JREE: Vol. 3, No. 3, (Summer 2016) 21-30

Journal of Renewable
Energy and Environment

Research Article

Journal Homepage: www.jree.ir

# Estimation of Monthly Mean Daily Global Solar Radiation in Tabriz Using Empirical Models and Artificial Neural Networks

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*PAPER INFO*

*Paper history:*
Received 10 January 2016
Accepted in revised form 04 September 2016

*Keywords*:
Solar Energy
Meteorological Data
Sunshine Hours
Prediction
Artificial Neural Networks

*ABSTRACT*

Precise knowledge ofthe amount of global solar radiation plays an important role in designing solar energy systems. In this study, by using 22-year meteorologicaldata, 19 empirical models were tested for prediction of the monthly mean daily global solar radiation in Tabriz. In addition, various Artificial Neural Network (ANN) models were designed for comparison with empirical models. For this purpose, the meteorological data recorded by Iran Meteorological Organization (1992–2013) was used. These data include: monthly mean daily sunshine duration, monthly mean ambient temperature, monthly mean maximum and minimum ambient temperature and monthly mean relative humidity.The results showed that the yearly average solar radiation in the region was 16.37 MJ $m^{-2}$ $day^{-1}$.Among the empirical models, the best result was acquired for model (19) with correlation coefficient (r) of 0.9663. Results also showed that the ANN model trained with total meteorological data in input layer (ANN5) produces better results in comparison to others. Root Mean Square Error (RMSE) and r for this model were1.0800 MJ m-2 and 0.9714, respectively. Comparison betweenthe model 19 and ANN5, demonstrated that modeling the monthly mean daily global solar radiationthrough the use of the ANN technique, yields better estimates. Mean Percentage Errors (MPE) for these models were 7.4754% and 1.0060%, respectively.

## 1. INTRODUCTION

Nowadays, due to the environmental pollution caused by gas emissions, the use of renewable energies such as solar, wind, and geothermal is going to be highly emphasized and adopted by human kind across the world. Renewable energy technologies are clean sources of energy that have a much lower environmental impact rather than the conventional energy technologies. They can prevent and reduce air pollutantemissions as well as water consumption, waste, noise and adverse land-use impacts (Ramedani et al., 2014). Among different kinds of renewable energy sources, solar energy is considered as an immense source, since it is ubiquitous. Solar energy occupies one of the most significant positions among the various potential alternative energy sources in a way that it can fulfill abundant heat and electricity demands for a long timewithout polluting the air, nevertheless its potentials are largely unexploited yet(Khorasanizadeh et al., 2014).

Precise knowledge of the amount of solar radiation reached to the earth's surface is by far the most important factor in designing and programming the applicationsutilized in some devices related to climatology, agriculture, and solar energy converters.In other words, prediction of daily global solar radiation plays an important role in designing renewable energy systems. Such knowledge will aid solarenergy product marketing and also enhancesthe development ofsolar applications. Among different components of solar radiation such as direct, diffuse and total solar irradiation, the daily mean total solar irradiation is suggested to be a key variablein programming any of the above mentioned applications (Jafarpur & Yaghoubi, 1989). Various estimation procedures have been developed toevaluate the global solar radiation by applying the integral of solar irradianceover a time period.

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There have been numerous researches involving the estimation of the global solar radiation incident on a horizontal surface (Jin et al., 2005; Robaa, 2009; Li et al., 2013; Chandel and Aggarwal, 2011; Shamim et al., 2015). Chandel et al. (2005) introduced anew correlation modelto estimate the monthly average global solar radiation using temperature data and latitude and altitude of a site.The results indicated that the estimated values of global radiation using temperature datawere sufficiently accurate and can be utilized for sites for whicheven sunshine hour data are not measured.Sen (2007) proposed a nonlinear model with three parameters for estimation of global solar radiation from available sunshine duration data. This model was an Angström type model with a third parameter appearing as the power of the sunshine duration ratio. In the study carried out by Sabziparvar and Shetaee (2007), global solar radiation in arid and semi-arid climates of east and west of Iran was estimated using different radiation models and various input parameters.Comparison of the model results indicates that calibration of the coefficients made to the diffuse formula against the longer period experimental data can improve the estimations of global solar radiation. El-Sebaii et al. (2009) used the metrological data from 1996 to2007 of Jeddah (Saudi Arabia) to predict global, direct, and diffuse solar radiation on horizontal and tilted surfacesfrom hours of bright sunshine, mean daily ambient temperature, maximum and minimum ambient temperatures, relative humidity, and amount of cloud cover.Results showed that the isotropic model is able to estimate theglobal radiation on tilted surfacemore accuratelythan the anisotropic one.

Hasni et al. (2012) used an Artificial Neural Network (ANN) for estimating the Global Solar Radiation (GSR) as a function of air temperature and relative humidity data in the south-western region of Algeria.Obtained results showed that neural networks are well capable of estimating GSR from temperature and relative humidity. Ozgoren et al. (2012)developed an artificial neural network (ANN) model based onmulti-nonlinear regression method for estimating the monthly mean daily sum of global solar radiationat any place of Turkey.The resultsobtained by the ANN model were compared with the actual data, and error values were found withinacceptable limits. Also correlationcoefficient (r) value was obtained to be about 0.9936 for the testing data set. Bhardwaj et al. (2013) used a new approach by combining continuous density HiddenMarkov Model with Generalized Fuzzy model for estimating solar radiation. In this model, the inherent property of inter-dependence of solar radiation and other meteorological parameters was used for prediction of solar radiation.

In the study carried out in Tehran province of Iran, artificial neural networks were used to estimate daily global solar radiation. For this propose,various ANN models were designed and implemented by combiningdifferent meteorologicaldata including: daily values of maximum, minimum, and mean temperatures; relative humidity; sunshine duration and precipitation.Results showed thatANN model can be used successfully for estimating the dailyglobal solar radiation for Tehran province (Ramedani et al., 2013).Waewsak et al. (2014)used alternative approach to assess global solar radiation using Artificial NeuralNetworkscombined with classical observed meteorological data. Results showed that the ANN modeling has sufficient performance to predict the monthly mean GSR over an area where classical meteorological data were measured. Yadav and Chandel (2015) used J48 algorithm in Waikato Environment for Knowledge Analysis (WEKA) for selecting input parameters of ANN model in order to predict global solar radiation. They reported that the most relevant input parameters were temperature, altitude, and sunshinehours. Kheradmand et al. (2016) applied an Integrated Artificial Neural Network approachforoptimumforecastingtheclearnessindexbyconsideringenvironmentalandmeteorologicalfactors. The results of the study were used to produce Geographic Information System (GIS) map in Iran.

This study aimed to predict the monthly mean daily global solar radiationbased on long-term meteorological data using19 most usedempirical models.Moreover, artificial neural networks (ANN) technique was used for comparing the empirical models. Finally, the most suitable model was determined to predict global solar radiation in Tabriz.

## 2. MATERIALS AND METHODS

### 2.1. Empirical models

This study was carried out in Tabriz city, center of east Azarbaijan, located in the north-west part ofIran, at geographical locationof 38°10′ N and 46°18′ E with elevation of 1364 m above thesea level.The city experiences mild climate in spring, dryand semi-hot in summer, humid and rainy in autumn and snowycold in winter.Measured daily data of 22 years for the period of 1992–2013, including: monthly mean daily sunshine duration,monthly mean ambient temperature,monthly mean maximum and minimum ambient temperature, and monthly mean relative humiditywere collected fromthe Islamic Republic of Iran Meteorological Office Data Center (IRIMO) in east Azarbayjan station.

The data collections of meteorological office contain some missing and invalid measurements. The missing values relate to some days in which, data have not been recorded and incorrect values relate to possible malfunction of instruments.The missing and invalid measurements were approximately 12% of the whole database.To overcome this problemand complete the dataandto obtain accurate models, the following method was used (Jiang, 2009;Khorasanizadeh and Mohammadi, 2013):

- A data collection for a month containing more than 5 daysmissing or incorrect values was excluded from the database.
- A data collection for global solar radiation values which were out of monthly mean clearness index range of (0.015 <KT< 1) were eliminated.
- For sunshine duration, data is rejected if all daily sums of sunshine hours exceeded the dailymaximum possible sunshine hours.

**TABLE 1.** Empirical models proposed in this study

| Model No. | Models | Reference |
|---|---|---|
| Category (1): $H = f\left(\frac{n}{N}, H_0\right)$ | | |
| 1 | $H = [a + b\left(\frac{n}{N}\right)]H_0$ | El-Metwally (2005) |
| 2 | $H = [a + b\left(\frac{n}{N}\right) + c\left(\frac{n}{N}\right)^2]H_0$ | Ogelman et al. (1984) |
| 3 | $H = [a + b\left(\frac{n}{N}\right) + c\left(\frac{n}{N}\right)^2 + d\left(\frac{n}{N}\right)^3]H_0$ | Jin et al. (2005) |
| 4 | $H = [a\left(\frac{n}{N}\right)^b]H_0$ | Togrul&Togrul (2002) |
| 5 | $H = [aexp\left(b\left(\frac{n}{N}\right)\right)]H_0$ | Togrul&Togrul (2002) |
| 6 | $H = [a + b\left(\frac{n}{N}\right)^c]H_0$ | El-Sebaii et al. (2010) |
| 7 | $H = [a^{\left(\frac{N}{n}\right)}]H_0$ | El-Metwally (2005) |
| Category (2): $H = f\left(\frac{n}{N}, T_{ave}, R_h, H_0\right)$ | | |
| 8 | $H = [a + b\left(\frac{n}{N}\right) + cT_{ave}]H_0$ | El-Sebaii et al. (2009) |
| 9 | $H = [a + b\left(\frac{n}{N}\right) + cR_h]H_0$ | El-Sebaii et al. (2009) |
| 10 | $H = [a + b\left(\frac{n}{N}\right) + cT_{ave} + dR_h]H_0$ | Abdalla (1994) |
| 11 | $H = [a + bT_{ave}]H_0$ | Adaramola (2012) |
| 12 | $H = [a + b\left(\frac{R_h}{100}\right)]H_0$ | Adaramola (2012) |
| 13 | $H = [a + bT_{ave} + cR_h]H_0$ | El-Sebaii et al. (2009) |
| Category (3): $H = f(T_{max}, T_{min}, H_o)$ | | |
| 14 | $H = [a(T_{max} - T_{min})^b]H_0$ | Allen (1997) |
| 15 | $H = [a(T_{max} - T_{min})^{0.5}]H_0$ | Adaramola (2012) |
| 16 | $H = [a(T_{max} - T_{min})^{0.5} + b]H_0$ | Hargreaves et al. (1985) |
| 17 | $H = [a + b\left(\frac{T_{min}}{T_{max}}\right)]H_0$ | Adaramola (2012) |
| Category (4): $H = f(T_{max}, T_{min}, R_h, H_0)$ | | |
| 18 | $H = [a + b\left(\frac{T_{min}}{T_{max}}\right)\left(\frac{R_h}{100}\right)]H_0$ | Adaramola (2012) |
| 19 | $H = [aT_{max} + bT_{min} + cR_h + d]H_0$ | Li et al. (2013) |

Many models and correlations have been documented in the literature to estimate the global solar radiation. These models have been developedusing various meteorological parameters such as sunshine duration, cloud cover, humidity,maximum and minimum ambient temperatures, mean ambient temperature, etc. In this study 19 models were selected from the literature and classified in 4 different categories. Table 2. shows the models used in the present study for estimating the global solar radiation onahorizontal surface and their categories. Also some parameters such as: the monthly mean daily extraterrestrial solar radiation on a horizontal surface (Ho), the monthly mean daily solar declination (δ), the sunrise hour angle (ωs) and the monthly mean daily maximum possible sunshine duration (N) were calculated using relationships reported in literature (Adaramola, 2012; Duffie & Beckman, 2013; Ajayi et al., 2014).

## 2.2. Artificial Neural Networks

Artificial Neural Networks are widely used in various fields, e.g., mathematics, engineering, meteorology, economics, etc. It is an information processing system that performs a computational simulation on behavior of neurons as in the human brain and has the ability to learn, recall and generalize from the training of data sets (Waewsak et al., 2014). It is able to develop a model relating the output of network to the existing actual data used as inputs (Ozgoren et al., 2012). The ANN structure consists of three layers,an input layer which receives data; an output layer whichsends computed information; and one or more hiddenlayers to link input and output layers (Kaushika et al., 2014). The first step in developingANN deals with the definition of the network architecture, which is defined by the basicprocessing elements (neurons) and by the way in which; they are interconnected (layers). The number of neurons in input and output layers depends on independent and dependent variables, respectively. ANNs are trained with known data and tested with data not used in training (Ramedani et al., 2013).

An ANN of the Multilayer Feed Forward (MLP) type with one input layer, one to three hidden layers and one output layer was used for estimating thesolar radiation from measured meteorological data (Rahimikhoob, 2010). Of this data, 60, 15, and 25% were used for training, cross validation and testing the network, respectively. Similar to many researchers, the number of hidden elements in training process was obtained by trial and error via considering MPE, MBE, RMSE and r values from the test data set (Ramedani et al., 2013; Taki et al., 2016).The transfer function in the networks was hyperbolic tangent and bias axon in the hidden and output layers (Taki et al., 2012b). The Levenberg Marquardt (LM) algorithm was used with an early stopping criterion to improve the speed and efficiency of network training. It minimizes a linear combination of squared errors and weights via gradient descent with a momentum algorithm suitable to avoid falling to a local minimum (Linares-Rodriguez et al., 2013). The number of hidden nodes in the ANN was determined empirically, considering the need to derive reasonable results.

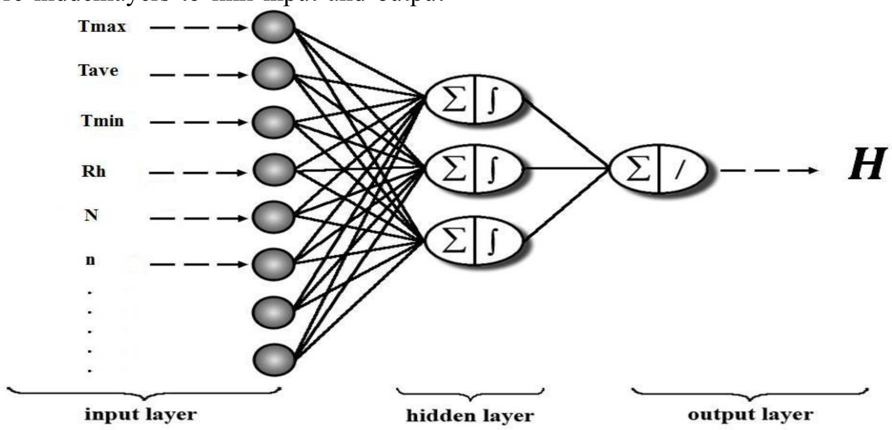


**Figure 1.** Schematic diagram of a multilayer feed forward neural network

**TABLE 2.** Combination of Different Data as Inputs of Estimated ANN Models

| Inputs of model | N | N | $T_{ave}$ | $T_{min}$ | $T_{max}$ | $R_h$ | $H_0$ |
|---|---|---|---|---|---|---|---|
| $ANN1 = f(n, N, H_0)$ | ✓ | ✓ | | | | | ✓ |
| $ANN2 = f(n, N, T_{ave}, R_h, H_0)$ | ✓ | ✓ | ✓ | | | ✓ | ✓ |
| $ANN3 = f(T_{min}, T_{max}, H_0)$ | | | | ✓ | ✓ | | ✓ |
| $ANN4 = f(T_{min}, T_{max}, R_h, H_0)$ | | | | ✓ | ✓ | ✓ | ✓ |
| $ANN5 = f(n, N, T_{ave}, T_{min}, T_{max}, R_h, H_0)$ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |

A typicaldiagram of a multilayer feed forward neural network architecture that consists of an input layer, a hidden layer, and an output layer is shown in Fig. 1 To consider the effect of inputs on predicting the solar radiation, five models of ANN were designed. In these models, number of neurons in input layer was the same as the inputs of categories which introduced in Table 1. Also a model of ANN including total parameters as input layer was designed. These models are summarized in Table 2. A program was developed in Neuro Solutions 5.07 package (2011) for the feed forward and back propagation network.

### 2.3. Statistical analysis

In order to predict the accuracy of themodelsand thereby selectthe best performing model, different statistical indicators including Mean Percentage Error (MPE), Mean Bias Error (MBE), Root Mean Square Error (RMSE) and correlation coefficient (r)were calculated based onevaluating the data series. In order to compare the selected ANN with the empirical models, same data used for the testing the neural network were used to testempirical models. The statistical indicators are given as below (Jinet al., 2005;Li et al., 2010; Zarzo& Marti, 2011; Ajayi et al., (2014):

$$MPE = \frac{1}{k}\sum_{i=1}^{k}\left(\frac{H_{i,c}-H_{i,m}}{H_{i,m}}\right) \times 100 \quad (1)$$

$$MBE = \frac{1}{k}\sum_{i=1}^{k}(H_{i,c} - H_{i,m}) \quad (2)$$

$$RMSE = \left[\frac{1}{k}\sum_{i=1}^{k}(H_{i,c} - H_{i,m})^2\right]^{0.5} \quad (3)$$

$$r = \frac{\sum_{i=1}^{k}(H_{i,c}-H_{c,ave})(H_{i,m}-H_{m,ave})}{\sqrt{[\sum_{i=1}^{k}(H_{i,c}-H_{c,ave})^2][\sum_{i=1}^{k}(H_{i,m}-H_{m,ave})^2]}} \quad (4)$$

## 3. RESULTS AND DISCUSSION

### 3.1. Determination of the best empirical model

Some meteorological parameters which were collected from the Iran Meteorological Office,are tabulated in Table 3. Results showed that the yearly averagesolar radiation in the region was16.37 MJ $m^{-2}$ $day^{-1}$and ranged from a minimum of MJ $m^{-2}$ $day^{-1}$ in Decemberto a maximum of 26.24 MJ $m^{-2}$ $day^{-1}$ in June.It was observed that solar radiation increases inaccordance with bright sunshine hours.The monthly mean daily clearness index $K_T = \frac{H}{H_0}$ which is defined asthe fraction of solar radiation at the top of the atmosphere reaching a particular location on the earth surface, varied between0.45 in Januaryto 0.65 in Septemberwith an annual average of 0.55. Also the monthly mean daily temperature ranged from a minimum of −0.98°C in January to a maximum of 26.43°C in August. Other parameters are listed in Table 3.

**TABLE 3.** Meteorological parameters for Tabriz city

| Parameter | Jan | Feb | Mar | Apr | May | Jun | Jul | Aug | Sep | Oct | Nov | Dec |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| H (MJ $m^{-2}$) | 7.41 | 10.78 | 14.02 | 17.47 | 22.08 | 26.24 | 24.90 | 22.78 | 20.03 | 14.28 | 9.53 | 6.97 |
| $H_0$(MJ $m^{-2}$) | 16.39 | 21.58 | 28.30 | 35.11 | 39.83 | 41.71 | 40.71 | 36.90 | 30.70 | 23.54 | 17.59 | 14.97 |
| n (h) | 4.45 | 5.66 | 6.48 | 6.85 | 8.99 | 10.95 | 11.25 | 10.94 | 10.02 | 7.80 | 5.98 | 4.73 |
| N (h) | 9.67 | 10.60 | 11.73 | 13.00 | 14.07 | 14.60 | 14.37 | 13.43 | 12.23 | 11.00 | 9.93 | 9.40 |
| $R_h$(%) | 71.54 | 64.96 | 53.48 | 52.82 | 47.07 | 37.70 | 35.50 | 33.85 | 38.01 | 46.03 | 62.09 | 68.65 |
| $T_{ave}$ (°C) | -0.98 | 1.55 | 6.69 | 12.25 | 17.54 | 23.03 | 26.13 | 26.43 | 21.78 | 15.23 | 6.85 | 1.24 |
| $T_{max}$ (°C) | 3.82 | 6.72 | 12.38 | 18.07 | 23.70 | 29.67 | 33.05 | 33.41 | 28.82 | 21.94 | 12.40 | 6.16 |
| $T_{min}$ (°C) | -4.39 | -2.45 | 1.75 | 6.95 | 11.62 | 16.51 | 20.06 | 20.22 | 15.45 | 9.48 | 2.65 | -2.25 |

Regression analysis for 19 models in 4 different categories for the study region was conducted using establishing data series. The regression coefficients obtained are presented in Table 4. These coefficients were determined using the least square approach.In order to determine the best model in each category, it was necessary to determine the performance level of the models. The best model in each category was recognized by comparing the statistical parameters related to all of the models in the same category. Table 5. shows the statisticalindicatorsfor 19 models.

In category (1), the best result was acquired for model (2) with correlation coefficient of 0.9623.In this category, solar radiation was predicted based on monthly mean dailysunshine,maximum possible sunshine hours,and monthly mean daily extraterrestrial radiation on horizontal surface.Thestatistical indexes of MPE, MBE, and RMSE for this model were13.5510%,-2.5607MJ$m^{-2}$ and 2.9735 MJ$m^{-2}$, respectively. Therefore in this category, model (2) in which:

$$H = [0.1218 + 0.8213\left(\frac{n}{N}\right) - 0.2748\left(\frac{n}{N}\right)^2]H_0 \quad (5)$$

is assessed as the best model among all.In a research conducted in China,this model was reported as the best. The regression coefficients of this model were determined based on latitude and altitude of the study region (Jin et al., 2005).Khorasanizadeh and Mohammadi (2013) used data of 11 years of Tabriz (1992–1994 & 1998–2005) and suggested the following model for Tabriz. The coefficient of determination ($R^2$) for this model was 0.9853:

$$\frac{H}{H_0} = 1.3244 - 4.9422\left(\frac{n}{N}\right) + 8.7139\left(\frac{n}{N}\right)^2 - 4.5485\left(\frac{n}{N}\right)^3 \quad (6)$$

In category (2) solar radiation was predicted based on monthly mean daily sunshine hours, maximum possible sunshine hours, ambient temperature, relative humidity, and monthly mean daily extraterrestrial radiation on horizontal surface. The result obtained in this categoryshowed that the model (13) was assessed as the best model among all. The correlation coefficient for this model was calculated as 0.9610. Also thestatistical indexes of MPE, MBE, and RMSE for this model were -11.2783%, -2.0674MJm$^{-2}$ and 2.4255 MJm$^{-2}$, respectively.As it can be seen from Table 5. the correlation coefficient of this model is lower than that of model (2).To sumit up,the following model is the best model in category (2):

$$H = [0.5665 + 0.0037T_{ave} - 0.0016R_h]H_0 \quad (7)$$

**TABLE 4.** Regression coefficients of different models applied for Tabriz city

| Category | Model | A | B | c | d |
|---|---|---|---|---|---|
| 1 | 1 | 0.2244 | 0.4758 | - | - |
| | 2 | 0.1218 | 0.8213 | -0.2748 | - |
| | 3 | 0.2834 | -0.0525 | 1.2274 | -0.8255 |
| | 4 | 0.6837 | 0.5596 | - | - |
| | 5 | 0.2963 | 0.8927 | - | - |
| | 6 | -0.2188 | 0.8967 | 0.3921 | - |
| | 7 | 0.3850 | - | - | - |
| 2 | 8 | 0.2158 | 0.4966 | -0.0004 | - |
| | 9 | 0.1482 | 0.5361 | 0.0007 | - |
| | 10 | 0.1231 | 0.5254 | 0.0008 | 0.0012 |
| | 11 | 0.4556 | 0.0058 | - | - |
| | 12 | 0.7340 | -0.3973 | - | - |
| | 13 | 0.5665 | 0.0037 | -0.0016 | - |
| 3 | 14 | 0.1248 | 0.6053 | - | - |
| | 15 | 0.1611 | - | - | - |
| | 16 | 0.1908 | -0.0993 | - | - |
| | 17 | 0.5289 | 0.0083 | - | - |
| 4 | 18 | 0.5301 | 0.0103 | - | - |
| | 19 | 0.0435 | -0.0413 | 0.0035 | -0.1471 |

El-Sebaii et al. (2013) used this model for Jeddah, Saudi Arabia. They reported the regression coefficients of a, b and c for this model was 0.139, -0.0003 and 0.896, respectively. Also the R2 for this model was calculated as 0.963.

In category (3), the best result was acquired for model (14) with correlation coefficient of 0.9608. In this category solar radiation was predicted based on monthly mean maximum and minimum ambient temperature and monthly mean daily extraterrestrial radiation on horizontal surface.

The statistical indexes of MPE, MBE and RMSE for this model were -8.5019%, -1.6725 MJ m$^{-2}$ and 2.1465 MJ m$^{-2}$, respectively.This model can be used when no data is available for sunshine hours.Therefore, in this category the following model is the best model:

$$H = [0.1248(T_{max} - T_{min})^{0.6053}]H_0 \quad (8)$$

In category (4), solar radiation was predicted based on monthly mean relative humidity, maximum ambient temperature,minimumambient temperature,and monthly mean daily extraterrestrial radiation on horizontal surface.

Result showed that in this category, the best result was acquired for model (19) with correlation coefficient of 0.9663.The statistical indexes of MPE, MBE and RMSE for this model were -7.4754%, -1.5297MJ m$^{-2}$ and 2.1244MJ m$^{-2}$, respectively. Therefore, in this category the following model is the best model:

$$H = [0.0435T_{max} - 0.0413T_{min} + 0.0035R_h - 0.147 \quad (9)$$

Farhadi-Bansouleh et al. (2009) used the Angstrom and Hargreaves formulasfor solar radiation estimation, based on monthly and annual weather data for threeweather stations in Esfahan province.Result showed that $R^2$ for the monthly values of Angstrom equation was higher than that of the Hargreaves equation.

Comparison between the measured and predicted globalsolar radiation usingthe best-performed models in each category,are presentedin Fig. 2 It is clear from this figure that there is a good agreement between the predicted and measured global solar radiation data. In addition, the agreement depends on the used model.

**TABLE 5.** MPE, MBE, RMSE, and r of different models for Tabriz city

| Category | Model | MPE (%) | MBE ($MJm^{-2}$) | RMSE ($MJm^{-2}$) | r |
|---|---|---|---|---|---|
| 1 | 1 | -13.6144 | -2.5852 | 3.0300 | 0.9612 |
| | 2 | -13.5510 | -2.5607 | 2.9735 | 0.9623 |
| | 3 | -13.6350 | -2.5617 | 2.9759 | 0.9620 |
| | 4 | -13.5512 | -2.5682 | 2.9997 | 0.9620 |
| | 5 | -13.5650 | -2.5980 | 3.0671 | 0.9606 |
| | 6 | -13.5534 | -2.5629 | 2.9900 | 0.9623 |
| | 7 | -4.5205 | -2.1116 | 4.9024 | 0.8112 |
| 2 | 8 | -13.7501 | -2.6289 | 3.1016 | 0.9604 |
| | 9 | -14.0794 | -2.7011 | 3.2041 | 0.9586 |
| | 10 | -12.5095 | -2.4261 | 2.9186 | 0.9593 |
| | 11 | -11.5014 | -2.1113 | 2.4956 | 0.9591 |
| | 12 | -11.6167 | -2.1789 | 2.5906 | 0.9608 |
| | 13 | -11.2783 | -2.0674 | 2.4255 | 0.9610 |
| 3 | 14 | -8.5019 | -1.6725 | 2.1465 | 0.9608 |
| | 15 | -8.6129 | -1.7848 | 2.3490 | 0.9600 |
| | 16 | -8.5080 | -1.6834 | 2.1675 | 0.9607 |
| | 17 | -10.6546 | -2.5466 | 3.6318 | 0.9453 |
| 4 | 18 | -10.6021 | -2.5522 | 3.6598 | 0.9446 |
| | 19 | -7.4754 | -1.5297 | 2.1244 | 0.9663 |

**TABLE 6.** MPE, MBE, RMSE, and r of different ANN-models for Tabriz city

| Category | ANN Models (Number of hidden layer) | MPE (%) | MBE ($MJ\ m^{-2}$) | RMSE ($MJ\ m^{-2}$) | r |
|---|---|---|---|---|---|
| 1 | ANN1(1) | 4.6986 | 0.3159 | 3.0984 | 0.9164 |
| | ANN1(2) | 2.7577 | 0.0458 | 3.2229 | 0.9068 |
| | ANN1(3) | 5.7113 | 0.7275 | 3.2417 | 0.8981 |
| 2 | ANN2(1) | 4.8619 | 0.2192 | 3.0512 | 0.8982 |
| | ANN2(2) | -5.3965 | -0.9376 | 3.2693 | 0.9157 |
| | ANN2(3) | 0.4721 | -0.3723 | 3.1587 | 0.9067 |
| 3 | ANN3(1) | 3.6365 | -0.0588 | 3.0597 | 0.9355 |
| | ANN3(2) | 0.8096 | -0.3776 | 2.8825 | 0.9417 |
| | ANN3(3) | 0.7722 | -0.3546 | 3.0569 | 0.9318 |
| 4 | ANN4(1) | 0.6997 | -0.3728 | 2.7216 | 0.9401 |
| | ANN4(2) | 1.5561 | -0.1881 | 2.7645 | 0.9369 |
| | ANN4(3) | 1.6097 | -0.4140 | 2.7524 | 0.9318 |
| 5 | ANN5(1) | 2.5518 | 0.1442 | 1.6422 | 0.9509 |
| | **ANN5(2)** | **1.0060** | **0.1529** | **1.0800** | **0.9714** |
| | ANN5(3) | 1.3632 | -0.1626 | 2.5532 | 0.9412 |

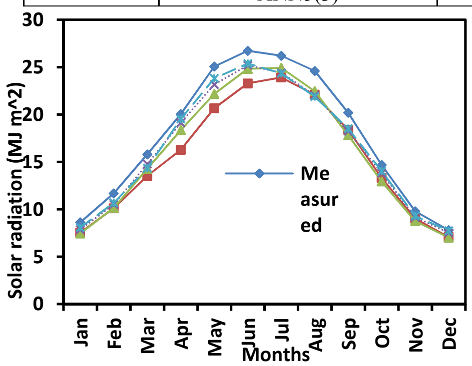


**Figure 2.** Comparison between the measured and predicted monthly mean global solarradiation using different models

### 3.2. Results of artificial neural networks method

Different ANN-Models were trained and tested in order to compare and evaluate the performances of ANN methods.Obtained results ofdifferent ANN-models for Tabriz city, are summarized in Table 6. Results showed that with increasing the number of inputs in ANN models, the correlation coefficient of the models was increased.Comparing the results of ANN models, it was seen that the performance values of the ANN5 (2) model was betterthan those of the others.This model was trainedwith seven input variables, two hidden layers, and a single output variable. For this model, MPE, MBE, RMSE, and 'r' values were found to be 1.0060, 0.1529, 1.0800and 0.9714, respectively.The desiredglobal solar radiation values by the best ANN model were compared with the actualvalues for the testing period and are shown in Fig. 3 Ramedani et al.(2013) reported thatin Tehran province, ANN with maximum and minimum temperature,sunshine duration, daylight hours, extraterrestrial radiation, and number of days inthe year as inputs, had the best performance.

In order to assess the predictive ability and validity of the developed models, a sensitivity analysis was performed using the best network selected (Fig. 4). The robustness of the model was determined by examining and comparing the output produced during the validation stage with the calculated values. The MLP model was trained by withdrawing each input item one at a time while not changing any of the other items for every pattern (Taki et al., 2012a). According to the obtained results in Fig. 4 the share of each input item of developed MLP model on desired output (monthly mean global solar radiation) can be seen clearly. Sensitivity analysis provides insight into the usefulness of the individual variables. With this kind of analysis, it is possible to judge what parameters are the most and the least significant during generation of the satisfactory MLP. It is evident that N had the highest sensitivity(71.34%) on output, followed by H0 (13.55%).

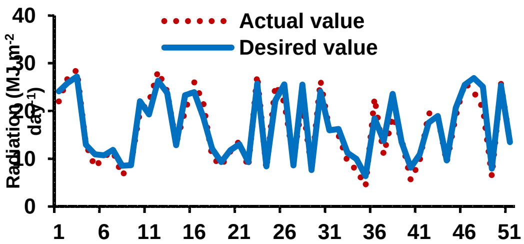


**Figure 3.** Desired by the best ANN model and actual monthly mean global solar radiation on testing data

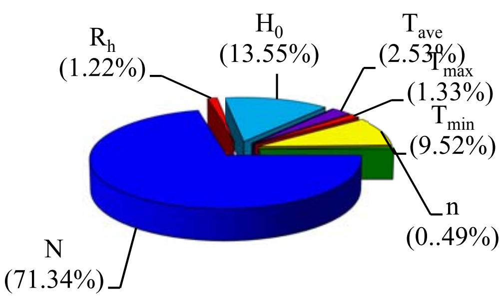


**Figure 4.** Sensitivity analysis of input items

The comparison between two models demonstrated that modeling the global solar radiation through the use of theANNtechnique, gave better estimates than the empirical model.As it was mentioned, in order to compare the selected ANN with the empirical models, the data used for the testing the neural network and empirical models were the same. Rahimikhoob (2010) compared the ANN model withthe HS equationfor estimating the dailyglobal solar radiation based on the measured temperature data. Results showed that theANNtechnique had better performance than the HSequation.

## 4. CONCLUSIONS

The main objective of the present studywas to predict global solar radiationin Tabriz based onmeteorological data using simple empirical models and artificial neural network technique. Based on the results of the investigations, the following conclusions were drawn:

1. Among empirical models, the best result was acquired for model (19) with correlation coefficient of 0.9663. In this model, solar radiation was predicted based on monthly mean relative humidity, maximum ambient temperature, minimum ambient temperature, and monthly mean daily extraterrestrial radiation on horizontal surface.
2. Among ANN models, the best results were obtained for the ANN5 (2) model. This model was trained with seven input variables, two hidden layers, and a single output variable.
3. Sensitivity analysis results showed that N had the highest sensitivity (71.34%)on monthly mean daily global solar radiation, followed by H0 (13.55%).
4. The comparison between two models showed that ANN model outperformed empirical models and can be successfully used for estimating the monthly mean daily global solar radiation in Tabriz city.

## 5. ACKNOWLEDGEMENT

The financial support provided by the University of Tabriz, Iran, is duly acknowledged.Also thanks are extended to meteorological organization of east Azarbayjan for providing raw data.

### Nomenclature

| | |
|---|---|
| ANN | artificial neural network |
| H | monthly mean daily global radiation on horizontal surface (MJ $m^{-2}$) |
| $H_0$ | monthly mean daily extraterrestrial radiation on horizontal surface (MJ $m^{-2}$) |
| $H_{c,ave}$ | average calculated values of H(MJ$m^{-2}$) |
| $H_{i,c}$ | *i*th calculated values of H (MJ$m^{-2}$) |
| $H_{i,m}$ | *i*th measured values of H (MJ$m^{-2}$) |

| | |
|---|---|
| $H_{m,ave}$ | average measured values of H($MJm^{-2}$) |
| k | number of data points |
| $K_T$ | monthly mean daily clearness index ($K_T = \frac{H}{H_0}$) |
| MPE | mean percentage error (%) |
| MBE | mean bias error ($MJm^{-2}$) |
| n | monthly mean daily sunshine hours (h) |
| N | monthly mean daily maximum possible sunshine hours (h) |
| r | Correlation coefficient |
| RMSE | root mean square error(MJ $m^{-2}$) |
| $R_h$ | monthly mean relative humidity (%) |
| $T_{ave}$ | monthly mean ambient temperature (°C) |
| Tmax | monthly mean maximum ambient temperature (°C) |
| Tmin | monthly mean minimum ambient temperature (°C) |
| δ | solar declination angel (deg) |
| $\omega_s$ | sunrise hour angle (deg) |

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