning algorithms and logistic sigmoid transfer function are used in the network. Meteorological and geographical data is used as input to the network. Solar radiation is the output.

In recent years many studies showed that global solar irradiance at ground could be estimated successfully using the meteorological satellite data [20]. The reason is that these satellites can observe large areas at different wavelengths within a small period and with proper pixel resolution. In addition [21–23], also show that the irradiation estimated by use of satellite data is better than from interpolation technique where the distance to stations greater than 34 km for hourly irradiation and 50 km for daily irradiation. These advantages force us to use the satellite data to estimate the global irradiation at ground level.

The present study compares estimated values from ANN and Physical method by using root mean squared (RMS) and correlation coefficient (R) with the values obtained from ground measurement collected by the Turkish State Meteorological Service (TSMS) at 12 measuring stations located in Turkey.

Table 1
Geographical parameters for the cities

City	Latitude (°)	Longitude (°)	Altitude (m)
Antalya	36.42	30.44	54
Artvin	41.11	41.49	628
Edirne	41.40	26.34	51
Kayseri	38.45	35.29	1093
Kütahya	39.25	29.58	969
Van	38.27	43.19	1661
Adana	36.59	35.21	27
Ankara	39.57	32.53	891
İstanbul	41.01	28.59	0
Samsun	41.17	36.18	4
İzmir	38.26	27.10	29
Diyarbakır	37.54	40.14	677

2. Artificial neural networks

The use of the ANNs for modeling and prediction purposes has increasingly become popular in the last decades [24,25]. Researchers have been applying the ANN method successfully in various fields of mathematics, engineering, medicine, economics, meteorology, psychology, neurology, in the prediction of mineral exploration sites, in electrical and thermal load predictions and in adaptive and robotic control and many other subjects. ANN is trained to overcome the limitations of the conventional approaches to solve complex problems. This method learns from given examples by constructing an input–output mapping in order to perform predictions [26]. In other words, to train and test a neural network, input data and corresponding output values are necessary [27].

Fundamental processing element of a neural network is a neuron. Each neuron computes a weighted sum of its p input signals, y_i, for i = 0,1,2,...,n, hidden layers, w_{ij} and then applies a nonlinear activation function to produce an output signals u_j. The model of a neuron is shown in Fig. 2.

A neuron j may be mathematically described with the following pair of equations [28]:

$$u_j = \sum_{i=0}^{p} w_{ji} y_i \tag{1}$$

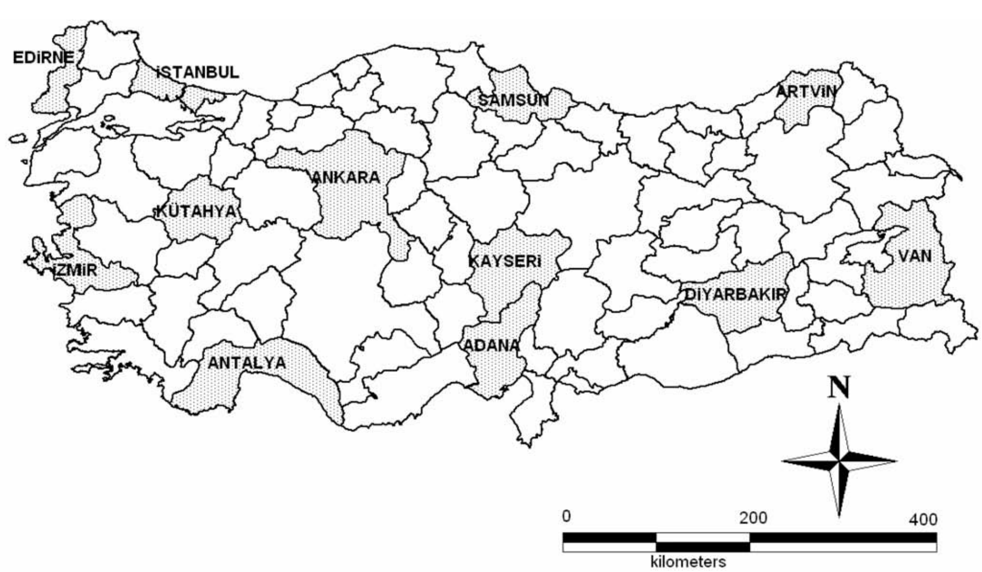

Fig. 1. Solar radiation measuring stations in Turkey.

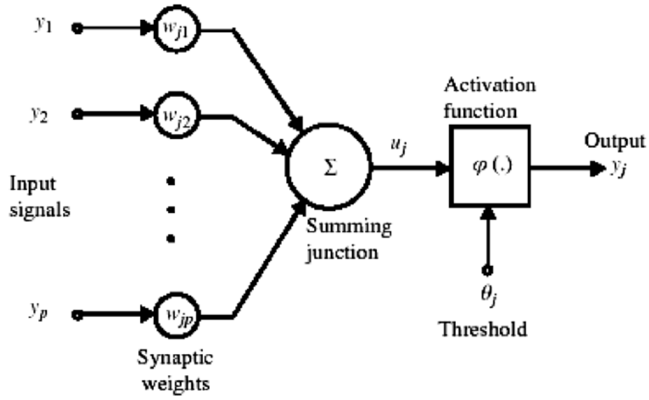

Fig. 2. Nonlinear model of a neuron [25].

and

$$y_j = \varphi(u_j - \theta_j). \tag{2}$$

The use of threshold θ has the effect of applying an affine transformation to the output of the linear combiner in the model of Fig. 2 [28,29].

The sigmoid logistic nonlinear function is described with the following equation [30]:

$$\varphi(x) = \frac{1}{1 + e^{-x}}. \tag{3}$$

3. Calibration and normalization of radiometer counts

Digital counts recorded by the satellite sensor are converted to the radiances by using the following equation [31]:

$$L^t(i,j) = a^t(CN^t - CN^t_{\text{dark}}) + b^t. \tag{4}$$

Here a^t, CN^t_{dark} and b^t represent the Meteosat calibration parameters and CN^t is the digital count recorded by the satellite sensor. By assuming the surface is Lambertian radiances the apparent albedo $\rho^t(i,j)$ *for the pixel (i,j) is calculated using equation:*

$$\rho^t(i,j) = \frac{\pi L^t(i,j)}{I_0 \varepsilon(t) \cos \Theta_s(t,i,j)}, \tag{5}$$

where I_0 is the solar constant (1367 W m^{-2}), $\varepsilon(t)$ is the correction used to allow for the variation of sun-earth distance from its mean value and Θ_S is the sun zenithal angle.

4. Cloud index

If cloud cover index (ratio) over the region is known then the partly cloudy or overcast sky global irradiation reaching at surface can be estimated with acceptable accuracy by including the known position of the sun. The cloud cover index N_t, *at any pixel for a given time t* is defined as [32]:

$$N_t(i,j) = \frac{\rho_t(i,j) - \rho_{\text{ga}}(i,j)}{\rho_{\text{cm}} - \rho_{\text{ga}}(i,j)}, \tag{6}$$

where $\rho_t(i,j)$ is the apparent albedo at pixel (i,j) at any time t, ρ_{ga} is the ground albedo of pixel (i,j) and ρ_{cm} is the mean value of maximal of the albedo. In this way the value of cloud cover index for any region (pixel) can be computed by using satellite images.

5. Clear-Sky model

In solar energy applications the atmospheric transmission factor is commonly expressed in terms of either clear-sky index or the clearness index. The clear-sky index K_{clear} is equal to the ratio of the global irradiation at ground on a horizontal surface G to the same quantity but for clear skies G_{clear}:

$$K_{\text{clear}} = \frac{G}{G_{\text{clear}}} \tag{7}$$

The global irradiation at ground on a horizontal surface for clear-sky, G_{clear}, is the sum of its direct and diffuse horizontal irradiance and can be written as

$$G_{\text{clear}} = G_{\text{direct}} + G_{\text{diffuse}}. \tag{8}$$

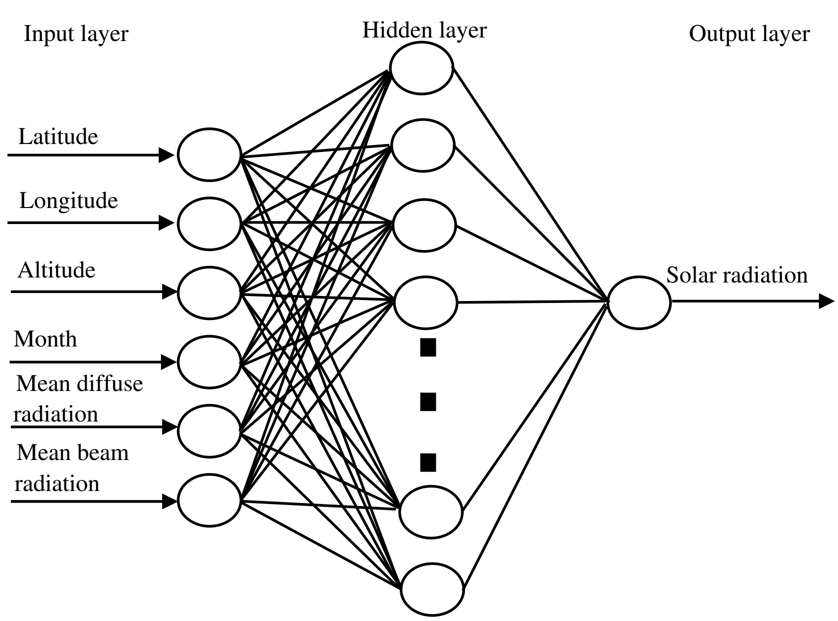

Fig. 3. ANN architecture used for six neurons in a single hidden layer.

Here, diffuse and direct component of horizontal global irradiation is calculated as a function of optical air mass, turbidity factor and Rayleigh optical thickness for clear-sky. The Linke Turbidity factor is used here since it takes account of scattering and absorption by both atmospheric aerosol and atmospheric gases [33].

6. Relation of cloud index and global irradiation

The relationship between clear-sky and cloud cover index has shown as [33]:

$$K_{\text{clear}} = 1 - N \tag{9}$$

In this way clear-sky index is combined with clear-sky model. This shows that use of clear-sky index together with an explicit model of the atmospheric backscatter results in a producer where no ground based data is necessary for the calibration.

7. Calculation of global irradiance

The global irradiance at the ground is determined by clear-sky irradiation and the atmospheric transmittance. The atmospheric transmittance is derived from the satellite data and represented by clear-sky index. Clear-sky irradiance is modeled with site specific turbidity. In terms of all introduced parameters the global irradiance at the surface of any pixel at any time can be calculated by the use of the following equation:

$$G = KG_{\text{clear}} \tag{10}$$

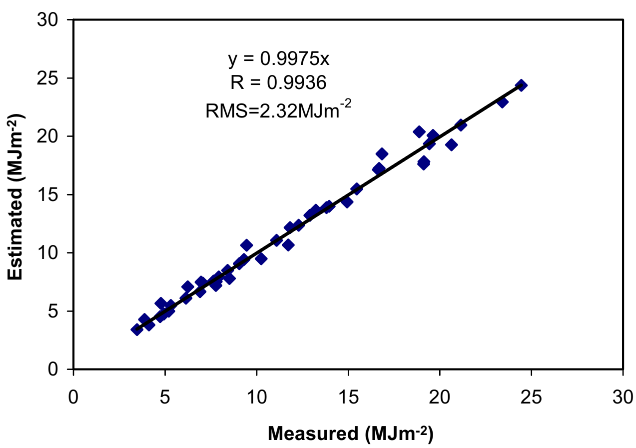

Fig. 4. Comparison of monthly mean daily sum measured and estimated concerning training stations together during the study period for ANN values.

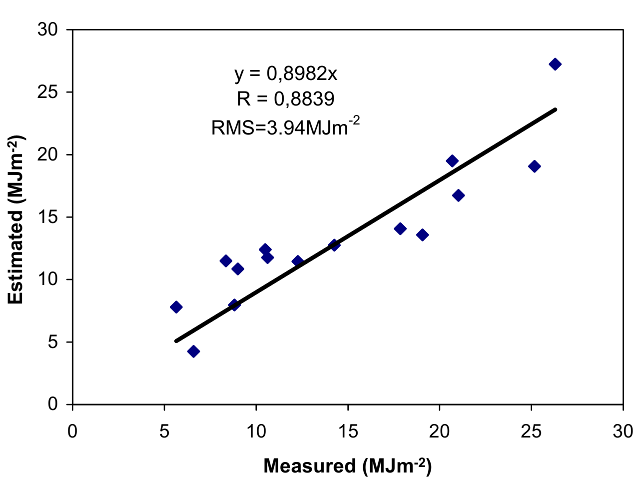

Fig. 5. Comparison of monthly mean daily sum measured and estimated concerning testing stations together during the study period for ANN values.

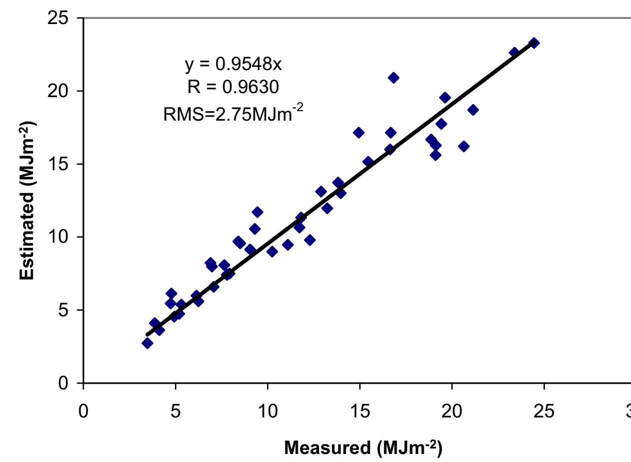

Fig. 6. Comparison of monthly mean daily sum measured and estimated concerning training stations together during the study period for Physical method values.

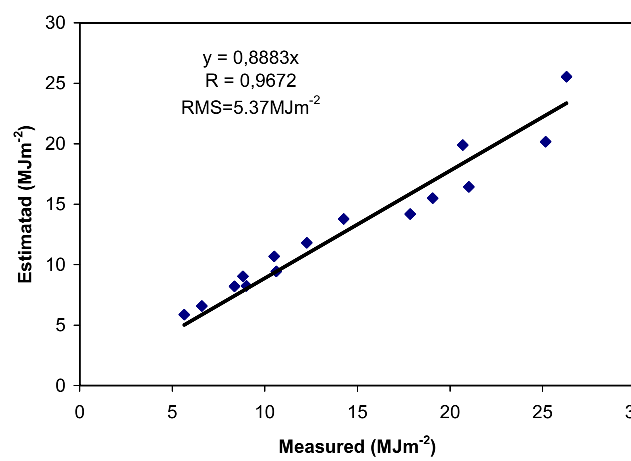

Fig. 7. Comparison of monthly mean daily sum measured and estimated concerning testing stations together during the study period for Physical method values.

Table 2
Error values of the ANN and Physical method approach

	Station	Physical method		ANN	
		R	RMS (%)	*R*	RMS (%)
Cities used in training	Antalya	98.97	0.87	98.96	0.07
	Artvin	99.35	4.7	98.80	1.1
	Edirne	99.62	1.45	98.97	0.33
	Kütahya	98.37	1.28	99.91	0.64
	Adana	98.15	4.21	98.80	0.49
	Ankara	99.45	3.93	99.51	0.86
	İstanbul	99.50	0.34	98.69	0.03
	Samsun	99.46	1.11	99.72	0.33
	Diyarbakır	99.65	3.02	99.64	0.11
Cities used in test	Kayseri	97.60	4.46	84.51	0.08
	Van	99.93	0.89	94.99	1.47
	İzmir	96.84	3.94	98.99	4.91

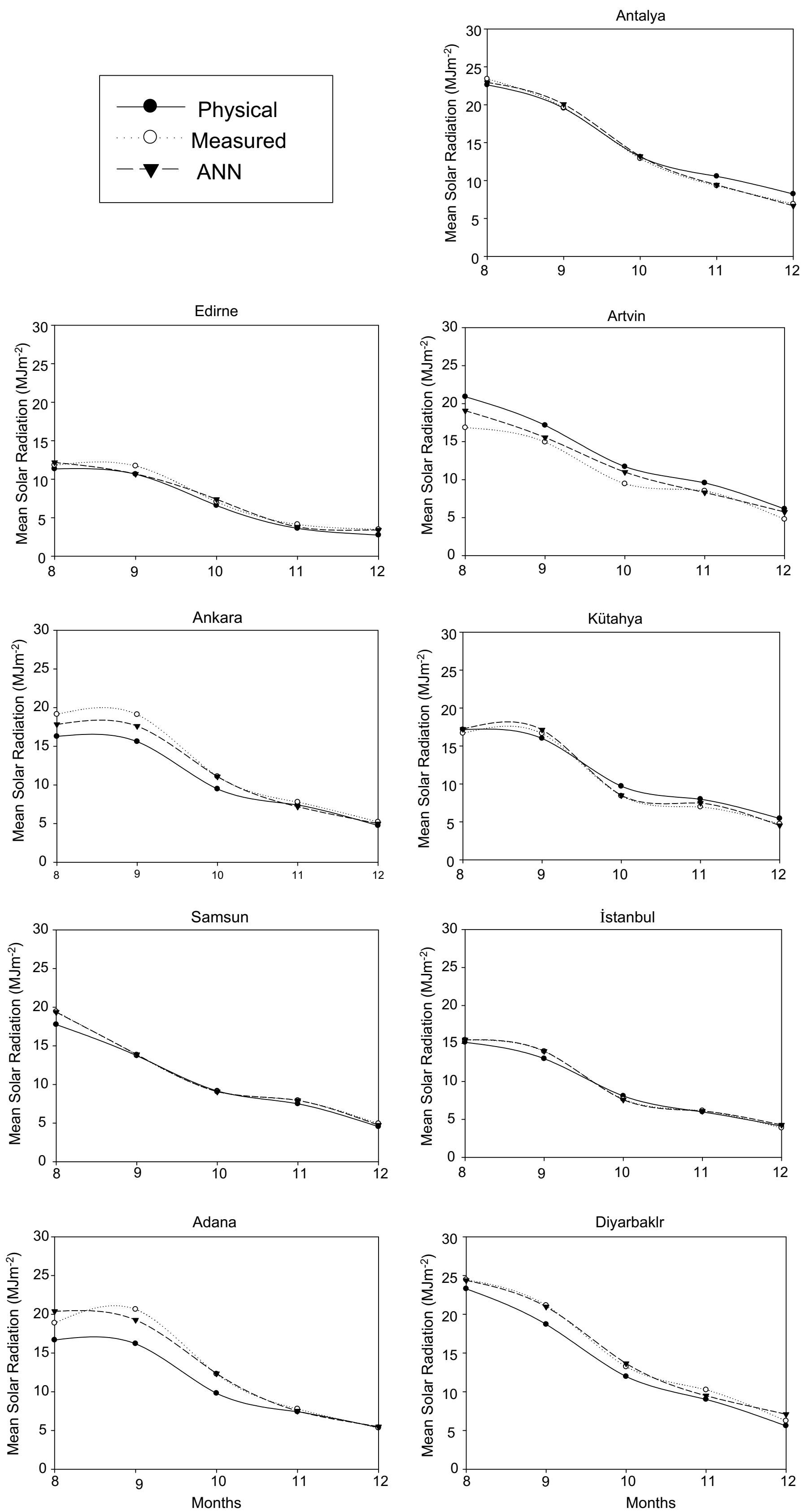

Fig. 8. Comparison for the solar radiation between the ANN, physical and measured values (training cities).

8. Results and discussions

ANN is used for modeling solar radiation in Turkey. This network consists of an input layer, single hidden layers and an output layer. Inputs for the network are latitude, longitude, altitude month, mean diffuse radiation and mean beam radiation; output is solar radiation. Variants of the algorithm used in the study are resilient propagation (RP), Scale conjugate gradient (SCG). Logistic sigmoid transfer function (logsig) and linear transfer function (purelin) are used in the hidden layers and output layer of the network as an activation function.

MATLAB software has been used to train and test the ANN on a personal computer. For the training, six neurons are used in a single hidden layer. The selected ANN structure is shown in Fig. 3. The stations used for training data are at Antalya, Artvin, Edirne, Kütahya, Adana, Ankara, İstanbul, Samsun, Diyarbakır. In test data, stations, İzmir, Van and Kayseri are used. In order to train the neural network, meteorological data measured by the Turkish State Meteorological Service (TSMS) for the period from August 1997 to December 1997 in Turkey from the above 12 stations were used as training and testing data. Separately, rectified and calibrated Meteosat-6 satellite C3 D data in the visible range were used. In order to calculate the solar radiation, clear-sky radiation, cloud cover index and clear-sky index values were determined. Solar radiation was estimated as monthly mean by using physical method over 12 cities in Turkey.

In the current study, ground data of the twelve national stations were used. These stations were selected in such a way that they represent widely changing climatic conditions of Turkey. The monthly mean daily sum global solar radiation over Turkey was determined to be a correlation coefficient 99.36% and RMS 2.32 MJ m^{-2} corresponding to 54 W m^{-2} (Fig. 4), 88.39% and RMS 3.94 MJ m^{-2} (91 W m^{-2}) (Fig. 5)for ANN values (training and testing cities). In the case of monthly mean daily sum correlation coefficient and RMS was found to be 96.30% and 2.75 MJ m^{-2} (64 W m^{-2}) (Fig. 6), 96.72% and 5.37 MJ m^{-2} (125 W m^{-2}) (Fig. 7) for Physical values (training and testing cities).

The performance values for all stations, such as RMS and R for training, testing and Physical method values are given in Table 2. The RMS values, ranging from 0.07% to 4.91%, differ from the actual value for all stations. The maximum RMS was found to be 4.91% for İzmir station in the testing values, while the best result was found to be 0.07% for Antalya station in the training values. The maximum correlation coefficient was found to be 99.93% for Physical method values of Van station, while the minimum correlation coefficient was found as 84.51% for Kayseri station. Moreover, another significant point in this table, the performance values of the training are generally better than the performance values of the testing regarding Physical method. Fig. 8 and 9 shows a comparison between measured, ANN and physical values for the twelve cities (training and testing cities).

9. Conclusion

Generation of typical solar radiation is significant for the calculations concerning many solar energy models. By using ANN and Physical method, a production of solar radiation were used over 12 cities in Turkey. The monthly mean daily sum values were found as 54 W/m^2 and 64 W/m^2 (training cities), 91 W/m^2 and 125 W/m^2 (testing cities), respectively. Construction of solar radiation database is very useful for solar energy, environmental, agricultural and other applications. Using ANN and satellite data are cheap and effective way for estimation of solar radiation and in constructing solar database. ANN model, which needs no satellite data, was used to estimate the monthly mean daily sum at ground level. On the other hand, since the Physical method needs no ground data and presents valuable results it can be applied to any region of the application of these models are more suitable particularly for places where the distances between the stations are very large. According to the results of these 12 locations, correlation values indicate a relatively good agreement between the observed ANN values and the predicted satellite values. These methods can be used by researchers in Turkey and other countries.

These results represent the limited values of 1997 for solar radiation although values that are available between August and December are enough for prediction of solar radiation. In 1997 there was limited satellite data for solar radiation. Nowadays satellite data are available for twelve-month period. In future we will be

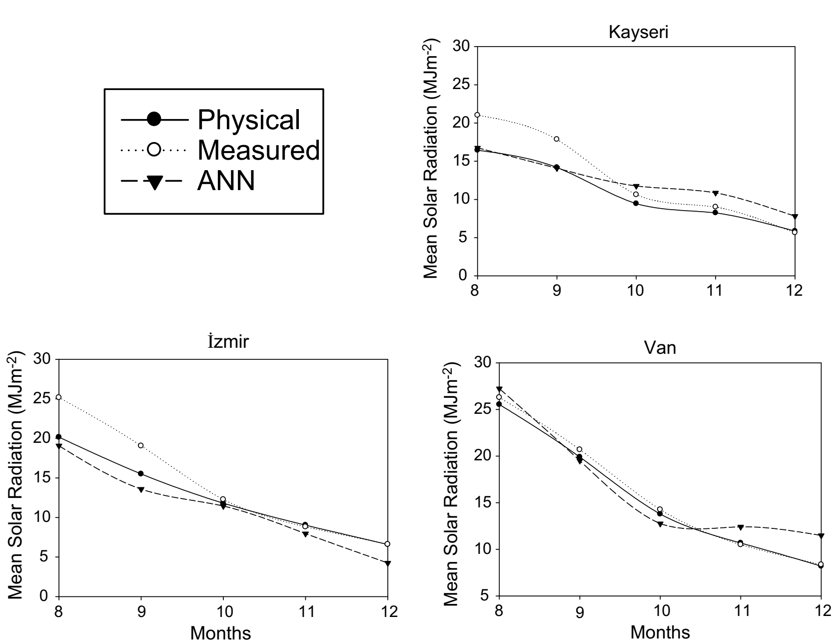

Fig. 9. Comparison for the solar radiation between the ANN, physical and measured values (testing cities).

able to discuss the prediction of solar radiation in twelve-month period and then compare with old data in order to show correlation between long term and short term data.

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