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Modeling of Solar Radiation Potential in Iran Using Artificial Neural Networks

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ABSTRACT

Solar radiation data play an important role in solar energy relevant researches. These data are not available for some locations due to the absence of the meteorological stations. Therefore, solar radiation data have to be predicted by using solar radiation estimation models. This study presents an integrated Artificial Neural Network (ANN) approach for estimating solar radiation potential over Iran based on geographical and meteorological data. For this aim, the measured data of 31 stations spread over Iran were used to train Multi-Layer Perceptron (MLP) neural networks with different input variables, and solar radiation was the output. The accuracy of the models was evaluated using the statistical indicators of Mean Absolute Percentage Error (MAPE), Root Mean Square Error (RMSE), and Correlation Coefficient (R); hence, the best model in each category was identified. The Stepwise Multi NonLinear Regression (MNLR) method was used to determine the most suitable input variables. The results obtained from the ANN models were compared with the measured data. The *MAPE* and *RMSE* were found to be 2.98% and 0.0224, respectively. The obtained R value was about 99.85% for the testing data set. The results testify to the generalization capability of the ANN model and its excellent ability to predict solar radiation in Iran.

Keywords*:* ANN, Meteorological data, Multi non-linear regression, Solar radiation.

INTRODUCTION

Solar energy is the portion of the sun's energy available at the earth's surface for an extensive collection of useful applications. Solar energy is known as an ancient clean source, and it is the basic ingredient of almost all fossil and renewable types of energy on Earth. This abundant source of energy is accessible in most places and its utilization is important, especially at the present time that the price of fossil fuels is rising day by day and the global warming has become an issue with increasing international concern (Khatib *et al.,* 2012).

Iran is a rich land in terms of renewable energy resources. In particular, Iran has great potential of solar energy, as it is located in the sun-belt, and two months of the country's incoming radiation is equal to the total reservoirs of fossil fuels (Bahrami and Abbaszadeh, 2013; Moini *et al.,* 2011; Gorjian *et al*., 2013). The level of annual incoming solar radiation has been calculated as 2,000 kWh m^{-2} which is thirteen times higher than the total Iranian energy consumption (Mirzahosseini and Taheri, 2012).

An accurate, detailed, and long-term knowledge of the accessibility and variability of solar radiation intensity in time and special domain is a primary important prerequisite to the design and development of solar energy applications in any geographical location (Gorjian *et al.,* 2012; Behrang *et al*., 2010; Mohandes *et al*., 1998; Nguyen *et al*., 1997; Yaghoubi and Sabzevari, 1993). Such data should be contemporary, reliable, and available for

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estimating the dynamic behavior of solar systems' processes and simulating long-term operations of solar technologies (Almorox *et al.,* 2011; Jacovides *et al*., 2006). Solar radiation received on a horizontal surface is also the most vital meteorological factor modeling hydrological process, soil water balance, reference evapotranspiration, and determining crop productivity (Reddy and Ranjan, 2003; Li *et al*., 2010). In addition, solar radiation data are always the necessary basis for feasibility studies of the possible implementation of solar energy projects (Khalil and Fathy, 2008). For these reasons, the global solar radiation and its components play a vital role in the development of solar systems (Kaushika *et al.,* 2014; Bilgili and Ozgoren, 2011). Apparently, the best way to acquire such reliable data is through the installation of proper radiation monitoring sensors at the areas of interest (Hejase *et al.,* 2014; Mohandes *et al*., 1998). Unfortunately, such equipment requires regular maintenance, recording, and calibration. Therefore, their installation is feasible only in a few meteorological stations, especially in developing countries due to both historic and economic reasons (Hejase *et al.,* 2014; Nguyen *et al*., 1997; Mohandes *et al*., 1998; Soares *et al*., 2004). As a result, the limited availability of a vast network of radiation monitoring stations and also the cost and difficulty in measurements, motivates the development of alternative computational procedures to estimate solar radiation from the available meteorological data (Dorvlo *et al.,* 2002; Moreno *et al.,* 2011; Ouammi *et al*., 2012).

Based on previous studies, the solar prediction models can be classified into three main categories of "empirical models", "radiative transfer models", and "artificial neural network models". The almost simple empirical models usually require a few measurable sunshine parameters as well as some empirical coefficients. Despite low accuracy, these models are useful due to their simplicity and availability (Angstrom, 2007; Al-Alawi and Al-Hinai, 1998). The "radiative transfer models" necessitate complex geographical and meteorological parameters. These mathematical models provide considerable accuracy in their final outputs. Of course, the capability of these models has been limited because of the required calculations and also numerous input parameters which are not available in most of the locations (Adaramola, 2012; Almorox *et al.,* 2011). The ANN models have been trying to gather the superiorities of the two prior explained models as simplicity and accuracy (Elminir *et al.,* 2007; Rehman and Mohandes, 2008; Şenkal, 2010; Wang *et al.,* 2011).

In remote areas, direct measurement of solar radiation is either absent or scarce, while other meteorological parameters are available due to their application in other fields of meteorology and agriculture. Therefore, it makes a sense to develop a reliable model by applying artificial neural networks to determine the effects of these parameters and estimation of solar radiation (Kaushika *et al.,* 2014). Several researchers reported the application of the ANNs to estimate global solar radiation from weather data (Bilgili, 2010; Benghanem *et al.,* 2009; Hasni *et al*., 2012; Koca *et al*., 2011; Rahimikhoob, 2010; Rumbayan *et al.,* 2012; Şenkal and Kuleli, 2009;Yacef *et al.,* 2012). Al-Alawi and Al-Hinai (1998) used an ANN model to predict global radiation from climatological variables. Results showed a good prediction accuracy of about 93%. Dorvlo *et al*. (2002) used ANN methods based on Radial Basis Function (RBF) and MultiLayer Perceptron (MLP) models to estimate solar radiation using long-term data in Oman. The results indicated that both the RBF and MLP were good, but the RBF was to be preferred as it requires less computing power and time. Sözen *et al*. (2004) used an ANN-based technology to predict solar radiation in Turkey. The predicted values were given in the form of monthly maps. Tymvios *et al*. (2005) compared a variety of models to estimate solar radiation on horizontal surfaces. In this case, three Ångström models and seven ANN models were compared. The ANN models were run

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with different configurations of the input variables. The findings presented the ANN methodology as a promising alternative to the traditional approaches.

An ANN model was presented by Jiang (2008) for estimating monthly mean daily diffuse solar radiation over China. The results were compared with empirical regression models. The ANN-based estimated data were in good agreement with actual data. A feed-forward Back-Propagation (BP) algorithm was also presented by Jiang (2009) for estimating monthly mean daily global solar radiation of 8 typical cities in China. The estimated results of the both ANN and empirical regression models were compared with measured data. It was found that the ANN models were superior to other available empirical models.

Behrang *et al*. (2010) estimated the daily global solar radiation in Dezful city based on meteorological variables using Multi-Layer Perceptron (MLP) and Radial Basis Function (RBF) neural networks. Comparing the obtained results and different conventional models showed a very good improvements with MAPE about 5.21%. Moreno *et al*. (2011) compared three methods of the Bristow-Campbell (BC), ANN and Kernel Ridge Regression (KRR) to estimate the daily global solar radiation over Spain. Results showed that the ANN method produces the best global solar radiation estimates with a mean absolute error of 2.33 MJ m^{-2} day^{-1}. Bilgili and Ozgoren (2011) investigated a model to estimate the daily total global solar radiation in Adana city of Turkey using three methods of Multi-Linear Regression (MLR), Multi-NonLinear Regression (MNLR) and a feed-forward ANN model. Based on the results, the ANN was claimed as the best among the other estimating methods.

Ozgoren *et al*. (2012) developed an ANN model based on Multi-NonLinear Regression (MNLR) method for estimating the monthly mean daily global solar radiation over Turkey. A Stepwise MNLR method was used to determine the most suitable independent variables. The Mean Absolute Percentage Error (MAPE) of 5.34% and Correlation Coefficient (R) value of about 0.994 were reported for testing data set. Ouammi *et al*. (2012) employed an ANN model to forecast the annual and monthly solar irradiation in Morocco. The final results were given in the shape of the annual and monthly maps. It was shown that the method could be used to provide helpful information for decision makers in terms of site selection for new solar plants. Chen *et al*. (2013) presented a solar radiation forecast technique based on fuzzy and neural networks. They claimed that estimations by using fuzzy logic and neural network together can follow the real values very well under different sky and temperature conditions.

Hejase *et al*. (2014) employed ANN models to estimate global horizontal irradiance for three major cities in the United Arab Emirates (UAE), namely, Abu Dhabi, Dubai and Al-Ain. Several ANN models using MLP and RBF techniques were developed. Results proved the suitability of the ANN models for estimating the global horizontal irradiance in different locations of the UAE. Piri and Kisi (2015) developed non-linear models including Adaptive Neuro-Fuzzy Inference System (ANFIS) and Neural Network Auto-Regressive model with exogenous inputs (NN-ARX) along with empirical models to estimate the solar radiation. The results of artificial intelligence models were compared with the empirical models. The findings showed that ANFIS and NN-ARX performed better than the empirical models in estimating daily solar radiation.

As seen from the literature survey outlined above, the ANNs are the most promising methods for estimating global solar radiation, especially in remote areas where there are no solar measurement devices. So far, all the ANN-based solar potential estimations in Iran have provided solar radiation estimations only for a few specific locations. However, determining the most suitable input variables for these estimations

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has not been studied yet. The main objective of the present study was therefore providing an integrated ANN approach for estimating the monthly mean daily global solar radiation at any location of Iran as a function of geographical and meteorological data. For this aim, the most suitable independent variables (inputs) were determined by using the Stepwise Multiple NonLinear Regression (MNLR) method. It is expected that results of this study will give an idea about solar energy potential in various parts of Iran, because the data used represent different climatic conditions.

Artificial Neural Networks (ANN)

The ANNs learn from examples without explicit derivation of the model equation (Gandhidasan and Mohandes, 2011; Sözen *et al*., 2005). An ANN consists of interconnected processing units called neurons. Each connection to a neuron has an adjustable weight associated with it. The ANNs come in different paradigms. The Back Propagation (BP) neural network consists of fully connected layers with rows of processing units. The layers which are not the input or output are called hidden layers. Figure 1 shows a feed-forward network that has one hidden layer. The BP algorithm is a supervised iterative training method for multilayer feed-forward nets with sigmoidal nonlinear threshold units. It uses a training dataset consisting of S pairs of input-output vectors that specifies the problem. Using a generalized least-mean-square algorithm, the BP algorithm, minimizes the mean square deviation between the real network output and the desired output (Haykin, 1994). Each neuron sums its weighted inputs to create an internal activity level a_i,

$$a_i = \sum_{j=1}^{n} W_{ij}x_{ij} - W_{io} \quad (1)$$

Where, W_{ij} is the weight of the connection from input j to neuron i, and W_{io} is the threshold associated with unit i. The a_i is communicated to the subsequent layer through a non-linear function,φ, to make the output y_j,

$$y_j = \varphi(a_i) \quad (2)$$

Several differentiable activation functions have been proposed with the most popular being the logistic function of the form,

$$\varphi(a_i) = 1/1 + \exp\,(-a_i) \quad (3)$$

The error functions that the BP algorithm minimizes are Mean Absolute Percentage Error (MAPE) and Root Mean Square Error (RMSE) as follow:

$$MAPE = 1/s \sum_s \sum_k (d_{sk} - o_{sk}/o_{sk}).100 \quad (4)$$

$$RMSE = 1/S \sqrt{\sum_s \sum_k (d_{sk} - o_{sk})^2} \quad (5)$$

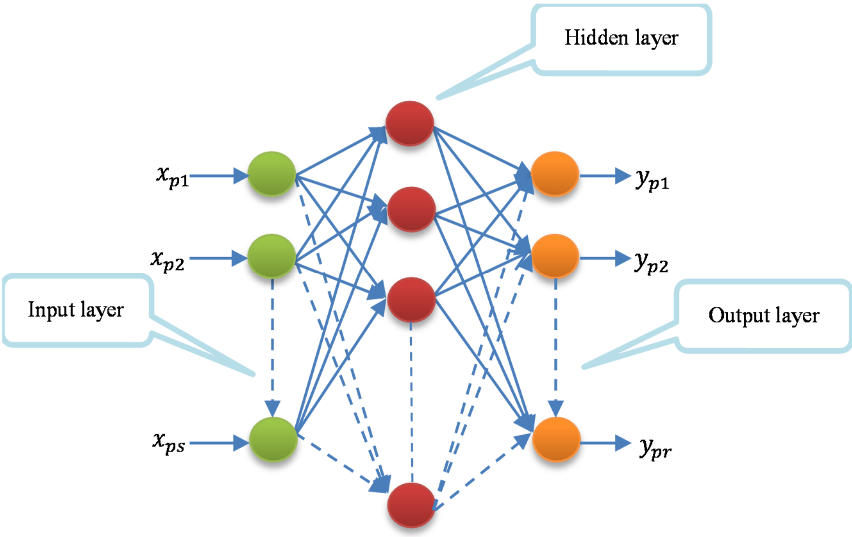

Figure 1. Schematic diagram of a simple BP neural network.

Where, s is the index of the S training pairs, k is the index of elements in the output vector, d_{sk} is the kth element of the sth desired pattern vector, and o_{sk} is the kth element of the output vector when pattern s is presented as input to the network (Gandhidasan and Mohandes, 2011). The weight adjustment of the connection between neuron i in layer m and neuron j in layer $m+1$ can be expressed as:

$$\Delta W_{ji} = \eta \delta_j O_i \quad (6)$$

Where, i is the index of units in layer m, η is the learning rate, O_i is the output of unit i in the mth layer, and δ_j is the delta error term back propagated from the jth unit in layer $m+1$. Choosing a small learning rate, η, decreases the rate of convergence. However, too large values of η cause oscillations. A simple way to increase the learning rate without any oscillation is adding a momentum term as:

$$\Delta W_{ji}(n+1) + \eta \delta_j o_i + \alpha \Delta W_{ji}(n) \quad (7)$$

Where, n is the iteration number, and α is a positive constant which determines the effect of past weight changes on the current direction of movement in weight space (Gandhidasan and Mohandes, 2011).

MATERIALS AND METHODS

Study Area Description

Iran is located in western Asia and borders the Caspian Sea, Persian Gulf, and the Gulf of Oman. The country lies between 25° and 39° N latitude and between 44° and 63° E longitude with the area of about 1,648,000 km^2 (Figure 2). From the perspective of climate, the country is located in the arid and semi-arid region of the globe and 70% of its area is in the dry and semi-arid region (Soltani *et al.,* 2011; Dinpashoh *et al.*, 2004). The western and southwestern parts have a hot, dry, desert climate with annual average temperatures above 18°C. The northeastern and northern areas of the country have a cold, semi-arid climate with dry summers and mild winters. The southern and southeastern areas have a hot-desert climate. The mountainous regions of northern Iran have also a cold snowy climate with dry summers and wet winters (Moini *et al.,* 2011).

Meteorological Dataset

The meteorological data used in this study were mainly taken from Islamic Republic of Iran Meteorological Organization (IRIMO) for 31 stations spread over Iran during 2005-2010. As can be seen in Figure 3, these stations cover almost all areas of the country. Geographical coordinates and measuring periods of these stations are shown in Table 1. Stations extend from latitude 27.2° to 38.15° N and longitude 45.1° to 60.9° E, while the elevations of stations above the sea level vary between 0 m and 2430 m. The information provided by these stations include month of the year, latitude, longitude, altitude, monthly mean daylight hours, air temperature (℃), earth temperature (℃), wind speed (m s^{-1}), relative humidity (%), atmospheric pressure (kPa) and precipitation (mm day^{-1}) over Iran. The run-test and limit checkers were carried out on the daily observed total meteorological data to make sure that the data are homogeneous and the variability of daily observed data is caused only by climatic influences and not from other sources of errors (e.g. systematic errors caused by instruments, calibration problems, data transferring, etc.

RESULTS AND DISCUSSION

Multi-nonlinear Regression Method

It is well known that global solar radiation is related to various meteorological variables and seasonal variations. Therefore, the

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Figure 2. Geographical map of Iran.

Figure 3. Study area with the considered meteorological stations.

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Table 1. Geographical coordinates and measuring time periods of the considered stations.

Stations	Latitude	Longitude	Altitude (m)	Period
Ahwaz	31.3	48.7	22	2005-2010
Arak	34.1	49.8	1708	2005-2010
Ardebil	38.15	48.17	1332	2005-2010
Bandar Abbas	27.2	56.4	10	2005-2010
Birjand	32.9	59.2	1491	2005-2010
Bojnurd	37.47	57.3	1511	2005-2010
Bushehr	28.9	50.8	0	2005-2010
Esfahan	32.5	51.7	1550	2005-2010
Gorgan	36.8	54.5	1364	2005-2010
Hamadan	34.9	48.5	1749	2005-2010
Ilam	33.6	46.4	1101	2005-2010
Karaj	35.8	51	1328	2005-2010
Kerman	30.3	57	1754	2005-2010
Kermanshah	34.3	47.1	1322	2005-2010
Khoramabaad	33.5	48.4	1810	2005-2010
Mashhad	36.3	59.6	999	2005-2010
Orumieh	37.5	45.1	1316	2005-2010
Qazvin	36.15	50	1278	2005-2010
Qom	34.7	51	1546	2005-2010
Rasht	37.32	49.6	37	2005-2010
Saari	36.33	53	23	2005-2010
Sanandaj	35.3	47	1373.4	2005-2010
Semnan	35.6	53.4	1451	2005-2010
Shahrekord	32.3	50.9	2430	2005-2010
Shiraz	29.5	52.5	1481	2005-2010
Tabriz	38.1	46.3	1361	2005-2010
Tehran	35.7	51.3	1191	2005-2010
Yasuj	30.8	51.7	1940	2005-2010
Yazd	31.9	54.4	1230	2005-2010
Zahedan	29.5	60.9	1370	2005-2010
Zanjan	36.7	48.5	1663	2005-2010

Monthly Mean Daily Global Solar Radiation (H) at any place of Iran can be characterized as the function of Latitude (LT), Longitude (LN), Altitude (A), Month of the year (M), Minimum Air Temperature (T_{min}), Maximum Air Temperature (T_{max}), Minimum Soil Temperature (ET_{min}), Maximum Soil Temperature (ET_{max}), Relative Humidity (RH), Wind Speed (W), Precipitation (P), Atmospheric Pressure (Pr) and Sunshine Duration (S). The relationship between H and the independent variables can be expressed as:

$$Hf = (LT, LN, A, M, T_{min}, T_{max}, ET_{min}, ET_{max}, RH, W, P, Pr, S) \quad (8)$$

However, one of the most important steps in developing a satisfactory ANN model is the choice of the most appropriate independent variables. Because, these variables determine the structure of the designed model and affect the weighted coefficient and the final results. For this reason, firstly, all independent variables were added to a simple Multi-NonLinear Regression (MNLR) model. Namely, "Enter" regression method was applied by using SPSS, which is a famous statistical and data management software package program. Table 2 shows the summary of the method. It seems that the Enter method did not give acceptable results. This can be seen when comparing the last column of Table 2. Four significance values are very much higher than 0.05, therefore, this model estimates from Enter method was rejected. Then, in order to define the relationship

Table 2. The multi-nonlinear regression with constant using "Enter" method.

Model	Unstandardized Coefficients		Standardized coefficients		
	B	Std. error	β	T	Significant
1 Constant	2.458	0.641		3.835	0.000
M	-0.033	0.006	-0.69	-5.273	0.002
LT	-0.086	0.008	-1.51	-10.582	0.003
LN	-0.026	0.005	-0.063	-5.133	**0.614**
A	0.000	0.000	0.044	3.047	0.045
S	0.761	0.027	0.708	27.752	0.000
T_{max}	0.020	0.005	0.131	3.957	0.023
T_{min}	0.030	0.005	0.171	6.556	0.001
ET_{min}	-0.011	0.006	-0.059	-1.778	0.043
ET_{max}	-0.009	0.003	-0.087	-3.499	0.035
W	-0.001	0.004	-0.002	-0.186	**0.405**
RH	-0.003	0.002	-0.036	-1.249	**0.895**
Pr	-0.027	0.006	-0.073	-4.188	0.039
P	-0.339	0.045	-1.41	-7.458	**0.765**

between H and independent variables, and also to regulate the best independent variables, ''Stepwise'' regression method was performed and applied. The significance levels (P values) were used to evaluate estimator performance of the regression methods. By comparing the Enter and Stepwise regression methods, the Stepwise method is claimed to be more accurate due to the significance values which are very much lower than 0.05 (Table 3). Therefore, the best independent variables were selected as the M, S, LT, LN, A, P, Pr, T_{min}, T_{max} and ET_{max}. However, there was no relationship between the H and ET_{min}, W, and RH. Consequently, these variables were not recorded as independent variables and were rejected.

Artificial Neural Network Model

According to the Stepwise regression method, ten ANN models consisting of several combinations of the independent variables (inputs) were developed. In order to start training the ANNs, the data set of 31 stations were divided into two sets; a set of 27 stations for training and a set of 4 stations (Ahwaz, Arak, Hamedan, and Semnan) for

Table 3. The multi-nonlinear regression with constant using "Stepwise" method.

Model	Unstandardized Coefficients		Standardized coefficients		
	B	Std. error	β	T	Sig.
1 Constant	2.948	0.606		4.864	0.000
S	0.744	0.026	0.692	28.229	0.000
LT	-0.088	0.008	-0.155	-11.387	0.003
Pr	-0.032	0.006	-0.088	-5.496	0.000
T_{min}	0.027	0.004	0.151	7.087	0.002
P	-0.34	0.043	-0.142	-7.840	0.000
LN	-0.025	0.005	0.061	-5.044	0.000
M	-0.036	0.006	0.074	-5.787	0.000
T_{max}	-0.017	0.004	0.110	4.269	0.001
A	0.000	0.000	0.045	3.140	0.001
ET_{max}	-0.006	0.002	-0.051	-2.743	0.000

testing and validating of each model.

The first model was developed by entering S as the only independent variable and H as the target. The subsequent models were constructed by entering the other independent variables, one by one into the first ANN model to develop a new model (Table 4).

All ten combinations of input variables were developed in the MATLAB software in the form of computer codes. The *H* was considered to be the target for an output neuron in the ANN architectures. The training algorithm of "TRAINLM" was used in all the ANN models and "Logsig" as a non-linear activation function and "Purelin" as a linear activation function in hidden layer(s) and output layer, respectively.

In order to determine the best network architecture, the optimum numbers of neurons in the hidden layer(s) were determined using the trial and error procedure by considering the values of *MAPE, RMSE* and *R.* The numbers of neurons in hidden layer(s) ranged from 3 to 30. All models were trained and tested in order to compare and evaluate the operations of the ANN models.

The networks were trained to reach the best performance with the minimum values of *MAPE* and *RMSE.* The Correlation Coefficients (R) for training and testing data set were also recorded as shown in the last columns of the Table 2.

According to the derived results, the values of R_{train} range from 94.70% to 99.98%, while the values of R_{test} (for 4 testing stations), which were obtained based on the testing data set, range from 94.06% to 99.85%. Among several simulations, the best performance was obtained for the ANN10 with the architecture of 10-25-1. The obtained R_{test} was 99.85%, which is higher than the other ANN configurations. The *MAPE* and *RMSE* were 2.85% and 0.0224, respectively. The architecture of the best performance ANN10 is shown in Figure 4. The scatter plots between the estimated and measured solar radiation data by ANN10 (10-25-1) as the best performing architecture for both training and test data set are shown in Figure 5. The estimated values of ANN10 (10-25-1) were compared with the measured values for each station. The values of *RMSE* and *MAPE* were used as statistical indicators. As can be seen from Table 5, *RMSE* values vary between 0.0157 kWh m^{-2} day^{-1} (for Mashhad Station) and 0.0606 kWh m^{-2} day^{-1} (for Kermanshah Station). The highest *MAPE* was found for Kermanshah station with a value of 3.77%, while the lowest *MAPE* was found as 2.44% for Mashhad station. The performance of the ANN10 (10-25-1) model for the testing stations is shown in Figure 6, while Figure 7 shows that of the six chosen training stations (Tehran, Kermanshah, Esfahan, Kerman, Zahedan, and Bandar Abbas). As can be seen from these figures, the estimated values of the monthly mean daily global solar radiation are very close to the actual values for all months. A small perceptible deviation is observed for the testing values. As can be seen from all graphs (testing and training), estimated values have fairly close agreement with the corresponding actual measurements. In addition, a comparison is given with the published literature on similar studies which used ANNs in Table 6. As shown in this table, the *MAPE* values, ranging from the maximum value of 12.61 to the minimum value of 0.48, have been reported before. As shown in the table, based on the values of *MAPE*, the performance of the ANN model for the present study is the best among the others.

The results obtained render the ANN methodology as a promising alternative method for estimating the monthly mean daily global solar radiation as a function of geographical and meteorological parameters in Iran.

CONCLUSIONS

Determination of solar radiation is necessary for solar systems design and power generation. In this context, different ANN models were used to predict solar

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Table 4. MAPE, RMSE and R of the ANN models with different input combinations.

ANN architecture (MLP)	MAPE (%)	RMSE (kWh m^{-2}day^{-1})	R_{train} (%)	R_{test} (%)
$ANN1, H = f(S)$				
$1 \times 3 \times 1$	38.23	0.538702	94.70	94.06
$1 \times 5 \times 1$	36.53	0.535443	95.10	94.56
$1 \times 10 \times 1$	33.31	0.432203	95.60	95.75
$1 \times 15 \times 1$	29.36	0.554166	95.90	95.24
$1 \times 10 \times 15 \times 1$	42.23	0.465080	96.63	96.30
$ANN\,2, H = f(S, LT)$				
$2 \times 3 \times 1$	6.95	0.105830	97.80	97.72
$2 \times 5 \times 1$	8.29	0.110000	97.76	97.80
$2 \times 10 \times 1$	7.15	0.100498	98.39	97.64
$2 \times 15 \times 1$	6.28	0.084852	98.79	98.97
$2 \times 10 \times 10 \times 1$	8.63	0.128841	97.86	97.26
$ANN\,3, H = f(S, LT, Pr)$				
$3 \times 5 \times 1$	7.95	0.090553	98.41	99.06
$3 \times 7 \times 1$	7.08	0.088317	98.69	98.46
$3 \times 10 \times 1$	5.76	0.088317	98.90	98.78
$3 \times 15 \times 1$	6.33	0.087178	98.99	98.60
$3 \times 10 \times 15 \times 1$	7.91	0.086023	98.90	98.12
$ANN\,4, H = f(S, LT, Pr, T_{min})$				
$4 \times 5 \times 1$	4.98	0.088882	99.07	99.00
$4 \times 10 \times 1$	4.55	0.072111	99.61	98.37
$4 \times 15 \times 1$	4.44	0.067823	99.44	99.17
$4 \times 20 \times 1$	4.41	0.064031	99.86	99.12
$4 \times 5 \times 20 \times 1$	5.86	0.082462	99.61	98.69
$ANN\,5, H = f(S, LT, Pr, T_{min}, P)$				
$5 \times 5 \times 1$	4.08	0.067082	99.36	99.05
$5 \times 10 \times 1$	5.53	0.066332	99.32	98.74
$5 \times 15 \times 1$	4.38	0.055677	99.75	98.75
$5 \times 15 \times 10 \times 1$	4.76	0.081240	99.51	99.25
$ANN\,6, H = f(S, LT, Pr, T_{min}, P, LN)$				
$6 \times 5 \times 1$	4.1	0.072111	99.46	98.80
$6 \times 10 \times 1$	4.21	0.063245	99.7	99.33
$6 \times 15 \times 1$	4.36	0.048989	99.82	99.57
$6 \times 20 \times 1$	4.87	0.056568	99.65	99.26
$6 \times 10 \times 15 \times 1$	4.51	0.053852	99.80	99.47
$ANN\,7, H = f(S, LT, Pr, T_{min}, P, LN, M)$				
$7 \times 9 \times 1$	4.98	0.064031	99.84	99.45
$7 \times 14 \times 1$	5.54	0.056568	99.62	99.52
$7 \times 20 \times 1$	4.34	0.047958	99.79	99.44
$7 \times 25 \times 1$	4.46	0.062449	99.83	99.39
$7 \times 12 \times 15 \times 1$	5.43	0.048989	99.77	99.55
$ANN\,8, H = f(S, LT, Pr, T_{min}, P, LN, M, T_{max})$				
$8 \times 10 \times 1$	5.15	0.046904	99.66	99.63
$8 \times 20 \times 1$	4.33	0.052915	99.65	99.45
$8 \times 25 \times 1$	6.35	0.092195	98.90	98.21
$8 \times 10 \times 15 \times 1$	4.60	0.054772	99.40	99.40
$ANN\,9, H = f(S, LT, Pr, T_{min}, P, LN, M, T_{max}, A)$				
$9 \times 9 \times 1$	3.98	0.065574	99.60	99.11
$9 \times 14 \times 1$	3.64	0.051961	99.98	99.34
$9 \times 25 \times 1$	3.54	0.045826	99.97	99.57
$9 \times 30 \times 1$	4.71	0.057446	99.93	99.34
$9 \times 15 \times 15 \times 1$	3.56	0.048989	99.95	99.50
$ANN10, H = f(S, LT, Pr, T_{min}, P, LN, M, T_{max}, A, ET_{max})$				
$10 \times 15 \times 1$	4.25	0.056568	99.54	99.37
$10 \times 20 \times 1$	3.35	0.041721	99.87	99.75
$10 \times 25 \times 1$	2.85	0.022426	99.98	99.85
$10 \times 30 \times 1$	3.60	0.048989	99.85	99.60
$10 \times 12 \times 20 \times 1$	3.74	0.060110	99.70	99.30

Table 5. Error values of the ANN10 (10-25-1) model for the considered stations.

Stations	MAPE (%)	RMSE (kWh $m^{-2}day^{-1}$)
Stations used in training		
Ardebil	3.50	0.0359
Bandar Abbas	2.25	0.0244
Birjand	2.35	0.0267
Bojnurd	2.09	0.0213
Bushehr	3.12	0.0350
Esfahan	2.34	0.0220
Gorgan	3.99	0.0429
Ilam	2.95	0.0258
Karaj	3.13	0.0335
Kerman	3.43	0.0432
Kermanshah	3.30	0.0606
Khoramabaad	2.11	0.0183
Mashhad	2.44	0.0157
Orumieh	2.68	0.0297
Qazvin	3.03	0.0310
Qom	3.51	0.0335
Rasht	3.34	0.0344
Saari	2.51	0.0267
Sanandaj	3.67	0.0317
Shahrekord	3.52	0.0454
Shiraz	2.98	0.0267
Tabriz	3.39	0.0334
Tehran	2.95	0.0199
Yasuj	3.41	0.0396
Yazd	3.36	0.0298
Zahedan	2.35	0.0264
Zanjan	3.55	0.0378
Stations used in testing		
Ahwaz	2.66	0.0198
Arak	3.35	0.0290
Hamedan	2.83	0.0187
Semnan	2.76	0.0164

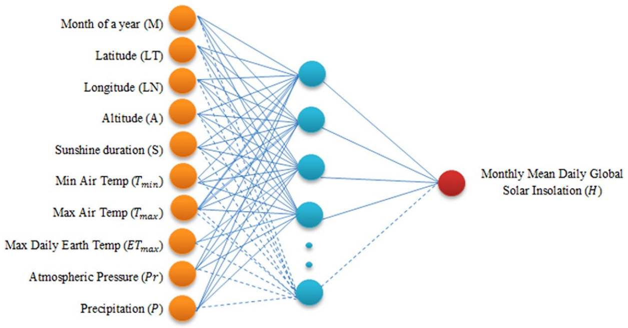

Figure 4. Architecture of the ANN10 model with one hidden layer.

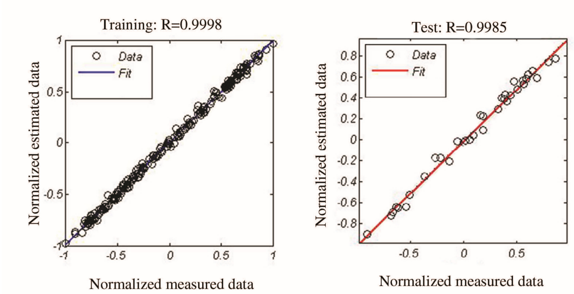

Figure 5. Scatter plots for measured and estimated solar insolation data (ANN10; 10-25-1).

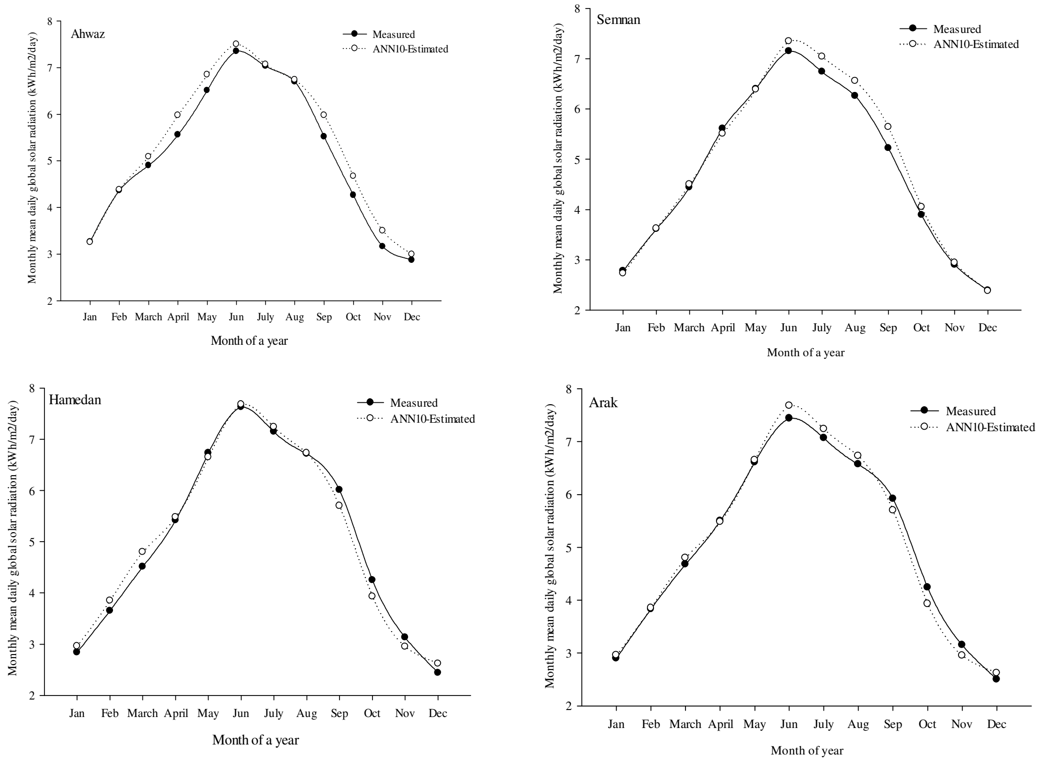

Figure 6. Comparison between estimated and measured data for testing meteorological stations (ANN10; 10-25-1).

Table 6. Comparison between the results of the present study and the similar studies.

Study	Location	Network type	MAPE (%)
Mohandes et al. (1998)	Saudi Arabia	ANN/MLP	12.61
Mohandes et al. (2000)	Saudi Arabia	ANN/RBF	10.09
Sözen et al. (2004)	Turkey	ANN/BP	6.73
Sözen et al. (2005)	Turkey	ANN/MLP	6.780
Rehman and Mohandes (2008)	Saudi Arabia	ANN/MLP	4.490
Azadeh et al. (2009)	Iran	ANN/MLP	6.700
		ANN/MLP	5.210
Behrang et al. (2010)	Iran	ANN/RBF	5.560
Fazel Ziaei Asl et al. (2011)	Iran	ANN/MLP	6.080
Rumbayan et al. (2012)	Indonesia	ANN/MLP	3.4
Ozgoren et al. (2012)	Turkey	MNLR + ANN	5.34
Chen et al. (2013)	Singapore	Fuzzy + ANN	8.96 (sunny days)
			6.03 (cloudy days)
		ANN/MLP	4.86
Hejase et al. (2014)	United Arab Emirate (UAE)	ANN/RBF	4.99
Present study	Iran	MNLR + ANN/MLP	2.850

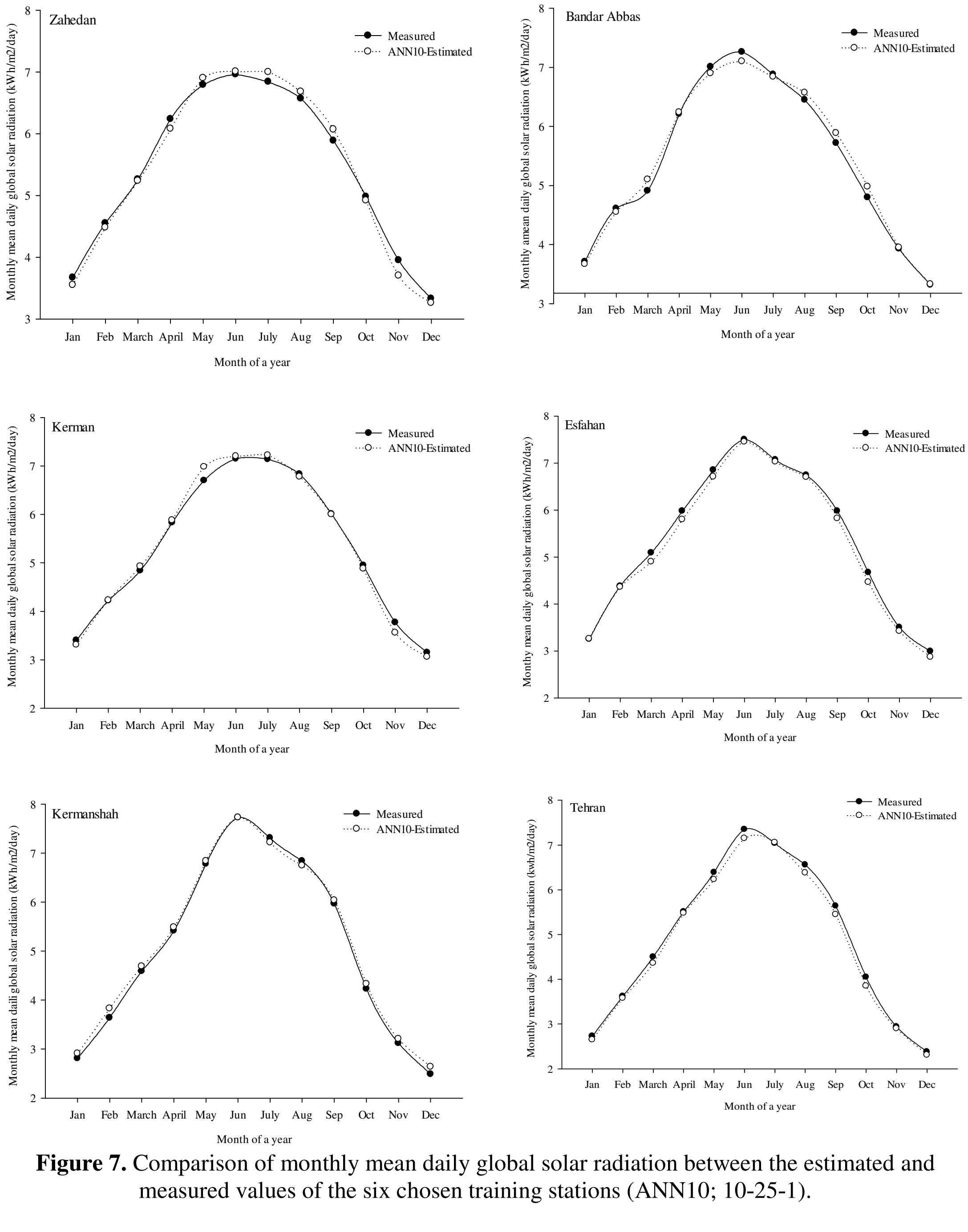

Figure 7. Comparison of monthly mean daily global solar radiation between the estimated and measured values of the six chosen training stations (ANN10; 10-25-1).

radiation based on geographical and meteorological data in different parts of Iran. The ANN models were found to predict solar radiation more accurately than conventional predicting models. The obtained results showed a relatively good agreement between the measured and the predicted values. Comparing the statistical parameters for all models presented in this work, showed that the ANN10 (10-25-1) had the best accuracy with *MAPE* of 2.85% and RMSE of 0.0224. However, for each developed ANN-model the Correlation Coefficient (R) was greater than 94%. This

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is while that the values of R_{train} and R_{test} for the best performing architecture of ANN10 were obtained to be 99.98% and 99.85%, respectively.

The ANN-based prediction models discussed in this study enable researchers and solar power plant installers to determine solar radiation data with better accuracy at places where meteorological stations are not established. In addition, this method can be utilized by researchers or engineers in terms of site selection and solar maps creation.

As a recommendation, the future researches should be directed to identification of the promising site selection and installation of the optimal technology. In particular, the focus should be devoted to the design and planning of solar technology foundations. The studies should concern the development of optimal configurations that may satisfy not only criteria related to the solar resource availability, but also the criteria that seem important from economic and environmental viewpoints.

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مدلسازی پتانسیل تابش خورشیدی در ایران بااستفاده از شبکه های عصبی مصنوعی

ش. گرجیان، ب. قبادیان، و ت. توکلی هشجین

چکیده

داده های تابش خورشیدی نقش مهمی در پژوهشهای مرتبط با انرژی خورشیدی دارند .این داده ها برای برخی مناطق به دلیل نبود ایستگاههای هواشناسی موجود نمی باشند. به همین دلیل این داده ها بایستی به دقت و با استفاده از مدلهای تخمین تابش خورشیدی تخمین زده شوند. پژوهش حاضر یک روش یکپارچه بر پایه شبکه های عصبی مصنوعی برای تخمین پتانسیل تابش خورشیدی در ایران و با استفاده از داده های جغرافیایی و هواشناسی ارائه می کند. بدین منظور، داده‌های ۳۱ ایستگاه که در سرتاسر ایران پراکنده شده‌اند برای یادگیری شبکه‌های عصبی پرسپترون چندلایه با متغیرهای ورودی مختلف استفاده شدند. دقت مدل‌ها با استفاده از شاخص‌های آماری درصد خطای مطلق متوسط (MAPE)، ریشه میانگین مربع خطا (RMSE) و ضریب همبستگی (R) ارزیابی شدند. تا آنجایی که بهترین مدلها در هر گروه انتخاب شدند. در ابتدا، همه متغیرهای مستقل وارد مدل رگرسیون Enter شدند. سپس روش رگرسیون چندگانه‌ی غیرخطی Stepwise به منظور تعیین مناسب‌ترین متغیرهای ورودی استفاده شد. با استفاده از این متغیرهای ورودی، نتایج به دست آمده از مدل‌های ANN با داده‌های اندازه‌گیری شده مقایسه شدند. نتایج نشان دادند که مقادیر خطا در محدوده‌های قابل قبولی قرار دارند. مقدار R در حدود ۹۹/۸۵٪ برای داده‌های آزمون به دست آمد .نتایج قابلیت تعمیم مدل ANNو توانایی آن را در تولید تخمین‌های دقیق در ایران تائید می‌کنند.

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