ANN-Based Estimation of Monthly Global Solar Radiation in Tehran City

Abstract
The main objective of Present study is based on meteorological variables to estimate monthly Global Solar Radiation (GSR) on a horizontal surface. Monthly mean of maximum air temperature, relative humidity, sunshine hours and wind speed values between 1974 and 2008 for Tehran city in Iran (35_41N, 51_19E), are used in this study. In order to investigate the effect of each meteorological variable on monthly GSR estimation, different combinations of input variables are considered and Recurrent Neural Network (RNN) and Multi-layer perceptron (MLP) are applied on each model.

Keywords: Recurrent Neural Network (RNN); Multi-layer perceptron (MLP); Global solar Radiation (GSR); Estimation

1. Introduction

Regarding the inevitable significance of energy conservation and environmental protection, the world today is moving into a new era; transition from almost total dependence on the fossil fuel to a greater use of alternative sustainable sources of energy. According to geographical location of Iran, solar radiation is a promising potential renewable energy source.

Usually, the Global Solar Radiation (GSR) measurements are made at few locations in each country, especially in developing ones, which may not be as equal as the actual station of solar energy development and utilization. To know the behavior of solar radiation at the site of interest, long-term data from a nearby location along with some techniques such as empirical, semi-empirical, physical, neural network, etc. are exploited [1,2].

Numerous authors developed empirical regression models to estimate the monthly average daily GSR in their region using various parameters [3,4]. The mean daily sunshine duration was the most commonly applied and available parameter. The most popular model was the linear one by Angström-Prescott, which establishes a linear relationship between global radiation and sunshine duration with knowledge of extra-terrestrial solar radiation and the theoretical
maximum daily solar hours [2].

In recent years, several studies have been presented to estimate solar energy using ANN [1,5,6,7,8,9,10].

Most of the ANN models employ Feed-Forward Neural Networks (FFNN) such as the Multi-layer Perceptron (MLP) to estimate GSR on a horizontal surface; however, there are some drawbacks of using FFNNs. First, in the training of a FFNN, by any methods, one can never overcome the lack of short-term memory and an FFNN is thus dependent on the number of look back steps. Second, back-propagation only tunes the weights in the FFNN and does not affect the design of the network. In order to achieve short-term memory, a Recurrent Neural Network (RNN), i.e. an ANN with feedback connections, can be used. A RNN, in principle, is capable of storing all former input signals [11].

In this regard, we have investigated the estimation of solar radiation with RNN technique. We apply monthly Mean “maximum air temperature”, “relative humidity”, “sunshine hours” and “wind speed” values in five different combinations to estimate the monthly GSR on a horizontal surface for Mehrabad station located in Tehran city, Iran. At the end, the accuracy of RNN model is demonstrated and a comparison is made with MLP model.

2. Artificial Neural Network (ANN)

Neural networks are computational models of the biological brain, which have many applications in engineering problems regarding their great flexibility and adapting capability. Like the brain, a neural network comprises large number of interconnected neurons. Each neuron is capable of performing only simple computation; however, the architecture of an artificial neuron is simpler than a biological one. ANNs are constructed in layering structures in which layers connect to each others through weighted connections where the factual processing is performing. The first layer, represents inputs for the problem and the last one, where the results of the processing are acquired is the output layer. One or more hidden layers connects the inputs and the outputs and form the network. Learning in ANNs is achieved through particular training algorithms, which are expanded in accordance with the learning laws assumed to simulate the learning mechanisms of biological system. However, as an assembly of neurons, a neural network can learn to perform complex tasks including pattern recognition, system identification, trend estimation and process control [4].

2.1 Recurrent Neural Network (RNN)

Artificial Neural Network with the recurrent topology is called Recurrent Neural Network. It is similar to feed-forward network with no limitations regarding back-loops. In these cases information is no longer transmitted only in one direction, but it is also transmitted backwards. This creates an internal state of the network which allows it to exhibit dynamic temporal behavior. Recurrent artificial neural networks can take advantage of their internal memory to process any sequence of inputs.
The most basic topology of recurrent neural network is a fully artificial network where every fundamental building block (neuron) is directly connected to every other one in all directions. Other recurrent networks such as Hopfield, Elman, Jordan, bi-directional and, etc. are just special cases of this network [12].

**Elman and Jordan Artificial Neural Networks**

Elman network also referred as Simple Recurrent Network is special case of recurrent artificial neural networks. It differs from conventional two-layer networks in that the first layer has a recurrent connection. It is a simple three-layer artificial neural network that has back-loop from hidden layer to input. through so called context unit (Figure 1). This type of artificial neural network has memory that allowing it to both detect and generate time-varying patterns. The Elman artificial neural network has typically sigmoid artificial neurons in its hidden layer, and linear artificial neurons in its output. This combination of artificial neurons transfer functions can approximate any functions with arbitrary accuracy if only there are enough artificial neurons in hidden layer. Being able to store information, Elman artificial neural network is capable of generating temporal patterns as well as spatial patterns and responding on them [12].

Jordan network (Figure 2) is similar to Elman network. The only difference is that context units are fed from the output layer instead of the hidden layer [12].

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**Figure 1: Elman artificial neural network.**

**Figure 2: Jordan artificial neural network.**
3. Our approach

In this study, monthly maximum air temperature, relative humidity, sunshine hours and wind speed values, measured by Mehrabad station (located in Tehran city (35.41N, 51.19E), between 1974 and 2008, were applied for forecasting monthly GSR using different ANN techniques. The data of 272 months from 1974 to 1997 were utilized for the purpose of training and the data of 136 months from 1998 to 2008 were used for testing. For considering the effect of each input variable on GSR estimation, five following combinations of input variables were developed for this study as shown in Table 1.

Recurrent Neural Network (RNN) and Multi-layer Perceptron (MLP) were exploited for monthly GSR estimation based on proposed combinations.

Table 1: Models Based On Different Combinations of Input Parameters.

<table>
<thead>
<tr>
<th>Model</th>
<th>Input Parameters</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Temperature-Wind Speed-Sunshine-Relative Humidity</td>
</tr>
<tr>
<td>2</td>
<td>Wind Speed-Sunshine-Relative Humidity</td>
</tr>
<tr>
<td>3</td>
<td>Temperature-Sunshine-Relative Humidity</td>
</tr>
<tr>
<td>4</td>
<td>Temperature-Wind Speed-Sunshine</td>
</tr>
<tr>
<td>5</td>
<td>Temperature-Wind Speed-Relative Humidity</td>
</tr>
</tbody>
</table>

4. Experimental Result

4.1. Validation

A statistical analysis involving Root Mean Square Error (RMSE) and Mean Bias Error (MBE), is conducted to evaluate the performance accuracy of the developed models and to verify whether there is any underlying performance trend in the models under study. RMSE provides information on the short term performance which is a measure of the variation of estimated values around the measured data. The lower the RMSE, the more accurate is the estimation. MBE is an indication of the average deviation of the estimated values from the corresponding measured data and can provide information on long term performance of the models; the lower MBE the better the model is. A positive MBE value indicates the amount of overestimation in estimated GSR and vice versa.

The expressions for the aforementioned statistical parameters are [3,4]:

\[
MBE = \frac{1}{n} \sum_{i=1}^{n} (I_{p,i} - I_i)
\]

(1)

\[
RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (I_{p,i} - I_i)^2}
\]

(2)
\[ R^2 = (1 - \frac{\sum_{i=1}^{n} (I_{p,i} - I_i)^2}{\sum_{i=1}^{n} I_i}) \times 100 \]

(3)

Where \( I_{p,i} \) denotes the estimated monthly average daily GSR on horizontal surface in cal/cm\(^2\), \( I_i \) is the measured monthly average daily global radiation on horizontal surface, cal/cm\(^2\), and \( n \) is the number of observations.

### 4.2. ANN results

Both the RNN and MLP methods are applied for estimating the GSR in Tehran city based on the combinations indicated in Table 1. The procedure utilized in the development of the RNN and MLP models starts with input data normalization (i.e. target values) in the range of -1 to 1 followed by the dataset matrix size identification. After being normalized, sub-datasets are created and prepared for training and testing. The training set is first randomized before creating and training the ANN. The output values are generated and denormalized, and finally the performance of the ANN is verified by comparison of output and target values. All these steps are carried out using MATLAB tools.

In order to determine the optimal network architecture for each combination of input variables, various network architectures were designed; the number of neuron and hidden layer and transfer functions in the hidden/output layer were changed. For all combinations based on MLP network, logistic sigmoid transfer function (logsig) for all hidden layers, linear transfer function (purelin) for output layer were found to perform reasonably good estimation. Table 2 and 3 shows the architectures of MLP/RNN models and training/testing errors for all combinations.

#### Table 2: Statistical Error Parameters of the Developed MLP Models.

<table>
<thead>
<tr>
<th>Model</th>
<th>Network Structure</th>
<th>( R^2 )</th>
<th>RMSE</th>
<th>MBE</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>15-7-1</td>
<td>99.33</td>
<td>0.0643</td>
<td>0.0437</td>
</tr>
<tr>
<td>2</td>
<td>12-8-1</td>
<td>99.35</td>
<td>0.0632</td>
<td>0.0380</td>
</tr>
<tr>
<td>3</td>
<td>14-7-1</td>
<td>99.07</td>
<td>0.0754</td>
<td>0.0397</td>
</tr>
<tr>
<td>4</td>
<td>12-7-1</td>
<td>99.16</td>
<td>0.0719</td>
<td>0.0544</td>
</tr>
<tr>
<td>5</td>
<td>11-7-1</td>
<td>99.16</td>
<td>0.0719</td>
<td>0.0544</td>
</tr>
</tbody>
</table>

#### Table 3: Statistical Error Parameters of the Developed RNN Models.

<table>
<thead>
<tr>
<th>Model</th>
<th>Network Structure</th>
<th>( R^2 )</th>
<th>RMSE</th>
<th>MBE</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>13-6-1</td>
<td>99.07</td>
<td>0.0754</td>
<td>0.0348</td>
</tr>
<tr>
<td>2</td>
<td>14-7-1</td>
<td>99.39</td>
<td>0.0443</td>
<td>0.0252</td>
</tr>
<tr>
<td>3</td>
<td>13-6-1</td>
<td>99.04</td>
<td>0.0603</td>
<td>0.0769</td>
</tr>
<tr>
<td>4</td>
<td>14-7-1</td>
<td>99.04</td>
<td>0.0769</td>
<td>0.0357</td>
</tr>
<tr>
<td>5</td>
<td>14-8-1</td>
<td>98.94</td>
<td>0.0806</td>
<td>0.0580</td>
</tr>
</tbody>
</table>
Table 2 and 3 illustrate the computed values of $R^2$, RMSE and MBE for the developed ANN models (RNN and MLP) considering different network structures. For the network structure identification used in the second column of Table 2 and 3, the first number indicates number of neurons in the input layer, the last number represents neurons in the output layers, and the numbers in between represent neurons in the hidden layers. From Table 2, we note that the model two is the best among all the investigated MLP models for performance estimation as it yields the lowest values of MBE, RMSE and a 99.35% coefficient of determination. The input parameters utilized in the selected model are the wind speed, the sunshine, and the mean relative humidity. Table 3 on the other hand, shows that second RNN model is the best among all the studying ones. The input parameters for this model are the same as above MLP network. As you can see, the best model of RNN (RNN-2) has better accuracy for estimating the GSR compared to the best one in MLP (MLP-2).

Figure 3 illustrates the comparison between estimated MLP and RNN best models (model 2) and the measured GSR data. This validation is done using measured GSR data for years 1998-2008.
5. Conclusion

This study shows the results of an effort made to forecast the monthly GSR according to commonly accessible measured values of monthly “maximum air temperature”, “relative humidity”, “sunshine hours” and “wind speed”. Data for Mehrabad station, located in Tehran city from 1974 to 1997 and data of 136 months between 1998 to 2008 were used for training and testing different ANN techniques, respectively. Five different cases were applied for the estimation of the monthly GSR on a horizontal surface. The results indicated that using wind speed along with sunshine hours and relative humidity base on RNN (RNN-2) was better than the other ANN cases with RMSE of 0.04, MBE of 0.02 and absolute fraction of variance ($R^2$) of 99.39%, respectively. Also, the combination of above parameters base on MLP model (MLP-2) had an acceptable accuracy. Therefore, it can be utilized as a basic model with RMSE of 0.06, MBE of 0.03 and $R^2$ of 99.35%, respectively.

For future work, we plan to employ fuzzy techniques along with neural networks (Neuro-Fuzzy methods) to bring more control and accuracy in estimating and later predicting Global Solar Radiation.

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References


