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Estimating and Modeling Monthly Mean Daily Global Solar Radiation on Horizontal Surfaces Using Artificial Neural Networks in South East of Iran

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ABSTRACT

In this study, an artificial neural network based model for prediction of solar energy potential in Kerman province in Iran has been developed. Meteorological data of 12 cities for period of 17 years (1997–2013) and solar radiation for five cities around and inside Kerman province from the Iranian Meteorological Office data center were used for the training and testing the network. Meteorological and geographical data were used as inputs to the network, while the solar radiation intensity was used as the output of the network. The results show that the correlation coefficients between the predictions and actual global solar radiation intensities for training and testing datasets were higher than 97%, suggesting a high reliability of the model for evaluating solar radiation in locations where solar radiation data are not available. The predicted solar radiation values are illustrated in the form of maps that were made by ArcGIS.

1. INTRODUCTION

Solar radiation is radiant energy emitted by the sun from a nuclear fusion reaction that creates electromagnetic energy. The spectrum of solar radiation is close to that of a black body with a temperature of about 5800 K. The annual average radiation outside the terrestrial atmosphere is estimated at about 1379 W/m2. Solar radiation is the most important factor in many cases of designing systems in wide range of sciences including solar energy systems, estimation of crop productivity, meteorological research, and lots of renewable energy resources. Depending on the geometry of the earth land its distance from the sun, geographical location, and the clearance of the atmosphere, the incoming irradiation at any given point is different. Solar radiation data can be provided through measurements, but it is difficult to have measurements for all locations of interest. An alternative to obtaining solar radiation data is estimating it by using an appropriate solar radiation model. Many empirical models for estimation of global solar radiation on a horizontal surface based on linear, quadratic polynomial, logarithmic, exponential, cubic polynomial, and hybrid forms, have been developed. These models usually use sunshine hours, latitude, and altitude. The most widely used and the simplest equation relating radiation to sunshine duration is the Angström-Prescott relationship, which can be expressed as a linear regression expression [1-2].

Empirical linear models have developed by many researchers to estimate global solar radiation on a horizontal surface based on available meteorological parameters due to lack of solar radiation data. Liu and Jordan [3] have developed theoretical models for deriving the monthly mean hourly global and diffuse solar radiation from daily values, assuming that the ratio of hourly to daily values are the same on earth surface as it is extraterrestrial. They further assumed that atmospheric transmission does not depend on solar altitude. Collares-Pereira and Rabl [4] have improved Liu and Jordan equation, to suit the measured data of many stations across the globe, and this model has been accepted universally. Some researchers [5–6] have developed quadratic and cubic models and others [7–8] have developed hybrid and exponential empirical models to estimate global solar radiation on a horizontal surface.

Many works have been carried out by the above-mentioned methods but in spite of the simplicity and advantages of these empirical models, there are some weaknesses in these models, especially in linear ones, which may lead to unreliable predictions. For instance,

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Angström models ignore some important factors such as elevation, relative humidity, and temperature.

During recent years, numerous techniques such as artificial neural network (ANN) have been used to develop these models. Behrang et al. predicted daily global solar radiation on a horizontal surface based on meteorological variables using different artificial neural network techniques for Dezful city in Iran [9]. Daily mean air temperature, relative humidity, sunshine hours, evaporation, and wind speed values between 2002 and 2006 were used.

Karoro Angela et al. used ANN to estimate the monthly average of daily global solar irradiation on a horizontal surface based only on sunshine hours as a single parameter in Kampala, Uganda [10]. Results obtained using the proposed model showed good agreement between the estimated and actual values of global solar irradiation. Correlation coefficient was 0.963 with a mean bias error of 0.055 MJ/m2, and root mean square error was calculated 0.521 MJ/m2. This single parameter ANN model was shown as a suitable model for estimating global solar irradiation at places where monitoring stations are not established.

Moreno et al. used the Bristow–Campbell (BC), Artificial Neural Network (ANN) and Kernel Ridge Regression (KRR) methods to estimate the daily global solar irradiation [11]. BC is an empirical approach based on air maximum and minimum temperature. The experimental dataset included 4 years (2005–2008) of daily irradiation collected at 40 stations and temperature and precipitation data collected at 400 stations over Spain. Results showed that the ANN method produces the best global solar irradiation estimates.

Ozgoren et al. developed an artificial neural network (ANN) model based on multi-nonlinear regression (MNLR) method for estimating the monthly mean daily sum global solar radiation at any place of Turkey [12]. They added all independent variables (latitude, longitude, altitude, month, monthly minimum atmospheric temperature, maximum atmospheric temperature, mean atmospheric temperature, soil temperature, relative humidity, wind speed, rainfall, atmospheric pressure, vapor pressure, cloudiness and sunshine duration) to the regression model. The mean absolute percentage error (MAPE) was found to be 5.34% and correlation coefficient (R) value was obtained to be about 0.9936 for the testing data set.

Rajesh Kumar et al. developed a new model for the solar radiation estimation in hilly areas of North India [13]. This new model was developed based on Angstrom-Prescott model with 10 hidden neurons in ANN model to estimate the monthly average daily global solar radiation only using sunshine duration data. The monthly average global solar radiation data of four different locations in North India was analyzed with the neural fitting tool (nftool) of neural network of MATLAB Version 7.11.0.584 (R2010b). The values of maximum percentage error (MPE) and mean bias error (MBE) were in good agreement with the actual values. Artificial neural network application showed that data was best fitted for the regression coefficient of 0.99558 with best validation performance of 0.85906 for Solan, India. Amrouche and Le Pivert developed an ANN based model to predict the global solar radiation based on daily weather forecasts provided by the US National Oceanic and Atmospheric Administration (NOAA) for four neighboring locations [14]. The forecasts made by these models were compared to measured data and validation results indicated that the ANN-based method can estimate daily GHI with satisfactory accuracy.

Kadirgama et al. developed an ANN model with the effects of temperature, humidity, wind speed, wind chill, pressure and rain on solar radiation. The maximum mean absolute percentage error was found to be less than 7.74% and R2 values were about 98.9% for the testing stations, and 5.398% and 97.9 % for the training stations [15].

Amit Kumar Yadaf et al. have evaluated the most influencing input parameters in prediction of solar radiation using ANN [16]. They showed that the most relevant input variables for predicting the solar radiation are found to be temperature, maximum temperature, minimum temperature, altitude above mean sea level and sunshine hours. It was found that latitude and longitude have minimum effect on solar radiation prediction at any sites in India. They suggested further studies to estimate the solar potential of the region with greater accuracy can be undertaken. Future research is to be focused on finding most relevant input parameters from other meteorological variables with improved prediction accuracy of different ANN models.

In the present study, it is attempted to use ANN to evaluate the annual and seasonal mean global solar radiation on horizontal surface for Kerman province in Southeast Iran, for the first time. This province is one of the best regions in Iran with high solar radiation and different climate from north to south and east to west. Unfortunately, so far no data has been collected for solar radiation in cities of province except Kerman city. By developing the usage of renewable energy, it is very important and essential to know the values of radiation in each part the region. Furthermore, this information could be useful to calculate exergy of each part of the region, and of course, selecting the best way to use solar radiation in terms of photovoltaic or thermal usage of solar energy.

2. MATERIALS AND METHODS

Kerman is one of the 31 provinces of Iran. Kerman is located in Southeast Iran with its administrative center in the city of Kerman. Kerman province is bounded by the provinces of Fars on the west, Yazd on the north, South Khorasan on the northeast, Sistan va Baluchestan on the east, and Hormozgan on the south. Figure 1. shows the geographical location of the Kerman province in Iran. It includes the southern part of the central Iranian desert, the Dasht-e Lut.

The southern Lut is relatively dry and saline. Major part of the province is largely steppe or sandy desert. The climate in varies in different regions of the province. The north, northwest, and central areas experience a dry and moderate climate, whereas in the south and southeast, the weather is warm and relatively humid. The city of Kerman and the surrounding regions have a semi-moderate and dry climate.

Figure 1. Geographical location of the Kerman province in Iran.

3. ARTIFICIAL NEURAL NETWORKS

Artificial neural networks are a computational tool, based on the properties of biological neural systems. Neural networks excel in a number of problem areas where conventional computer systems have traditionally been slow and inefficient. The first practical application of artificial neural networks came in the late 1950s, with the invention of the perceptron network and associated learning rule by Frank Rosenblatt [17]. Rosenblatt and his colleagues built a perceptron network and demonstrated its ability to perform pattern recognition. Interest in neural networks had faltered during the late 1960s because of the lack of new ideas and powerful computers with which to experiment. During the 1980s both of these impediments were overcome, and research in neural networks increased dramatically.

Artificial neural networks are widely accepted as an alternative way to tackle complex problems. They are able to deal with nonlinear problems, and once trained, can perform predictions at very high speed [11]. The use of the ANNs for modeling and prediction purposes has become increasingly popular in the last decades. The fundamental processing element of a neural network is a neuron. A biological neuron receives inputs from other sources, combines them in some way, performs generally a nonlinear operation on the result, and then outputs the final result. An ANN is characterized by its architecture, training or learning algorithm and activation function. The architecture describes the connections between the neurons. It consists of an input layer, an output layer and generally, one or more hidden layers in-between as depicted in Figure 2. It shows one of the commonly used networks, namely, the layered feed-forward neural network with one hidden layer. An important subject of a neural network is the training step.

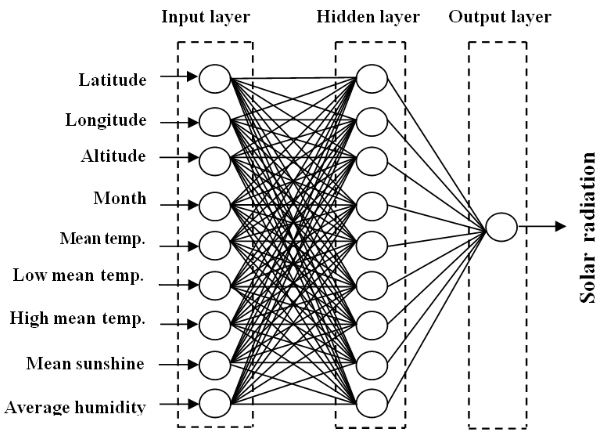

Figure 2. ANN architecture used for nine neurons in single hidden-layer.

There are different learning algorithms. A popular algorithm is the back-propagation algorithm. In addition, success in the algorithms depends on the user dependent parameters such as learning rate and momentum. Faster algorithms such as conjugate gradient, quasi-Newton, and Levenberg–Marquardt use standard numerical optimization techniques [18]. The back propagation algorithm is used in layered feed-forward ANNs. This means that the artificial neurons are organized in layers, and send their signals forward, and then the errors are propagated backwards. The network receives inputs by neurons in the input layer, and the output of the network is given by the neurons on an output layer. There may be one or more intermediate hidden layers. The back propagation algorithm uses supervised learning, which means that we provide the algorithm with examples of the inputs and outputs we want the network to compute, and then the error (difference between actual and expected results) is calculated. The idea of the back propagation algorithm is to reduce this error, until the ANN learns the training data. The training begins with random weights, and the goal is to adjust them so that the error will be minimal [19]. The validation set is used to test the performance of the network during training process. When the error of validation set reaches a minimum, then training process stops [11].

These algorithms eliminate some of the above mentioned disadvantages. ANN with back-propagation algorithm learns by changing the weights; these changes are stored as knowledge. Error during the learning is as root-mean-squared (RMS) and defined as follows:

$$RMS = \left(\left(\frac{1}{p} \right) \sum_j \left| t_j - o_j \right|^2 \right)^{\frac{1}{2}} \tag{1}$$

In addition, absolute fraction of variance (R2) and mean absolute percentage error (MAPE) are defined as follows:

$$R^2 = 1 - \left(\frac{\sum_j \left| t_j - o_j \right|^2}{\sum_j (o_j)^2} \right) \tag{2}$$

$$MAPE = \frac{o - t}{o} \times 100 \tag{3}$$

In order to suit the consistency of the model, all source data such as Input and output layer were normalized in the (-1, 1) range and then returned to original values after the simulation using:

$$X_{norm} = \frac{X - X_{min}}{X_{max} - X_{min}} \tag{4}$$

In the present work, ANN is used for modeling solar resource in Kerman province. Inputs for the network are latitude, longitude, altitude (as shown Tables 1 and 2), and month, mean sunshine duration, mean temperature, low and high mean temperature, and mean relative humidity, output is solar radiation.In order to train, test and validate the neural network, meteorological data measured by the Data Centre of Iranian Meteorological Office (IRIMO) for last 10 years (2003–2013) from the station in cities of Kerman, Yazd, Shiraz, Zahedan and Bandar Abbas (Table 3), were used as training and testing data. These cities are near Kerman province for where data is available from Data Centre of Iranian Meteorological Office (IRIMO). So, these meteorological data and monthly solar radiation records were used for validation and testing the results.

TABLE 1. Characteristics of input ground motion

City	Latitude (°N)	Longitude (°E)	Altitude (m)
Kerman	30.25	56.96	1753.8
Bam	29.12	58.23	1066.9
Sirjan	29.33	55.67	1739.4
Shahrbabak	30.1	55.17	1739.4
Jiroft	28.67	57.58	639
Baft	29.25	56.63	2280
Rafsanjan	30.5	55.9	1521
Anar	30.92	55.22	1408.8
Kahnuj	28.17	57.5	469.7
Zarand	30.83	56.58	1670
Shahdad	30.42	57.7	482
Lalehzar	29.52	56.83	2775

Computer program in MATLAB environment has been performed. In the training, 20 neurons used in a single hidden layer. The number of hidden nodes in the ANN was determined empirically, considering the need to derive reasonable results. The Levenberg–Marquardt (LM) algorithm with 2500 epochs was used.

TABLE 2. The geographical information around Kerman province.

City	Latitude (°N)	Longitude (°E)	Altitude (m)
Kerman	30.25	56.96	1753.8
Yazd	31.54	54.17	1237.2
Shiraz	29.32	52.36	1484
Zahedan	29.28	60.53	1370
Bandar Abbas	27.13	56.22	9.8

TABLE 3. Monthly mean daily global solar radiation incident on a horizontal surface (kW/m2.day)

Months	Kerman	Shiraz	Yazd	Zahedan	Bandar Abbas
Jan	3.82	3.55	3.47	3.67	3.71
Feb	4.55	4.48	4.55	4.56	4.61
Mar	5.98	5.24	5.17	5.26	4.91
Apr	6.23	6.08	5.97	6.24	6.21
May	6.99	7.12	6.87	6.79	7.01
Jun	7.84	7.61	7.26	6.96	7.26
Jul	7.71	7.08	7.02	6.84	6.88
Aug	6.94	6.68	6.72	6.57	6.45
Sep	5.98	6.07	5.95	5.89	5.72
Oct	4.96	4.92	4.86	4.98	4.80
Nov	3.84	3.70	3.78	3.95	3.93
Dec	3.44	3.26	3.21	3.33	3.32

In this study, an ANN of the multilayer feed forward (MLF) type with one input layer, one hidden layer and one output layer was used for estimating global solar radiation from measured Meteorological and geographical data. The transfer function in the networks was log sigmoid. A back-propagation (BP) algorithm was used to train the MLF neural network. For the criterion, all the data were divided into three sets. The first set is the training set for determining the weights and biases of the network. The second set is the validation set for evaluating the weights and biases, and for deciding when to stop training. The third data set is for validating the weights and biases to verify the effectiveness of the stopping criterion, and to estimate the expected network operation on new data sets. Since the objective of this study was estimation of global solar radiation, the ANN has only one output variable.

4. RESULTS AND DISCUSSION

In 11 major cities of Kerman province (except city of Kerman), where no monitoring was made by Iranian

Meteorological Office (IRIMO), the solar radiations were predicted using the ANN. An artificial neural network was trained with real solar radiation data and then the network performance was tested and got validation to develop a corresponding global solar radiation prediction model for each of the other 11 cities in Kerman province.

Global solar radiation estimates from the ANN were compared with the actual data using simple error analysis, mean absolute percentage error and linear analysis with the following results as given in Table 4.

TABLE 4. The statistical model evaluation parameters of the predicted and observed data

City	R^2	MAPE	RMS
Kerman	0.97	-1.93	0.087
Shiraz	0.99	20.76	0.057
Yazd	0.96	-4.22	0.112
Bandar Abbas	0.97	-2.46	0.078
Zahedan	0.96	9.17	0.084

The ArcGIS module 9.3 (ESRI Inc., 2008) were used to generate maps. The interpolation technique estimates the values of global solar radiation over Kerman province from values of 12 cities data mentioned in Table 5.

The predicted radiation is given in Figure 3. as annual global solar radiation. From the figure, it can be seen that Anar has the highest solar radiation value during the year. Anar is in the north of Kerman province with dry and warm climate and high altitudes.

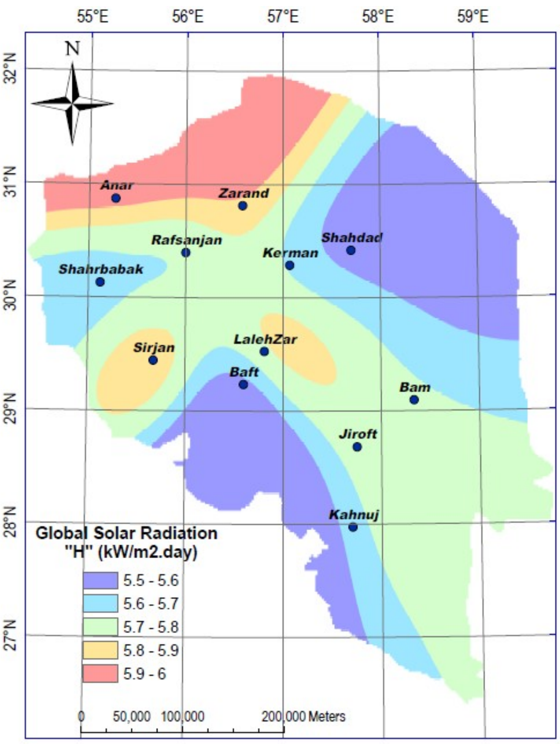

Figure 3. Predicted annual average solar radiation

The results show that Baft and Shahdad have the lowest solar radiation compared to all other cities of the province. After Anar and Zarand, cities like Sirjan and Zarand where there have clear sky during the year, or have the highest elevation from the sea, are in the second place.

TABLE 5. Solar radiation incident on a horizontal surface "H"

City	Total Annual (kW/m^2.day)
Kerman	5.69
Bam	5.73
Sirjan	5.85
Shahrbabak	5.65
Jiroft	5.75
Baft	5.56
Rafsanjan	5.72
Anar	5.95
Kahnuj	5.65
Zarand	5.88
Shahdad	5.56
Lalehzar	5.78

It can be seen from the Figures 4. and 5. that in winter and autumn, almost all cities are in the same range of receiving solar radiation. In autumn, north of province has still more incident radiation on a horizontal surface and the central parts of the province between the cities with high altitude has high values of incident radiation too.

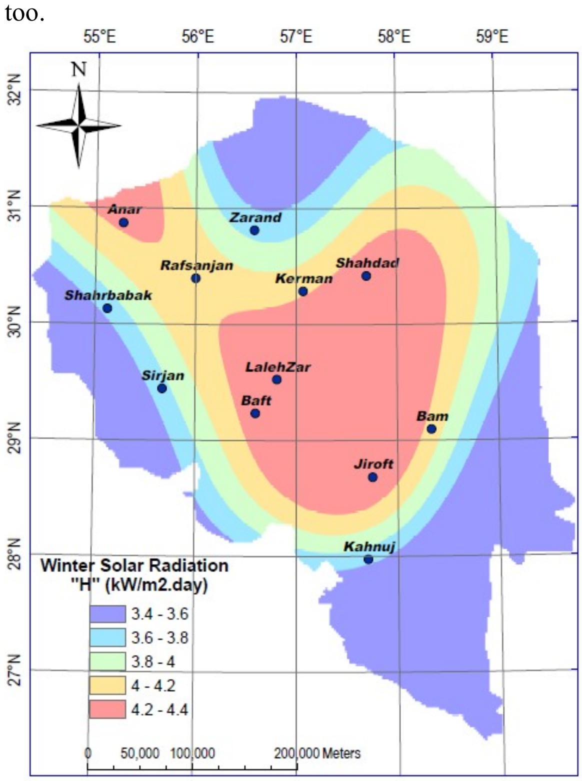

Figure 4. Predicted monthly average global solar radiation for winter

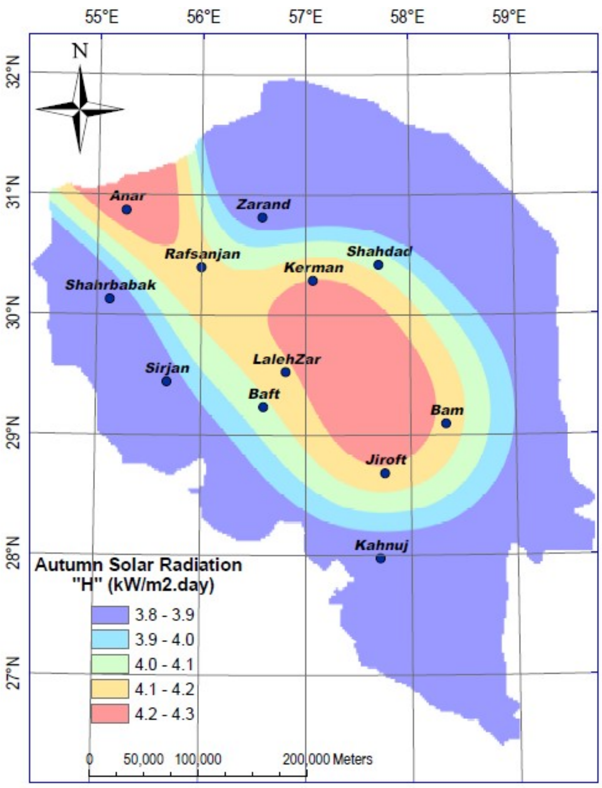

Figure 5. Predicted monthly average global solar radiation for autumn

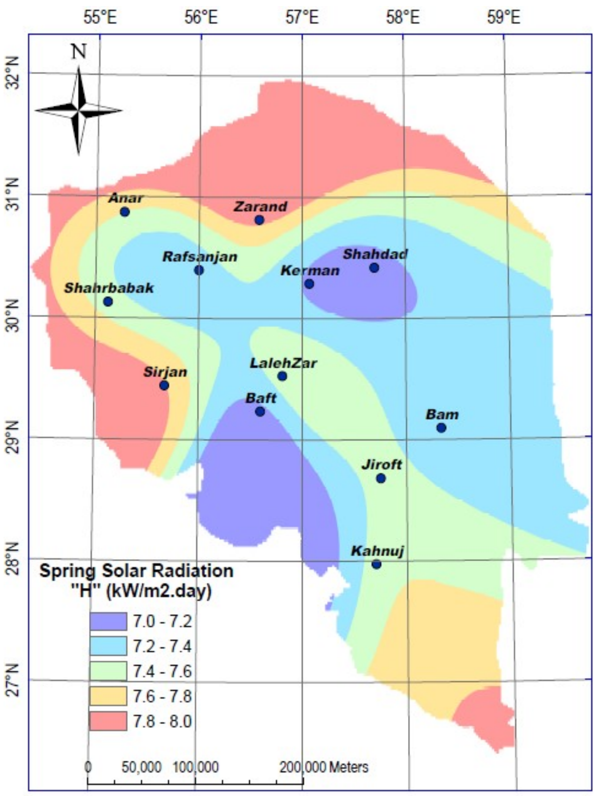

Figure 6. Predicted monthly average global solar radiation for spring

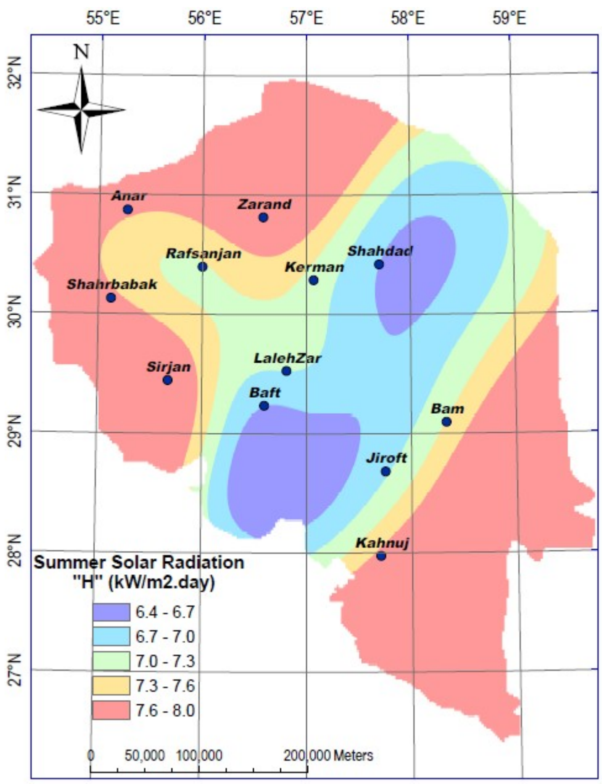

Figure 7. Predicted monthly average global solar radiation for summer

However, it extremely changes in spring and summer, when sun started shining perpendicular to the ground. The value of global solar radiation increased in spring and summer. Figures 6. and 7. show that the north and south part of Kerman province has the biggest values of global solar radiation.

5. CONCLUDING REMARKS

Artificial neural networks were used to develop prediction models for daily global solar radiation using measured sunshine duration. Twelve cities in Kerman province (the largest province in Iran) were considered. An ANN was trained for city of Kerman and the other four cities. The results were estimated for other cities. The results of this study indicate that the ANN based model for solar radiation is accurate for prediction of solar radiation in Kerman province. Solar radiation is clearly lower in autumn and winter and higher in spring and summer on horizontal surface. The ANN model can be used to predict and estimate solar radiation for any region where meteorological and geographical parameters are available. The present study has been successful in estimating the global solar radiation on horizontal surfaces. The results indicate that the ANN model evaluating the solar potential in places where there are no monitoring stations. From the figures, it can be concluded that solar radiation reaching the surface depends heavily on latitude, season, and altitude. Spatial extent of regions with high solar radiation energy significantly expands during the summer months and reduces to central and north of the regions in winter. In solar energy analysis it would be useful to specify those cities that are more suitable to install solar energy devices to get more energy.

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Nomenclature

o	Output value
p	Pattern
t	Target value
X	Original value
Xmin	Minimum of original values
Xmax	Maximum of original values
Xnorm	Normalized value

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