Comparative Study of Fuzzy System and Artificial Neural Networks in Predicting Solar Radiation in Tehran Province

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ABSTRACT

In this study, artificial neural networks (ANN) and Adaptive-Network-Basefuzzy inference system (ANFIS) are used to model daily global solar radiation (GSR) in Tehran province of Iran. In order to design the networks, a dataset of meteorological daily time series for eight years (1994-2002) collected by Iran Meteorological Office was used. Input parameters were maximum temperature, relative sunshine duration, day of the year and extraterrestrial solar radiation while the output parameter was the GSR in MJ/m² day. Various networks were designed and tested. The performances of best networks revealed that RMSE, MAE and MAPE were 2.77, 2.19, 0.12 for ANN and 2.8, 2.22, 0.12 for ANFIS, respectively. The results indicated that both approaches can be successfully applied for modeling GSR however ANN performs slightly better.

Keyword: Solar radiation; prediction; artificial neural network; neuro-fuzzy system.

1. INTRODUCTION

Solar radiation is a general term for the electromagnetic radiation emitted by the sun. We can capture and convert solar radiation into useful forms of energy, such as heat and electricity, using a variety of technologies. The technical feasibility and economical operation of these technologies at a specific location depends on the available solar radiation or solar resource. As solar radiation passes through the earth’s atmosphere, some of it is absorbed or scattered by air molecules, water vapor, aerosols, and clouds. The solar radiation that passes through directly to the earth’s surface is called Direct Solar Radiation. The radiation that has been scattered out of the direct beam is called Diffuse Solar Radiation. The direct component of sunlight and the diffuse component of sunlight falling together on a horizontal surface make up Global Solar Radiation (GSR). Atmospheric conditions can reduce direct beam radiation by 10% on clear, dry days and by 100% during thick, cloudy days. I.e. knowing sunshine duration and some meteorological parameters can help in determination and estimation of GSR. Generally, it is not feasible to measure the solar resource for all these potential uses; rather, one must use models to calculate the local incident solar radiation. In the other hand implementing every solar energy system needs condensed input data set of meteorological data mainly GSR.

The yearly average solar radiation in Tehran province is about 4.92 kWh/m² day [1]. Considering this great potential in the region, by installing solar energy systems in agricultural building such as greenhouse, aviculture, field and other agricultural buildings and systems for supplying heating need or electricity one can achieve economic efficiency and reduction in greenhouse gas emissions. Analysis of GSR and meteorological field can be performed with experimental techniques but measurement is very difficult and time consuming. Thus, soft programming techniques (Artificial Neural Network, Fuzzy-logic, Adaptive-Network-Based Fuzzy Inference System, etc.) can be used as a powerful tool to analyze and predict GSR.

Several researches have used ANNs to estimate GSR as a function of meteorological data. Angela et al. used five years of global solar radiation data to estimate the monthly average of daily global solar irradiation on a horizontal surface based on a single parameter, sunshine hours, using the ANN method [2]. Authors in reference [3] used wavelet network that is a combination of neural network and wavelet theory to find a suitable forecasting model for predicting the daily solar radiation. In Turkey, an ANN model was used to estimate the solar parameters for seven cities from Mediterranean region of Anatolia and affects of number of input parameters were tested on it that was output layer [4]. Authors in reference [5] developed several nonlinear including multi-layer perception (MLP), Elman neural network, neural network auto-regressive models with exogenous inputs (NNARX) and ANFIS models with the aid of Gamma test. Authors in reference [6] introduced an integrated ANN model for prediction of solar global by using monthly data in six nominal cities in Iran. Authors in reference [7] used ANN for prediction GSR in Tehran province of Iran. The optimum model had one hidden layer multi-layer perception (MLP) with 37 neurons in it when the inputs were number of the maximum and minimum temperature, sunshine duration, daylight hours, extraterrestrial radiation and number of day in the year. Results in reference [8] have shown good agreement between the estimated (with ANN) and measured values of global solar irradiation \(R^2=0.9996\). Authors in references [9], [10], [11] and [12] in Cyprus, Algeria, Turkey and Iran respectively are other researchers who estimated solar radiation with the help of neural networks. However, few studies have been published on the comparison ANN and ANFIS in estimating GSR. Therefore, this study was undertaken with the following objectives:

- To develop the ANN and ANFIS models with the aid of different combinations of time-series

- To determine the best input parameters of the models and the best structure of the neural network.
meteorological data as the inputs and solar radiation as the output

- To investigate the effect of changing in transfer function and the number of processing elements that exist in the hidden layer of the ANN and ANFIS on the forecasted parameters
- To compare the results obtained from each ANN- with ANFIS-models with the aim of statistical indicators.

2. MATERIAL AND METHODS

2.1 Data

Despite of the large spectrum of applications demanding solar radiation data, such direct measurements of solar energy are not widely available, rendering the use of numerical techniques essential alternatives. With such indirect techniques, other observed meteorological data are mathematically exploited in order to estimate the amounts of GSR reaching the earth. Except GSR, other meteorological data are parameters that are routinely recorded at a large number of climatologically stations (manned and automatic), due to the low cost of the respective recording instrumentation and the ease of data acquisition.

The Tehran province with an area of 730 square km was selected as the study area located in 35° N latitudes and 51° West longitude, in the north central of Iran. Measured daily data for 9 years for the period of 1994-2002 were collected from the Islamic Republic of Iran Meteorological Office data center [13] in Tehran station. The yearly average of solar radiation in the Tehran region that is the only solar radiation measurement station in Tehran province is 4.92 kWh/m² day [1]. The monthly mean daily temperature ranged from a minimum of -1.5°C in January and a maximum of 33.9 °C in July [13]. The area gets sufficient bright sunshine hours throughout the year. The average bright sunshine hours are about 8–9 h per day. In Fig. 1 yearly average sunshine durations for these locations are presented. The data sets contain daily information of temperatures (ºC), sunshine duration (h) and solar radiation (MJ/m² day). In this study, the following input parameters have been considered into the model: horizontal extraterrestrial radiation (Rₐ)[14], maximum air temperature, sunshine duration, day of the year [14] and solar radiation .The training and validation data sets were selected by the randomization of the input data.

Extraterrestrial radiation (MJ/m² day) and the number of day between 1 (January 1ˢᵗ) and 365 or 366 (December 31ˢᵗ) are two daily parameters that affect the solar radiation. The extraterrestrial solar radiation that is the solar radiation received at the top of the earth's atmosphere on a horizontal surface, for each day of the year and for different latitudes can be estimated by [14]:

\[
R_a = 24 \times 60 / \pi \left[ \omega_s \sin(\varphi) \sin(\delta) + \cos(\varphi) \cos(\delta) \sin(\omega_s) \right] G_{\infty} d_r.
\]

(1)

where \(R_a\) is extraterrestrial radiation (MJ/m² day), \(\omega_s\) is sunset hour angle (red), \(\varphi\) latitude (red) that is positive for the northern hemisphere and negative for the southern hemisphere, \(\delta\) is solar declination angle (red), \(G_{\infty}\) is solar constant that is equal to 0.0820 MJ/m² min, \(d_r\) is inverse relative distance of earth-sun (dimensionless). The expressions for \(d_r\), \(\delta\), and \(\omega_s\) can be found in reference [7].
2.2 Artificial Neural Networks

Artificial neural networks are mathematical models inspired by the organization and functioning of biological neurons. It can be characterized as massively parallel interconnections of simple neurons that function as a collective system. The prediction by a well-trained ANN is normally much faster than the conventional simulation programs or mathematical models as no lengthy iterative calculations are needed to solve differential equations using numerical methods, but the selection of an appropriate neural network topology is important in terms of model accuracy and model simplicity [15]. ANNs are constructed in layer connects to one or more hidden layers where the factual processing is performance through weighted connections. Each neuron in the hidden layer joins to all neurons in the output layer. The results of the processing are acquired from the output layer. MLPs are perhaps the most common type of feed forward networks. An MLP has three layers: an input layer, an output layer and a hidden layer. Neurons in input layer only act as buffers for distributing the input signals \( x_i \) to neurons in the hidden layer. Each neuron \( j \) (Fig. 2) in the hidden layer sums up its input signals \( x_i \) after weighting them with the strengths of the respective connections \( w_{ij} \) from the input layer and computes its output \( y_j \) as a function \( f \) of the sum [16], viz.

\[
y_j = f(\sum w_{ij} x_i)
\]

where \( f \) can be a simple threshold function or a sigmoidal, hyperbolic tangent or a radial basis function. The output of neurons in the output layer is computed similarly.

\[
f(\text{net}_j) = o_j = \frac{1}{1 + \exp(-\text{net}_j)} \quad (3)
\]

\[
f(\text{net}_j) = o_j = \frac{2}{1 + \exp(-2\text{net}_j)} - 1 \quad (4)
\]

where \( o_j \) is the output of the \( j \) neuron and \( \text{net}_j \) is the weighted sum of the inputs. Net is obtained by:

\[
\text{net}_j = \sum_{i=1}^{v} w_{ij} o_i
\]

for which \( \text{net}_j \) is the number of input connections, \( w_{ij} \) is a component of the weight vector, and \( o_i \) is the input activation of the \( i \) neuron in the preceding layer.

In this paper based trial and error, GD learning algorithm and LM training algorithm have been used in feed forward with one and two hidden layers. Both logistic sigmoid (logsig) as in Eq. (3) and tangent sigmoid (tansig) as in Eq. (4) transfer functions have been used in hidden layer (s) for these learning and training algorithms. A linear transfer function (purely) transfer function has been used in output layer in all cases.

2.3 ANFIS

ANFIS (Adaptive Neuro-Fuzzy Inference System) is the fuzzy-logic based paradigm that grasps the learning abilities of ANN to enhance the intelligent system’s performance using a prior knowledge. ANFIS is a class of adaptive multi-layer feed-forward networks, applied to non-linear forecasting where past samples are used to forecast the sample ahead. Using a given input/output data set, ANFIS constructs a FIS (Fuzzy Inference System) whose membership function (MFs) parameters are adjusted with learning algorithms. In the forward pass, with fixed premise parameters, the least squared error estimate approach is employed to update the consequent parameters and to pass the errors to the backward pass. In the backward pass, the consequent parameters are fixed and the gradient descent method is applied to update the premise parameters.

These techniques provide a method for the fuzzy modeling procedure to learn information about a data set, in order to compute the MFs parameters that best allow the associated fuzzy inference system to track the given input/output data. This learning method works similarly to that of neural networks. Fig. 3 illustrates a simple ANFIS model with two input variables, \( x \) and \( y \). Each variable has two fuzzy sub-sets, \( A_1 \) and \( A_2 \) for \( x \), and \( B_1 \) and \( B_2 \) for \( y \). The ANFIS model implements the Takagi–Sugeno functions to represent the fuzzy rules [18]:

Rule 1 : (if \( x \) is \( A_1 \) and \( y \) is \( B_1 \)) \quad (6)
then \( (f_1 = p_1x + q_1y + r_1) \)

Rule 1 : (if \( x \) is \( A_2 \) and \( y \) is \( B_2 \)) \quad (7)
then \( (f_2 = p_2x + q_2y + r_2) \)

where \( i \) are the outputs within the fuzzy region specified by the fuzzy rule; \( p_i \), \( q_i \) and \( r_i \) are the consequence parameters that are determined during the learning process (\( I = 1 \) or 2).
Layer-1: Every node in this layer is an adaptive node with a node function that may be one of six MFs: Singleton function, Singleton, Gaussian, bell, sigmoidal, triangular, trapezoidal shape functions. Fuzzification process takes place in this layer. Three membership functions used in this study were Gaussian, gbell, and triangular MFs. The later is defined as:

\[ \mu_{A_i}(x) = \max(\min(-a/b - a, c - a/c - b), 0) \]  

where \( a_i, b_i, \) and \( c_i \) are adaptive, and labeled as consequent parameters. Also \( x \) is the input to node \( i \) and \( A_i \) is the linguistic label (for example, low and high) associated with this node function. Premise parameters change the shape of the membership function.

Layer-2: Every node in this layer is a fixed node labeled \( \Pi \), representing the firing strength of each rule, and is calculated by the fuzzy AND connective of ‘product’ of the incoming signals by using Eq. (9):

\[ w_i = \mu_{A_i}(x) \times \mu_{B_i}(x) \quad i = 1, 2, \ldots \]

Layer-3: In this layer the normalization of the firing strengths is performed. The \( i \)th node calculates the ratio of the \( i \)th rule’s firing strength to all rules firing strength.

\[ w_i^* = \frac{w_i}{\sum_i w_i} \quad i = 1, 2, \ldots \]

Layer-4: Every adaptive node \( i \) in this layer is a square node with a node function:

\[ w_i^* f_i = w_i^* (p_i x + q_i y + r_i) \quad i = 1, 2, \ldots \]

where linear \( p, q, \) and \( r \) are consequent parameter set of the node.

Layer-5: The single node in this layer is a circle node labeled \( \Sigma \) that computes the overall output as the summation of all incoming signals, i.e.,

\[ \sum_i w_i^* f_i = \frac{\sum_i w_i^* f_i}{\sum_i w_i^*} \]

A comparative study using ANN and ANFIS models was conducted for prediction solar radiation in Tehran province. In this study, ANN-based and ANFIS-based models were developed having the same inputs; (I) number of day in the year (ii) maximum temperature (iii) sunshine duration; and (iv) extraterrestrial radiation, for calculating the same output; GSR. In this study we used three different types of input MFs: trimf, gbellmf and gaussmf. A linear function was used as output MFs. In addition, a hybrid learning algorithm that combines the least-squares estimator and the gradient descent method [19] is employed to determine the optimum values of the FIS parameters of the Surgeon-type.

![General architecture of an ANFIS network.](image)

Fig 3: General architecture of an ANFIS network. x, y: inputs of the ANFIS model; \( A_1, A_2, B_1, B_2 \): fuzzy sub-sets; \( \Pi \): layer 2 fixed nodes; \( w_i \): weight of a given fuzzy rule \( f_i \); \( N \): layer 3 fixed nodes; \( \overline{w_i} \): normalized weight; \( f_i \): fuzzy rule; \( f \): ANFIS model final output.

The ANN and ANFIS models require executable programs. In this paper, these were implemented using m-files in MATLAB [17].

2.4 Statistical Analysis

An accuracy measure is often defined in terms of the forecasting error which is the difference between the actual (desired) and the predicted values. There are a
number of measures of accuracy in the related literature and the most frequently used are:

\[ RMSE = \sqrt{\frac{1}{N} \sum (e_i)^2} \]  
(13)

\[ MAE = \frac{1}{N} \sum |e_i| \]  
(14)

\[ MAPE = \frac{1}{N} \sum \left( \frac{|e_i|}{y_i} \right) \times 100 \]  
(15)

\[ R^2 = 1 - \frac{\sum e_i^2}{\sum y_i^2} \]  
(16)

where, \( e_i \) is the individual forecast error; \( y_i \) is the actual value; and \( N \) is the number of error terms.

A model is often selected from a wide class of models by optimizing a statistical indicator such as coefficient of determination \( (R^2) \) in Eq. (16). The decision about the quality of each approach (algorithm, number of hidden layers and neurons) is made using some error criteria, which are given in Eqs. (13)–(16). \( R^2 \) approaching 1 and RMSE, MAE and MAPE approaching zero indicate that the solution of the problem gives the most accurate answers. Inputs and outputs are randomized in training and testing periods.

### 3. RESULTS AND DISCUSSION

#### 3.1 Sensitivity Analysis

To construct generalized and accurate ANN and ANFIS models, 8 effective factors on GSR including 6 meteorological parameters (minimum, maximum and average daily temperature, humidity, sunshine duration and precipitation) and 2 geographical parameters (day of the year and extraterrestrial radiation) classified into minor and major variables. The raw data are analyzed using simulation of ANN with sensitivity. As shown in Fig. 4, \( R_a \) has highest sensitivity on GSR and followed by sunshine duration. Among the three measured temperature, maximum temperature has more effect in determination GSR. At the end, for each day of year GSR has an approximate value and then selected as four parameters that used for modeling intelligent networks.

![Fig 4: Sensitivity analysis on influencing parameters on estimation GSR.](image)

#### 3.2 ANN Results

The performance of the various ANNs for modeling solar radiation in Tehran province was examined. This station is used both for training and testing ANN models. For this purpose different ANNs with LM training algorithms, logsig and tansig transfer functions, and hidden layers and nodes were constructed using Tehran meteorological data. The statistical error values such as the RMSE, MAE, MAPE and \( R^2 \) were used to select the best model. The results are given in Table 1. The values of RMSE, MAE, MAPE and \( R^2 \) for these models range from, 2.77 to 3.77, 2.19 to 3.08, 0.12 to 0.18 and 0.703 to 0.840 respectively. Among the trained networks, 3-7-1 topology from ANN model resulted best model estimating the daily GSR. From this table it is indicated that the best structure of ANN model uses tangent sigmoid transfer function in input layer and 7 neurons in its hidden layer. The values of RMSE, MAE, MAPE and \( R^2 \) for this model are 2.77, 2.19, 0.12 and 0.84.
Table 1: Statistical test for different simulation between measured and estimated ANN- and ANFIS models

<table>
<thead>
<tr>
<th>Transfer function</th>
<th>Neurons $(N_{h1}+N_{h2})$</th>
<th>RMSE</th>
<th>MAE</th>
<th>MAPE</th>
<th>$R^2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>logsig</td>
<td>3</td>
<td>2.85</td>
<td>2.31</td>
<td>0.13</td>
<td>0.832</td>
</tr>
<tr>
<td>logsig</td>
<td>5</td>
<td>2.84</td>
<td>2.29</td>
<td>0.12</td>
<td>0.832</td>
</tr>
<tr>
<td>logsig</td>
<td>7</td>
<td>2.83</td>
<td>2.3</td>
<td>0.12</td>
<td>0.834</td>
</tr>
<tr>
<td>logsig 3+2</td>
<td>3.77</td>
<td>3.08</td>
<td>0.18</td>
<td>0.703</td>
<td></td>
</tr>
<tr>
<td>logsig 5+3</td>
<td>3.09</td>
<td>2.46</td>
<td>0.14</td>
<td>0.8</td>
<td></td>
</tr>
<tr>
<td>logsig 7+5</td>
<td>2.85</td>
<td>2.32</td>
<td>0.13</td>
<td>0.831</td>
<td></td>
</tr>
<tr>
<td>tansig</td>
<td>3</td>
<td>2.84</td>
<td>2.27</td>
<td>0.12</td>
<td>0.832</td>
</tr>
<tr>
<td>tansig</td>
<td>5</td>
<td>2.83</td>
<td>2.31</td>
<td>0.13</td>
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<tr>
<td>tansig</td>
<td>7</td>
<td>2.77</td>
<td>2.19</td>
<td>0.12</td>
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<td>2.33</td>
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<td>2.87</td>
<td>2.29</td>
<td>0.13</td>
<td>0.929</td>
<td></td>
</tr>
</tbody>
</table>

3.3 ANFIS Results

In order to assess the ability of ANFIS models relative to that of a neural network model, an ANFIS model is constructed using the same input parameters to the ANN models. After training the ANFIS model, prediction performance was tested. The performance of ANFIS with different types of MFs model: Gaussian, bell and triangular which tested with number of two and three is reported in Table 2. The statistical error values such as the RMSE, MAE, MAPE and $R^2$ were used to select the best model.

Table 2: Statistical test for different simulation between measured and estimated GSR with ANFIS models

| MFs type       | MFs number | RMSE | MAE  | MAPE | $R^2$ | |
|----------------|------------|------|------|------|-------| |
| triangular     | 2          | 2.8  | 2.22 | 0.12 | 0.838 |
| triangular     | 3          | 3.56 | 2.44 | 0.14 | 0.745 |
| Gaussian       | 2          | 4.67 | 2.68 | 0.15 | 0.624 |
| Gaussian       | 3          | 2.88 | 2.25 | 0.12 | 0.827 |
| bell           | 2          | 2.88 | 2.26 | 0.13 | 0.827 |
| bell           | 3          | 3.95 | 2.59 | 0.15 | 0.705 |

Finally, Figs. 5(a) and 5(b) show the performance of best structure for ANN (with $R^2=0.840$) and ANFIS (with $R^2=0.938$) models, respectively. It can be seen from these figures that they are similar in trend and their obtained statistical indicators verify this point. Figure 6 shows the measured and predicted GSR (using ANN and ANFIS) is shown Fig. 6. It can be observed that ANN (red) and ANFIS (black) models overlap in some areas.
4. CONCLUSION

Three meteorological parameters were used for the analysis of solar irradiation in Tehran province of Iran. The prediction performance of various artificial neural networks and adaptive neuro-fuzzy inference system were assessed by comparing their predictions to actual data available in the IRIMO data center. By using mean absolute error (MAE), root mean square error (RMSE), mean absolute percentage error (MAPE) and coefficient of determination ($R^2$) the results were compared. The comparison between the best structure of best ANN-model (with $R^2=0.840$) and some ANFIS-model (with $R^2=0.938$) has shown the superiority of the ANN model. These models could be used to evaluate the solar potential of a location. The use of these models in the remote locations that solar measurement devices are not available can be beneficial as an effective tool to select the most efficient locations for using solar energy.

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REFERENCES


Fig 5: Comparison of scatter plots of the models used for solar radiation; (a) ANN, and (b) ANFIS results.

Fig 6: Comparison selected ANN, ANFIS and measured values of GSR.


