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Using Neuro-Fuzzy Techniques in Estimating Monthly Global Solar Radiation for Tehran, Iran

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ABSTRACT

Employing solar radiation as part of clean energy as a replacement to the fossile fuel for home and industrial usages is considered vastly nowadays. The main objective of present study is to estimate monthly Global Solar Radiation (GSR) on a horizontal surface. In order to estimate monthly GSR, we applied different Neuro-fuzzy techniques such as adaptive Neuro-fuzzy inference system (ANFIS) and Local Linear Model Tree (LOLIMOT), on input meteorological variables. 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), has been used in this study. The experimental results of ANFIS and LOLIMOT techniques showed a 0.08 and 0.06 perecision for RMSE and 98.48 and 99.25 percente for R^2 and 0.05 and 0.04 for MBE respectively.

KEYWORDS: Estimation, Global Solar Radiation (GSR), adaptive Neuro-fuzzy inference system (ANFIS), Local Linear Model Tree (LOLIMOT).

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 [1]. 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 stations of solar energy development and utilization. In Iran, several conventional models have been proposed by researchers to estimate GRS using different meteorological variables. Mardi H. and Jafar Kazemi F. in [2] as well as Behrang in [3] have reviewed some of the most important mathematical models for estimating GSR in Iran. Although, these mathematical models provide a considerable precision in their output results, their though capability has been limited due to tough required calculations and also numerous input parameters which are not available in most of the locations [4].

Recently, many soft computing techniques such as rule-based expert systems, fuzzy logic and neural networks (NNs) are widely used in renewable energy-based application for estimation of some parameters. Different approaches were formulated by many investigators to estimate the hourly global solar radiation and its related parameters. In [1], [5], [6], [7], [8], [9], [19] several studies have been presented to estimate solar energy using Artificial Neural Network (ANN).

Neuro-Fuzzy modeling is a prevailing technique for solving various problem tasks such as classification and estimation [11]. By employing neural networks with fuzzy systems together, Neuro-Fuzzy models gain more accurate & better results. Each Neuro-Fuzzy modeling technique uses a different architecture in order to solve its problems. ANFIS is used in many areas such as forecasting classifying, controlling, recognition and diagnosing [12]. Local Linear Neuro-Fuzzy (LLNF) modeling is another one among other various NF models, which its center idea is based on divide-and-conquer strategy [11].

In this paper, the estimation of solar radiation has been investigated by Neuro-Fuzzy techniques (ANFIS & LOLIMOT). Monthly Mean “maximum air temperature”, “relative humidity”, “sunshine hours” and “wind speed” values are applied to estimate the monthly GSR on a horizontal surface for Mehrabad station located in Tehran city, Iran. At the end, the results of both Neuro-fuzzy models are compared with each other to obtain an accurate and reasonable solution.

2. MATERIALS AND METHODS

2.1. Data Collection

The meteorological parameters such as 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 Neuro-Fuzzy techniques. We applied the data of 294 months from 1974 to 1998 for training and the data of 126 months from 1999 to 2008 for testing. Fig. 1 shows the input/output meteorological data.

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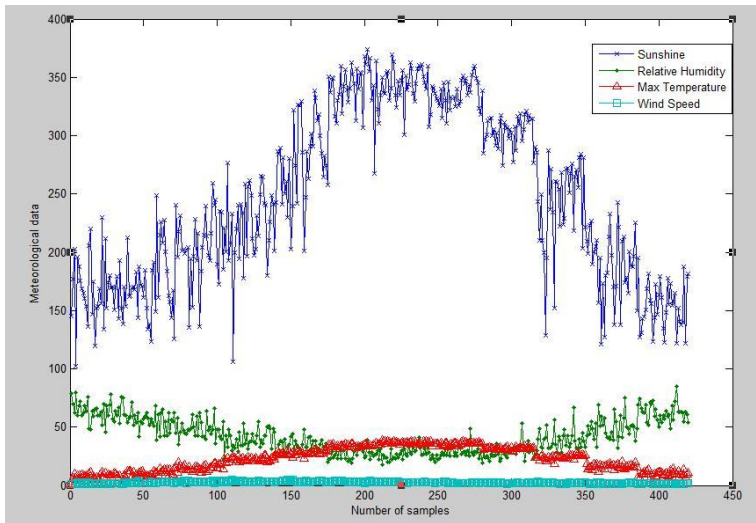
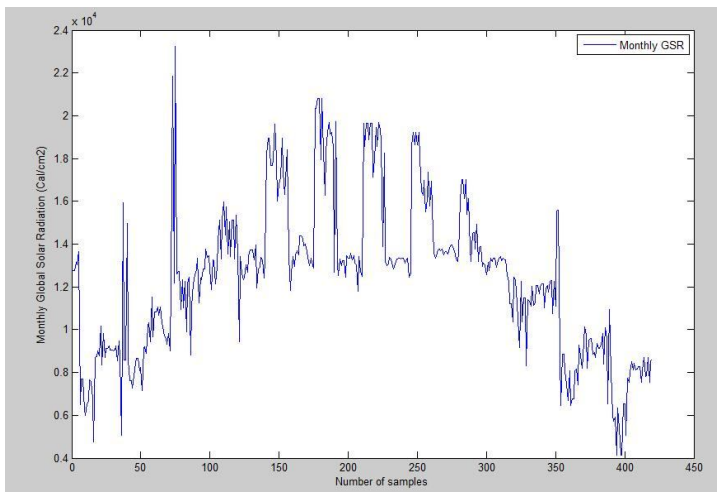


(a)



(b)

Fig. 1. Meteorological data: (a) input (b) output

2.2. ANFIS Model

ANFIS is a neuro-fuzzy model that employs neural network to compute and adjust membership functions in fuzzy inference system (FIS). Parameters of those functions are calculated and fine-tuned using a hybrid learning methods which usually includes back-propagation algorithm. By employing the calculative power of neural network and intellectual capabilities of fuzzy systems, ANFIS is capable of solving complex problems [12].

Considering a fuzzy inference system that has two inputs x and y and an output, the following Sugeno rules are defined:

Rule 1: If x is A_1 and y is B_1 ; then $f_1 = p_1x + q_1y + r_1$ (1)

Rule 2: If x is A_2 and y is B_2 ; then $f_2 = p_2x + q_2y + r_2$ (2)

Where *f* is output and *p*, *q* and *r* are parameters of the defiend rules that caculated through the learning process. In addition, *A* and *B* are defined as fuzzy sets. By considering O_i^l as the output of each layer in the model (i^{th} node output in l^{th} layer), we can construct a multi-layer network with five layers (Fig 2), which thier behavoir are descibed as follows:

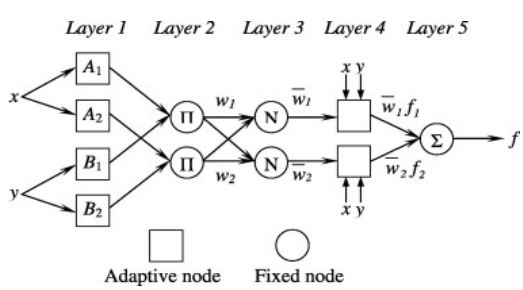


Fig. 2. The Architecture of ANFIS model

In the first layer, the process of fuzzyfing is performed, which results in computing membership functions of each node with respect to the fuzzy sets. Considering Using Gaussian memebership function, They are expressed as:

$$M_{Ai}(x) = e^{-\frac{1}{2}\left(\frac{x-c_i}{\sigma_i}\right)^2} \quad (3)$$

$$M_{Bi}(x) = e^{-\frac{1}{2}\left(\frac{x-c_i}{\sigma_i}\right)^2} \quad (4)$$

Consequently, Outputs for this layer are defined as:

$$O^1_i = \mu_{Ai}(x) \quad (5)$$

$$O^1_i = \mu_{Bi}(x) \quad (6)$$

The second layer calculates the firing strenght rule for each node by multiplying input values into it. The output of the layer is the algebraic product of the input signals which expressed as follows:

$$O^2_i = w_i = \mu_{Ai}(x)\,\mu_{Bi}(y) \quad i=1,2 \quad (7)$$

In the third and normalization layer, for every node, rules relative weight (that is i^{th} rule's firing strength to the sum of all rule's firing strength) are copmuted.

$$O_i^3 = \omega_i^n = \frac{\omega_i}{\omega_1+\omega_2}, \quad i = 1,2 \quad (8)$$

In the fourth layer, for every node, the output is calculated by:

$$O_i^4 = \overline{w_i} f_i = \overline{w_i}(p_i x + q_i y + r_i) \quad (9)$$

And finally, the last layer computes the output of the network by adding up all inputs to it [12].

$$O_i^5 = \sum_{i=1}^{2} \omega_i^n f_i = \frac{\omega_1 f_1 + \omega_2 f_2}{\omega_1+\omega_2} \quad (10)$$

2.3. LLNF Models and LOLIMOT Algorithm

The center idea behind the local linear Neuro-Fuzzy modeling is partitioning the input space into smaller linear sub spaces. Meanwhile, some fuzzy validity functions $\varphi_1(\mu)$ are used with respect to input data, which describe the regions where the LLMs for smaller sub-spaces are valid [11]. Fig. 3 shows the network formation of LLNF model. Each neuron realizes a local linear model and associated validity function.

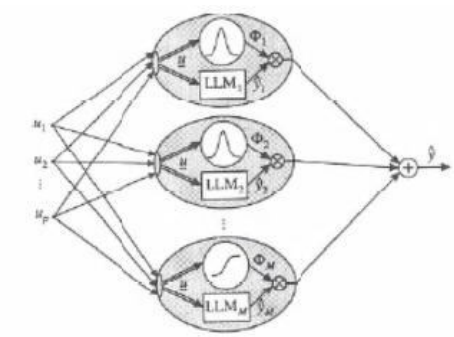


Fig. 3. Network structure of a LLNF model

The output of each LLM is computed as follows:

$$\varphi_1 = w_{i0} + w_{i1}u_1 + w_{i2}u_2 + \cdots \quad (11)$$

The output of a local linear Neuro-Fuzzy model simply becomes the weighted sum of the output of locally linear models and becomes:

$$\varphi = \sum_{i=1}^{M}(w_{i0} + w_{i1}u_1 + w_{i2}u_2 + \cdots + w_{ip}u_p) \quad (12)$$

2.4. 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, between 1974 and 2008, were selected for forecasting monthly GSR using different Neuro-fuzzy techniques; Then, the ANFIS and LOLIMOT algorithms were applied for monthly GSR estimation based on above proposed parameters.

2.4.1. ANFIS model

In this Study, we proposed an ANFIS model to predict the monthly GSR for given data, which contains ”maximum air temperature”, ”relative humidity”, ”sunshine hours” and ”wind speed”.A hybrid learning algorithm and sugeno fuzzy model has been applied To train the proposed ANFIS model.

The data of 272 months from 1974 to 1997 were applied for training and the data of 136 months from 1998 to 2008 were used for testing. In training step, first, the neural network which is included in ANFIS model catagorises the dataset in groups, find out patterns and moreover extend a clear fuzzy expert system. Then, the network adjusts these groups to fit best membership function in order to obtain the best output with the least epochs. In the learning step, new testing data samples which are different from the training dataset are given to the proposed model which is trained efficiency. The iterative process of giving input and getting output countinues untill the error function reaches to the minimum amount and best results are obtained by the model.

2.4.2. LOLIMOT model

LOLIMOT is an incremental tree-construction algorithm that partitions the input space by axis-orthogonal splits. It Implements a heuristic search for the rule premise structure and avoids a time-consuming nonlinear optimization. In each iteration, LOLIMOT, chooses the worst LLM and divides it in two halves along one of dimensions. The fuzzy validity functions are updated for the new LLM.

The LOLIMOT algorithm is a five steps algorithm according to [11]:

1. Start with an initial model: Start with a single LLM, which is a global linear model over the whole input space with $\varphi_1(u) = 1$, and set M =1. If there is a priori input space partitioning, it can be used as the initial structure.
2. Find the worst LLM: Calculate a local loss function, for example, mean square error (MSE), for each of the (i= 1,…,M) LLMs and find the worst performing LLM.
3. Check all divisions: The worst LLM is considered for further refinement. The hyper rectangle (more than a three dimensional rectangle or cube) of this LLM is split into two halves with an axis orthogonal split. Divisions in all dimensions are tried, and for each of the p divisions, the following steps are carried out. In this part, construct the multidimensional membership functions for both generated hyper rectangles and construct all validity functions: In part a, only the membership function of LLM that is split would change and the membership function of other neurons do not change, but all of the validity functions change that must be updated for all LLMs by (3). Second, estimate the rule-consequent parameters for newly generated LLMs and third, calculate the loss function for the current overall model.
4. Find the best division: The best of the p alternatives checked in step 3 is selected, and the related validity functions and LLMs are constructed. The number of LLM neurons is incremented M = M + 1.
5. Test the termination condition: If the termination condition is met, then stop; otherwise, go to step 2.

3. RESULTS AND DISCUSSION

3.1. Validation

A statistical analysis involving Root Mean Square Error (RMSE), Mean Bias Error (MBE) and absolute fraction of variance (R^2), 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 [2], [3]:

$$MBE = \frac{1}{n}\sum_{i=1}^{n}\left|(I_{p,i} - I_i)\right| \tag{13}$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(I_{p,i} - I_i)^2}{n}} \tag{14}$$

$$R^2 = \left(1 - \left(\frac{\sum_{i=1}^{n}\left|(I_{p,i} - I_i)^2\right|}{\sum_{i=1}^{n} I_i}\right)\right) * 100 \tag{15}$$

Where $I_{p,i}$ denotes the estimated monthly average daily global solar radiation 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.

3.2. Neuro-fuzzy results

Both the ANFIS and LOLIMOT fuzzy- neural network methods are applied for estimating the GSR in Tehran city based on the parameters which are mentioned above.

The procedure utilized in the development of the ANFIS and LOLIMOT models starts with input data normalization (i.e. target values) in the range of 0 to 1 followed by the dataset matrix size identification as following equation:

$$f(x) - \frac{X - \min(X)}{\max(X) - \min(X)} \qquad (16)$$

After being normalized, sub-datasets are created and prepared for training and testing including the data of 294 months from 1974 to 1998 for training and the data of 126 months from 1999 to 2008 for testing. The output values are generated from test data using two models and finally, the performance of the Neuro-fuzzy is verified by comparison of output and target values. All these steps are carried out using MATLAB software. Table 1 shows the result of ANFIS/LOLIMOT models on testing data.

Table 1. Comparison Between statistical Parameters for the measured estimated data of ANFIS and LOLIMOT model.

Neuro-Fuzzy Network	Input Parameters	R^2	RMSE	MBE
ANFIS	Maximum temperature , relative humidity, sunshine hours ,wind speed	98.48	0.0808	0.0588
LOLIMOT	Same as above	99.25	0.061	0401

Fig. 4, 5, 6 illustrates the comparison between estimated and measured GSR data based on ANFIS and LOLIMOT techniques. This validation is done using measured GSR data for years 1999-2008.

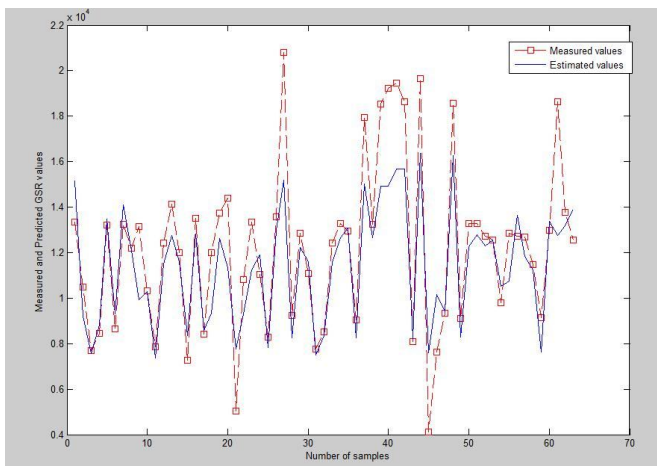


Fig. 4. Estimated and measured values of the proposed ANFIS model

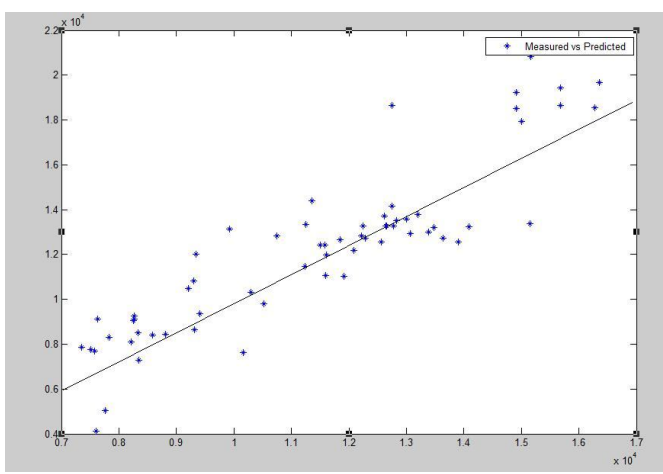


Fig. 5. Comparison of estimated and measured values of ANFIS model

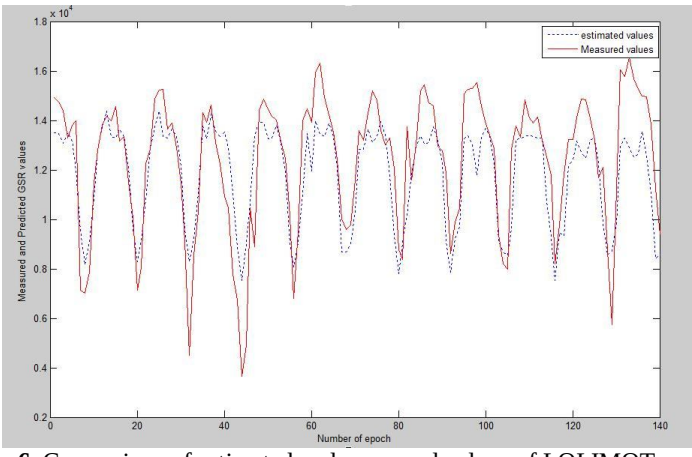


Fig. 6. Comparison of estimated and measured values of LOLIMOT model

4. 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 1998 were used for training and data of 126 months between 1999 to 2008 were applied for testing different Neuro-Fuzzy techniques.

An ANFIS model with 155 neurons and a LOLIMOT model with 4 neurons were used for estimation and result of 0.0808 and 0.061 accuracy for Root Mean Square Error (RMSE) as well as %98.48 and %99.25 precision for absolute fraction of variance (R^2) and 0.0588 and 0.0401 for Mean Bias Error (MBE) were gained respectively, which showed them as suitable solutions for solar energy conversion application. The findings demonstrate the estimating capability of Neuro-fuzzy models and its compatibility for any region with varying climatic conditions. Furthermore, it is suitable for a place, where a network of monitoring stations has not been setup.

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