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Comparison of Empirical Models and an Adaptive Neuro Fuzzy Inference System for Estimating Hourly Total Solar Radiation on Horizontal Surface at Alexandria City, Egypt

Abdulwahab S. Kassem[1], Abdulwahed M. Aboukarima[2*], Nasser M. El Ashmawy[2,3] and Moamen F. Zayed[2]

[1]Department of Agricultural and Bio-Systems Engineering, Faculty of Agriculture, Alexandria University, Alexandria, Egypt.
[2]Agricultural Research Center, Agricultural Engineering Research Institute, Testing and Research Station for Tractor and Farm Machinery, Alexandria, Egypt.
[3]Department of Agricultural Engineering, College of Food and Agricultural Sciences, King Saud University, P.O.Box 2460, Riyadh 11451, Saudi Arabia.

Authors' contributions

This work was carried out in collaboration between all authors. Author ASK managed the instrumentation system (Delta-T automatic weather stations), reviewed the measurements and the final manuscript. Author AMA made data analysis, managed the literature review and wrote the first draft of the manuscript. Author NMEA participated in data analysis and participated in writing the first draft of the manuscript. Author MFZ managed the literature review and participated in writing the first draft of the manuscript. All authors read and approved the final manuscript.

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ABSTRACT

Solar radiation data in a particular location is an important factor for agricultural applications and others. To estimate solar radiation, empirical models have been developed using different meteorological parameters. Recently, prediction models based on artificial intelligence techniques such fuzzy logic are available. The aim of this work was to develop an adaptive neuro fuzzy

**Corresponding author: E-mail: aboukarima@gmail.com;*

inference system (ANFIS) for estimating hourly total solar radiation on horizontal surface at Alexandria city, Egypt and to compare its efficiency with two empirical models namely clear sky hourly global solar radiation and global solar flux on a horizontal surface. Local time, Julian day, air temperature, relative humidity and relative sunshine duration data for the period 2005-2007 were used as inputs to ANFIS model. Delta-T automatic weather station which was located on the roof-top of Agricultural and Bio-Systems Engineering Department, Faculty of Agricultural, Alexandria, Egypt was employed to collect the required data. In testing phase, good results with all prediction methods were obtained, with root mean square error values of 165.42, 168.37 and 82.287 W/m^2 for clear sky hourly global solar radiation model, global solar flux on a horizontal surface model and ANFIS model, respectively. Meanwhile, coefficients of determination (R^2) were 0.6428, 0.6355 and 0.8949, respectively for clear sky hourly global solar radiation model, global solar flux on a horizontal surface model and ANFIS model when utilized testing data set for the validation process. Even though all the investigated models can be used to predict the hourly total solar radiation on horizontal surface, ANFIS model produced better estimates.

Keywords: Solar radiation; ANFIS; weather parameters; Egypt.

1. INTRODUCTION

Knowledge of available solar radiation data in a particular location is essential for different purposes such as assessment of solar drying systems [1], evaluating of solar cells performance [2,3] and building of crop models [4]. Moreover, the estimation of solar radiation is essential for utilization the solar energy, design wherever appropriate observations missing [5]. However, solar radiation data are often obtained from measurements taken at a particular location using various solar radiation measuring instruments. But due to high cost of calibration and maintenance of such instruments, solar radiation data are limited in many meteorological stations around the world [4]. Thus, prediction of solar radiation data is very useful in such case because it permits to generate solar data for locations where measurements are not available [6].

The difficulties in the measurement of solar radiation have resulted in development of so many models and algorithms for its estimation from some routinely measured meteorological parameters such as; sunshine hour, maximum, minimum and average air temperatures, relative humidity, and cloud factor [7]. Consequently, numerous empirical models for estimating solar radiation on horizontal surface have been developed [8-13]. Recently, soft computing methodologies, as an alternative to the conventional statistical methods, have the ability to track complicated dependencies between different variables, where traditional methods have their limits [14]. One of such methodologies is Adaptive Neuro-Fuzzy Inferences System (ANFIS). It is a hybrid intelligent system that merges technique of the learning power of the artificial neural networks with the knowledge representation of fuzzy logic. The main advantages of the ANFIS are computationally efficiency and adaptability [15]. The ANFIS can be served as a tool for estimating solar radiation data [16-21].

Mellit et al. [16] used ANFIS technique to model the global solar radiation based upon sunshine duration and air temperature. Moghaddamnia et al. [17] utilized ANFIS to estimate the daily global solar radiation using extraterrestrial radiation, precipitation, air temperature and wind speed. Sumithira and Kumar [18] employed ANFIS to predict the monthly global solar radiation using the real meteorological solar radiation data. The comparative test results proved the ANFIS based prediction is better than other models and proved its prediction capability for any geographical area with changing meteorological conditions. Khademi et al. [19] applied ANFIS to estimate monthly global solar radiation on a horizontal surface for Tehran city. Monthly mean of maximum air temperature, relative humidity, sunshine hours and wind speed values were acted as inputs to the ANFIS. The results proved that ANFIS could predict monthly global solar radiation on a horizontal surface in efficient way. Mohanty [20] employed ANFIS technique to predict monthly mean global solar radiation. Boata and Pop [14] developed ANFIS for estimation of daily global solar irradiation. Piri and Kisi [21] employed ANFIS technique to predict global solar radiation based on sunshine hour, air temperature and relative humidity as input parameters.

Solar radiation data are essential for most solar energy research and applications [22]. In their studies Iqdour and Zeroual [23], Tulcan-Paulescu and Paulescu [24], Rahoma et al. [25], Boata and Gravila [26], Saurabh et al. [27], Boata and Paulescu [28], Guclu et al. [29] and Hooshangi and Alesheikh [30] applied fuzzy logic technique to predict solar radiation data as the main advantage of fuzzy models is their ability to describe the knowledge in a descriptive human like manner in the form of simple rules using linguistic variables only. In this study, an application of ANFIS was proposed to develop a soft computing-based model for estimation of hourly horizontal global solar radiation. The inputs were local time, Julian day, air temperature, relative humidity and relative sunshine duration. For this purpose, hourly horizontal total solar radiation data for city of Alexandria, Egypt have been used. The potential of the developed ANFIS model is further appraised and verified by providing statistical comparisons between its predictions with those of clear sky hourly global solar radiation and global solar flux on horizontal surface models.

2. MATERIALS AND METHODS

2.1 Site of Application and Data Collection

Alexandria is located at latitude 31° 11' 53 N, longitude 29° 55' 9 E and is situated in the northern west part of Egyptian plateau. Being in the sun-belt, Alexandria province is an ideal location to benefit from the advantages of solar energy utilization and adoption of its related technologies. Therefore, solar energy devices can be operated with high performance [31]. In the present work, the measurements of meteorological parameters were taken by using Delta-T automatic weather station. It was located on the roof-top of Agricultural and Bio-Systems Engineering Department, Faculty of Agricultural, Alexandria, Egypt. All sensors are installed in a position relatively free from any external obstruction, and readily accessible for inspection and general cleaning. The measured parameters were: hourly total solar radiation (W/m^2), air temperature (°C), relative humidity (%) and mean relative sunshine duration (h/h). The measurements were acquired using a sampling time of 10 min. The measurements were carried out from September 2005 to December 2007, on a horizontal surface and the recorded data only from 6 a.m till 17 p.m were used in the analysis after averaged the 10 minuets readings. Total solar radiation was measured on an hourly basis using integrated device (called the BF3) sensor, Delta-T devices through Sunshine Pyranometer type SPN1. The whole collected data were randomized. The data set was split into two sets. The training data set: the group of data by which the ANFIS adjusts parameters, in order to reach the best fitting of the nonlinear function representing the phenomenon and it consisted of 3821 patterns. The testing data set: A set of new data used to evaluate the developed ANFIS model and it consisted of 72 patterns. The training and testing data sets were selected randomly from the covered period from September 2005 to December 2007.

2.2 Adaptive Neuro Fuzzy Inference System for Modeling Total Hourly Solar Radiation on Horizontal Surface

The concept of “fuzzy set” was introduced by Zadeh [32] who pioneered the development of fuzzy logic. However, fuzzy logic technique is now applied in agricultural researches for prediction [33-34] and for grading fruits [35-36]. In literature there were different sources that provide basic information on the concepts and operations of fuzzy algorithms. On the other hand, adaptive neuro fuzzy inference system (ANFIS) is a method based on the input–output data of the system under consideration [37]. It is a hybrid model composed of fuzzy and artificial neural networks models. It enjoys the advantage of being able to receive fuzzy rules from the expert’s knowledge and build a rule base adaptively. It can be stated that ANFIS is considered as a powerful, appropriate, and flexible tool for modeling uncertainties and implicitness present in the real world and expressing linguistic terms adopted from human experience and knowledge in the form of mathematical relations [38].

For simplicity, a fuzzy inference system with two inputs x and y, and one output is assumed [39]. In this inference system the output of each rule is a linear combination of input variables added by a constant term. The final output is the weighted average of each rule’s output. For a first-order Sugeno fuzzy model, a common rule set with two fuzzy if –then rules is defines as follows:

Rule 1: If x_1 is A_1 and x_2 is B_1, then $f_1=a_1x_1+b_1x_2+q_1$ (1)

Rule 2: If x_1 is A_2 and x_2 is B_2, then $f_2=a_2x_1+b_2x_2+q_2$ (2)

where, x_1 and x_2 are the crisp inputs to the node and A_1, B_1, A_2, B_2 are fuzzy sets, a_i, b_i and q_i (i = 1, 2) are the coefficients of the first-order polynomial linear functions.

The typical structure of ANFIS is shown in Fig. 1. A two-input first-order Sugeno fuzzy model with two rules is shown in Fig. 1 and consists of five layers. These layers are the fuzzy layer, the product layer, the normalized layer, the defuzzification layer, and the output layer. Every node at the same layer has similar function [40]. The framework of ANFIS can be expressed as following [40]:

The first layer is the fuzzy layer. The fuzzy layer contains of adaptive nodes that generate the membership grades of linguistic labels. Any appropriate parameterized membership function can be used such as the triangular-shape function. A1, A2, B1, B2 are the linguistic labels used in the fuzzy set for dividing the membership functions. The relationship between the output and input functions of this layer can be expressed as below:

$$O_{i,1} = \mu_{Ai}(x_1) \qquad i = 1,2 \tag{3}$$

$$O_{j,1} = \mu_{Bj}(x_2) \qquad j = 1,2 \tag{4}$$

Where, x_1 and x_2 are the inputs to node i (i = 1, 2 for x_1 and j = 1, 2 for x_2) and x_1 (or x_2) is the input to the i[th] node and A_i (or B_j) is a fuzzy label.

The second layer is the product layer. The product layer consists of rule nodes designated as Π which signifies the firing strength of each rule. The output of the product layer is the product of the input signal, which is defined as follows:

$$O_{2,i} = W_i = \mu_{Ai}(x_1)\mu_{Bi}(x_2) \qquad i = 1,2 \tag{5}$$

where $O_{2,i}$ is the output of the product layer, μ_{Ai} is the membership function of the fuzzy set A and μ_{Bi} is the membership function of the fuzzy set B.

The third layer is the normalized layer. In this layer the fixed nodes are labeled as N. The output of the normalized layer is to normalize the weight function or the sum of all the rules firing strength as following:

$$O_{3,i} = \overline{W}_i = \frac{w_i}{w_1 + w_2} \qquad i = 1,2 \tag{6}$$

Where $O_{3,i}$ is the output of the normalized layer and w_i is the output of the product layer.

The fourth layer is the Defuzzification layer. The nodes in the defuzzification layer are also adaptive nodes besides the nodes in the fuzzy layer. Those adaptive nodes calculate the rule outputs based on consequent parameters. The adaptive nodes of this layer calculate the rule outputs based on consequent parameters by following equation

$$O_{4,i} = \overline{W}_i f_i = \overline{W}(a_1x_1 + b_1x_2 + q_i) \qquad i = 1,2 \tag{7}$$

Where $\overline{W}_i$ is the output of layer 3 and a_i, b_i, q_i are the coefficients of linear combination in Sugeno inference system. These parameters of this layer are referred to as consequent parameters.

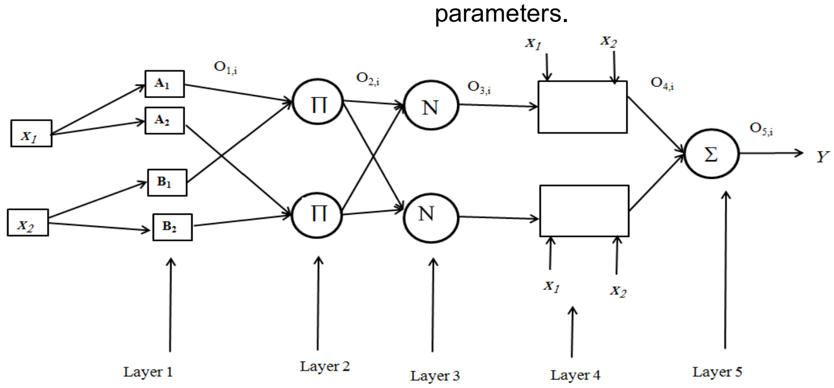

Fig. 1. A typical ANFIS architecture [41]

The fifth layer is the output layer. This layer is the final layer. The output layer gives the output by the summation of all incoming signals. The fixed node in this layer is labeled as Σ calculates the overall output from the sum of the node input signals. The output of the output layer can be expressed as below

$$O_{5,i} = Y = \sum_{1}^{2} \overline{W}_i f_i = \frac{\sum_{1}^{2} \overline{W}_i f_i}{\sum_{1}^{2} \overline{W}_i} \tag{8}$$

Where $O_{5,i}$ is the output of the fifth layer which is the academic marks and $\overline{W}$ is the output of the defuzzification layer.

ANFIS requires a training data set of desired input/output pair (x_1, $x_2 \ldots x_m$, Y) depicting the target system to be modeled. ANFIS adaptively maps the inputs (x_1, $x_2 \ldots x_m$) to the outputs (Y) through Membership Functions (MFs), the rule base and the related parameters emulating the given training data set. In this study, local time, Julian day, air temperature, relative humidity and relative sunshine duration were employed as input parameters to ANFIS as shown in Fig. 2.

There are no fixed rules for developing an ANFIS model. In this study, a three linguistic terms {L: low, M: Medium and H: High} were utilized. The ANFIS model was implemented in Matlab software system. Purpose of the training process in ANFIS model is to minimize the error between actual target and ANFIS output. The training error is the difference between the training data output value, and the output of the fuzzy inference system corresponding to the same training data input value. In the performance phase, a new data set (test data) that is not present in the training set is introduced to the learned system for evaluation. If the test error is adequately small, it indicates that the system has a good generalized capability.

To generate fuzzy IF-THEN rules, the first order was employed with five inputs. The hybrid learning algorithm is employed to determine the parameters of Sugeno-type fuzzy inference systems. Fuzzy membership functions can take many forms but linear functions are often preferred, as this makes the subsequent calculations easier [42]. Triangular-shaped membership function is the simplest possible and have been selected [28]. The training error was 64.2042 as shown in Fig. 3. The triangular-shaped membership function plots after training ANFIS model are presented in Figs. 4 through 8, respectively for local time, Julian day, air temperature, relative humidity and relative sunshine duration.

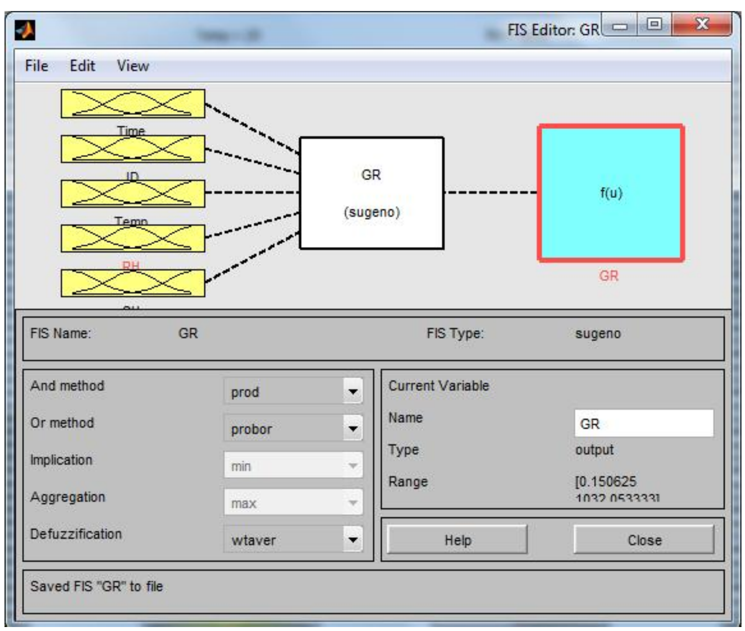

Fig. 2. Takagi-Sugeno ANFIS with five inputs for prediction of hourly total solar radiation on horizontal surface

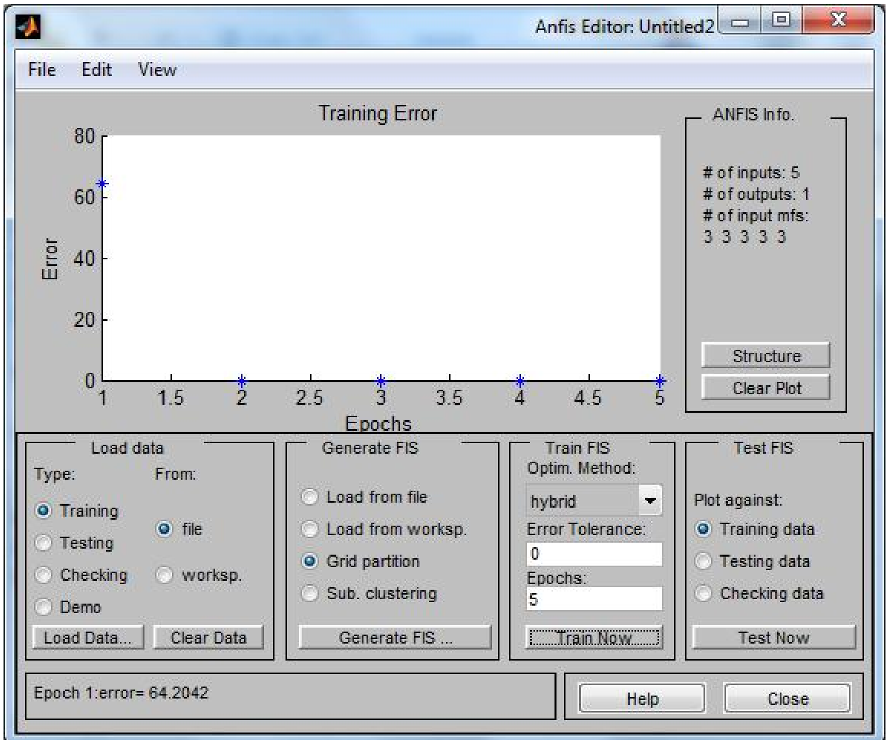

Fig. 3. The training error

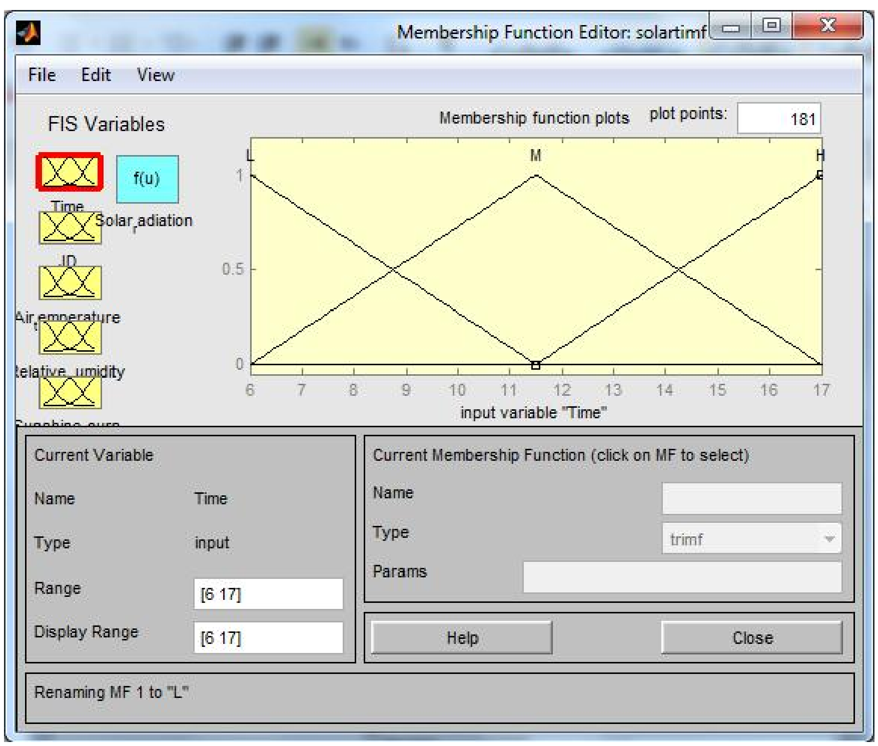

Fig. 4. Triangular –shape membership plots for local time

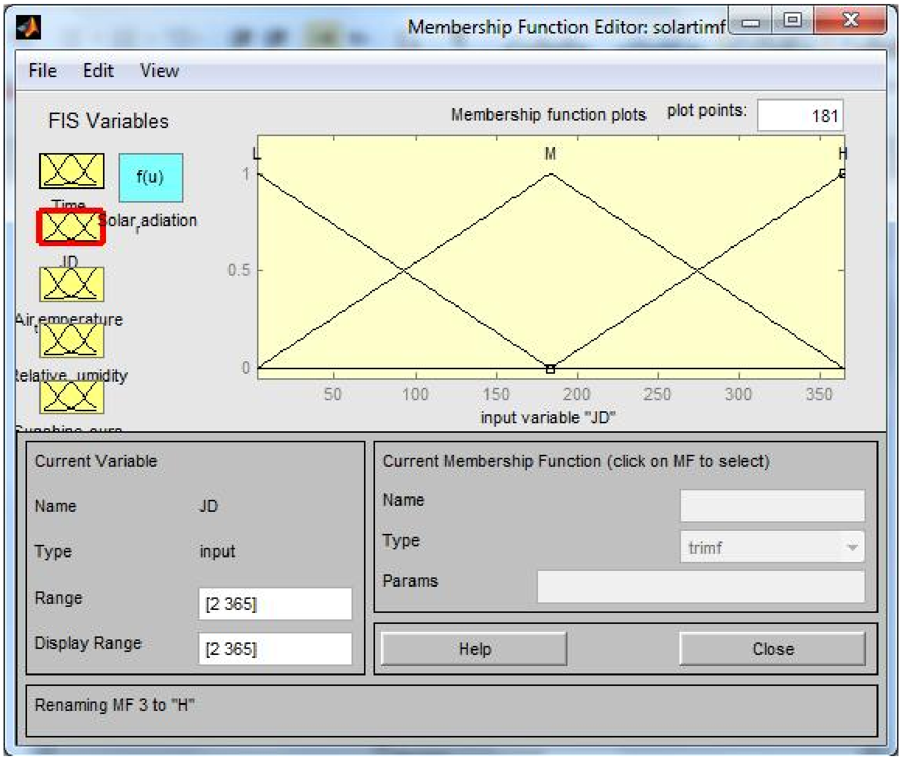

Fig. 5. Triangular –shape membership function plots for Julian day

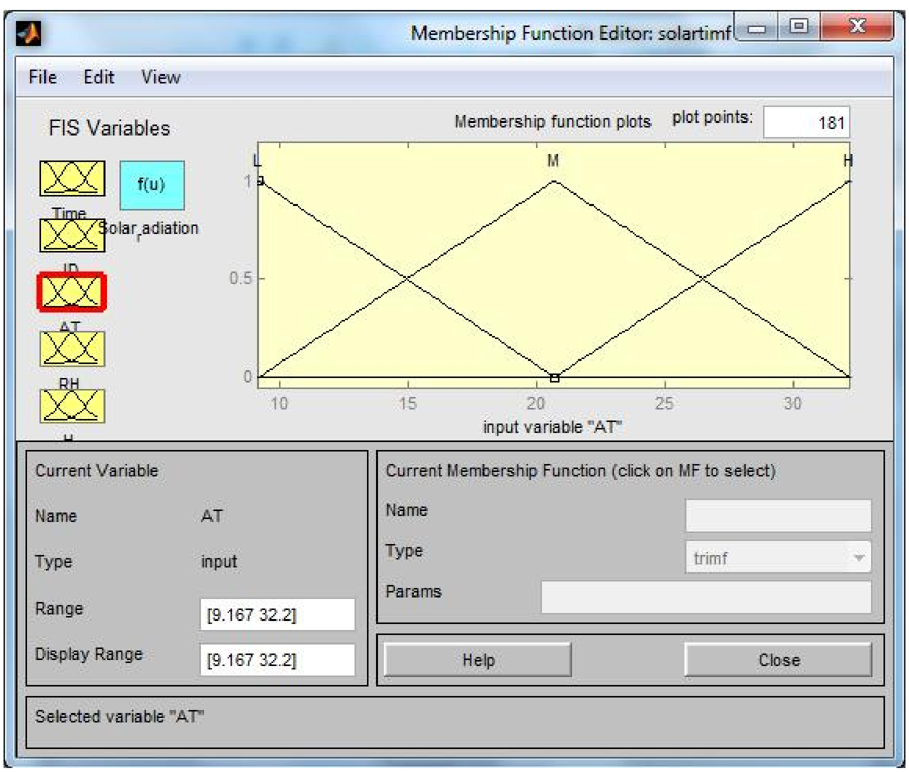

Fig. 6. Triangular –shape membership plots for air temperature

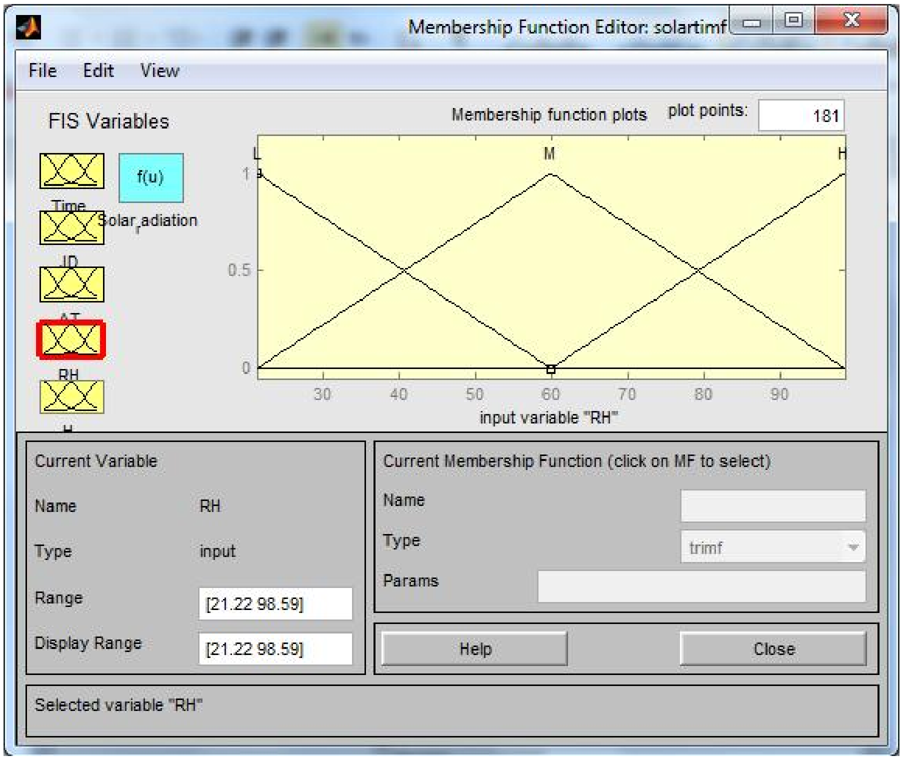

Fig. 7. Triangular –shape membership plots for relative humidity

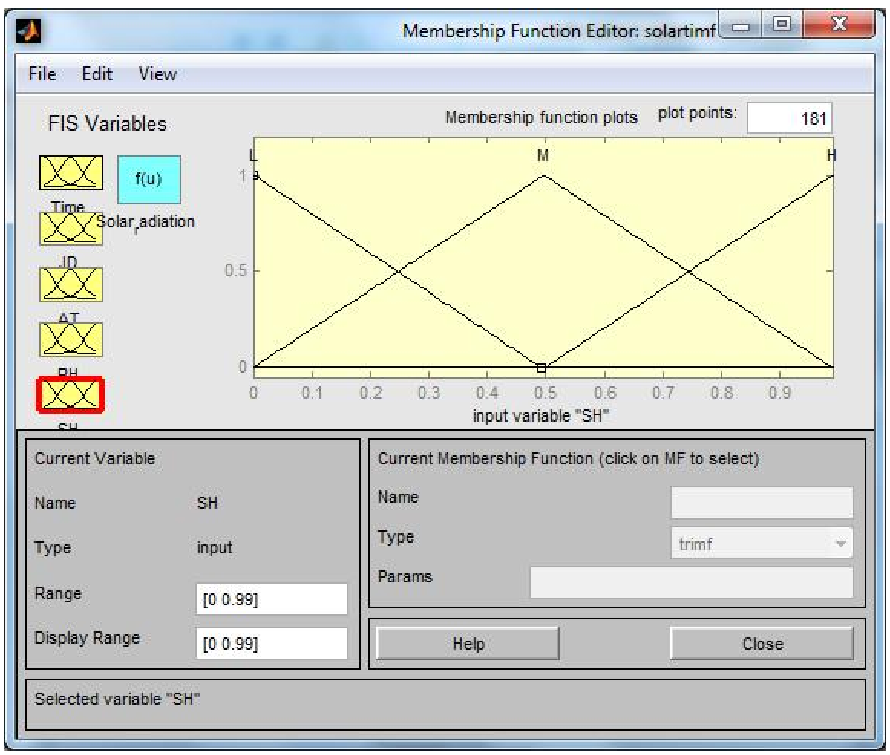

Fig. 8. Triangular –shape membership plots for relative sunshine duration

2.3 Clear Sky Hourly Global Solar Radiation Model

The clear sky hourly global solar radiation model was investigated by Al-Jumaily et al. [43]. They included the details of such model and they assumed the model neglecting the reflection component so the hourly global solar radiation intensity on a horizontal surface, $\overline{R}_h$ in clear sky model is given by Meinel and Mainel [44] as,

$$\overline{R}_h = \overline{R}_a \times 0.7^{m^{0.678}} \tag{9}$$

Where $\overline{R}_a$ is the extraterrestrial irradiance on a horizontal surface given by Markvart and Kreider [45] as,

$$\overline{R}_a = R_{SC}\left[1 + 0.033\cos\frac{2\pi J}{365}\right]\sin\alpha \tag{10}$$

Where m is the air mass ratio calculated for clear sky condition by Kreith and Kreider [46] as,

$$m = \left[1229 + (614\sin\alpha)^2\right]^{0.5} - 614\sin\alpha \tag{11}$$

Where α is the sun altitude angle (degree) obtained from Iqbal [5],

$$\sin\alpha = (\cos\phi\cos\delta\cos\omega + \sin\phi\sin\delta) \tag{12}$$

ϕ is the geographical latitude (degree) and δ is the solar declination angle (degree) defined by Iqbal [5]:

$$\delta = 23.5\sin\left[\frac{360}{365}(J + 284)\right] \tag{13}$$

Where J is the number of days of the year starting from January 1. The hour angle in degree (ω) is an angular measure of time and is equivalent to 15 per hour with morning (+) and afternoon (-). It is measured from noon-based local solar time (ST) from the equation given by

$$\omega = 15(12 - ST) \tag{14}$$

The local solar time (ST, hour) is calculated from the local standard time (LT, hour) and the equation of time (ET, min) as follows:

$$ST = LT + \frac{ET}{60} + \frac{4}{60}(L_S - L_L) \tag{15}$$

Where L_S is the standard meridian (degree) for the local time zone (Egypt standard meridian is 31.205753° E) and L_L is longitude of the location in degrees (Alexandria longitude is 29.924526° E). The equation of time is obtained from formula given by Tasdemiroglu [47] as:

$$ET = 9.87\sin 2B - 7.53\cos B - 1.5\cos B \tag{16}$$

Where $B = \frac{360(J - 81)}{365}$ in degrees (17)

An excel spreadsheet was developed for the model calculations.

2.4 Global Solar Flux on a Horizontal Surface Model

Global solar flux is the sum of the direct and diffuse solar radiation [11]:

$$G_h = I_h + D_h \tag{18}$$

Where I_h is direct solar flux (W/m^2). It can be calculated by the formula given by El Mghouchi et al. [11]:

$$I_h = R_{SC} C_t \Gamma \exp\left(-\frac{0.13}{\sin\alpha}\right)\sin\alpha \tag{19}$$

Where R_{SC} (W/m^2) is the solar constant and equals 1367 W/m^2 [48], C_t (dimensionless) is the correction of the earth–sun distance and can be calculated as described in El Mghouchi et al. [11] by the equation:

$$C_t = 1 + 0.034\cos(J - 2) \tag{20}$$

Γ (dimensionless) is the turbidity atmospheric factor for clear skies as mentioned by El Mghouchi et al. [11]. It can be calculated by the formula:

$$\Gamma = 0.796 - 0.01\sin[0.986(J + 284)] \tag{21}$$

D_h is the diffuse solar flux (W/m^2) and can be calculated by the formula given by El Mghouchi et al. [11]:

$$D_h = 120 \times \Gamma \exp\left(-\frac{1}{(0.4511 + \sin\alpha)}\right) \tag{22}$$

2.5 Statistical Criteria for Models Evaluation

The performance of the developed models in this study has been assessed using various standard statistical performance evaluation criteria. The statistical measures considered have been three criteria. The first criterion is coefficient of determination (R^2). The second one is mean absolute error (MAE). The third criterion is root mean square error (RMSE). The MAE and RMSE are calculated according to the following equations:

$$MAE = \frac{1}{N_a}\sum_{i=1}^{N_a}\left|Y_a - Y_p\right| \tag{23}$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N_a}(Y_a - Y_p)^2}{N_a}} \tag{24}$$

Where Y_a and Y_p are the observed and predicted data, respectively and N_a is the number of data points.

3. RESULTS AND DISCUSSION

3.1 Correlation Analysis between the Observed Total Solar Radiation and the Variables

When studying the results of the correlation analysis, there was a correlation between the observed total radiation and air temperature and relative sunshine duration as depicted in Table 1. The Pearson's correlation coefficient between the observed total solar radiation and the dependent variables analyzed (air temperature and relative sunshine duration) points to a positive correlation. In the scatter plots of Fig. 9, the relationship between the observed total solar radiation and the other variables is shown. The graphics displayed moderate correlation with air temperature and relative sunshine duration and low correlation with the rest variables was observed.

3.2 Performance of the Total Solar Radiation Prediction Models

In this study, the potential of ANFIS technique to estimate the hourly horizontal total solar radiation using local time, Julian day, air temperature, relative humidity and relative sunshine duration as inputs was appraised. To achieve further reliability in the evaluations, the developed ANFIS model was tested by a data set that was not used during the training process. The suitability of the proposed ANFIS system was assessed statistically using different well-known indicators. Then to ensure the accuracy level of the ANFIS model, its performance was compared against two empirical models. Values of coefficient of determination, mean absolute error and root mean square error between observed and estimated values of solar radiation using testing data for the investigated models are shown in Table 2. Scatter plots between observed and estimated solar radiation for the investigated models are depicted in Fig. 10 using testing data. It is clear that there are favorable agreements between the ANFIS predictions and the measured ones as the amount of deviations of data points are truly limited. This proves the high rate of correlation between the measured and the estimated values. The presented values in Table 2 indicate that small differences exist between the estimated total solar radiation values and the measured ones. In fact, the low values of MAE and RMSE along with the high value of R^2 demonstrate the high capability of the developed ANFIS model to estimate the hourly total solar radiation on horizontal surface based upon the investigated variables.

3.3 Behavior of the Proposed Models

To inspect the behavior of the proposed models to predict hourly total solar radiation on horizontal surface, the January data were averaged and represented in Fig. 11. It is clear that the trend curves of solar radiation of the proposed models flow the actual data. However, in morning and evening hours, lower solar radiation data are observed. The maximum solar radiation was observed at 12 a.m as shown in Fig. 11 with values of 475.24, 380.19, 525.24 and 602.04 W/m^2 for actual data, ANFIS data, clear sky hourly global solar radiation data and global solar flux on a horizontal surface data, respectively.

Table 1. Correlation matrix between total solar radiation and other meteorological variables using training data set

	Local time	Julian day	Air temperature	Relative humidity	Relative sunshine duration	Total solar radiation
Local time	1					
Julian day	-0.046	1				
Air temperature	0.095	0.253	1			
Relative humidity	-0.186	-0.048	0.007	1		
Relative sunshine duration	0.146	0.0008	0.388	-0.176	1	
Total solar radiation	-0.070	-0.034	0.474	-0.121	0.597	1

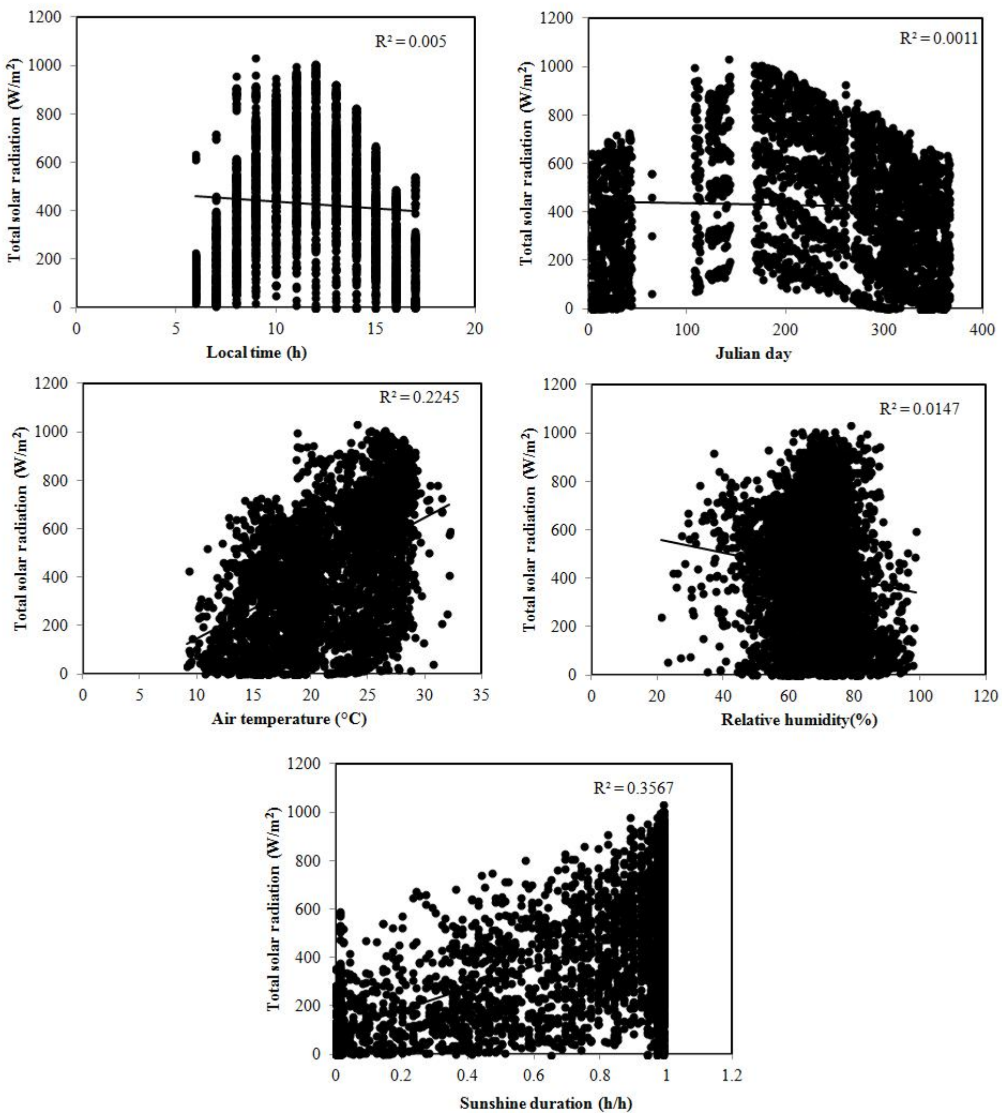

Fig. 9. Scatter plots of relationships between total solar radiation and other meteorological variables

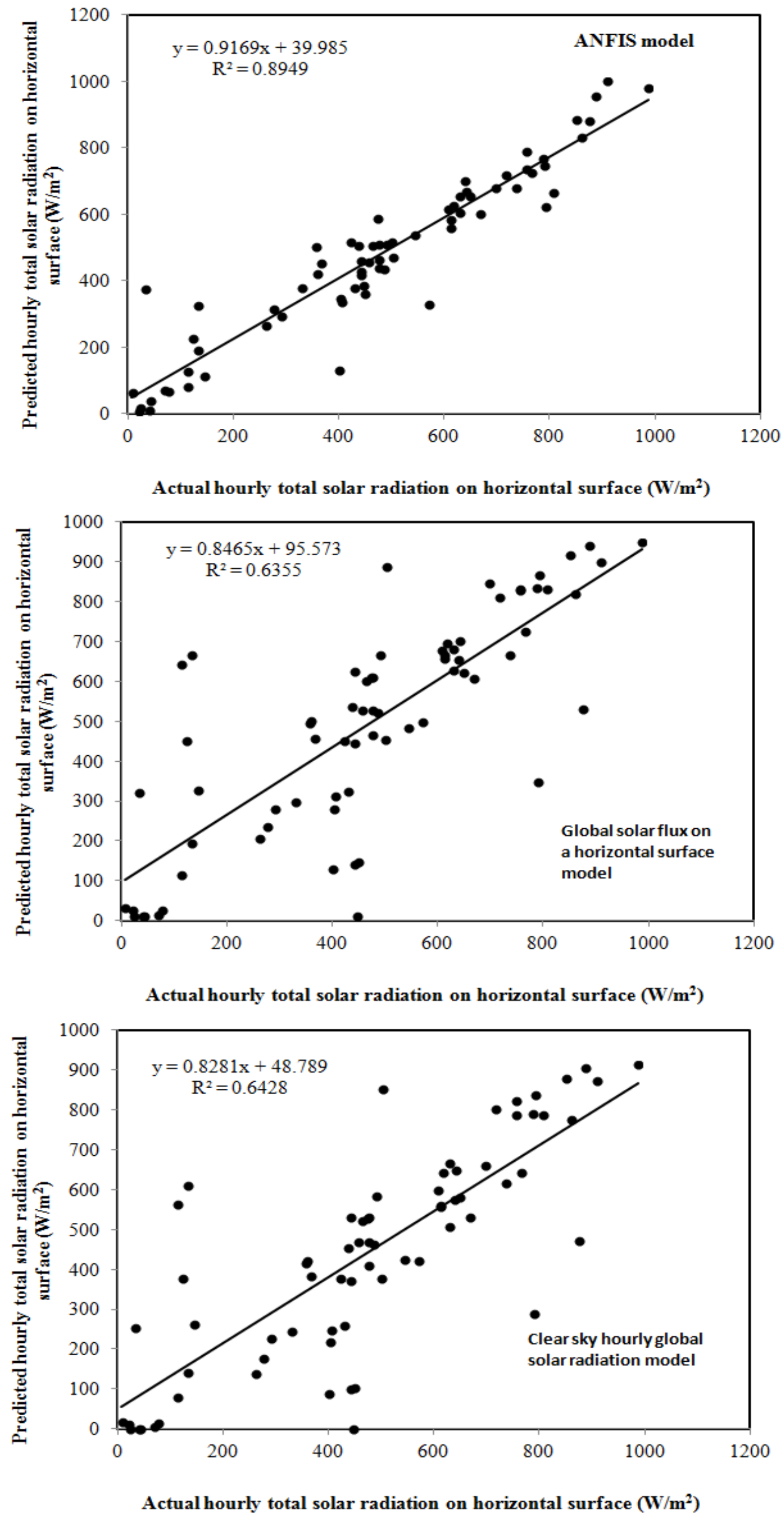

Fig. 10. Scatter plots between observed and estimated solar radiation for the investigated models

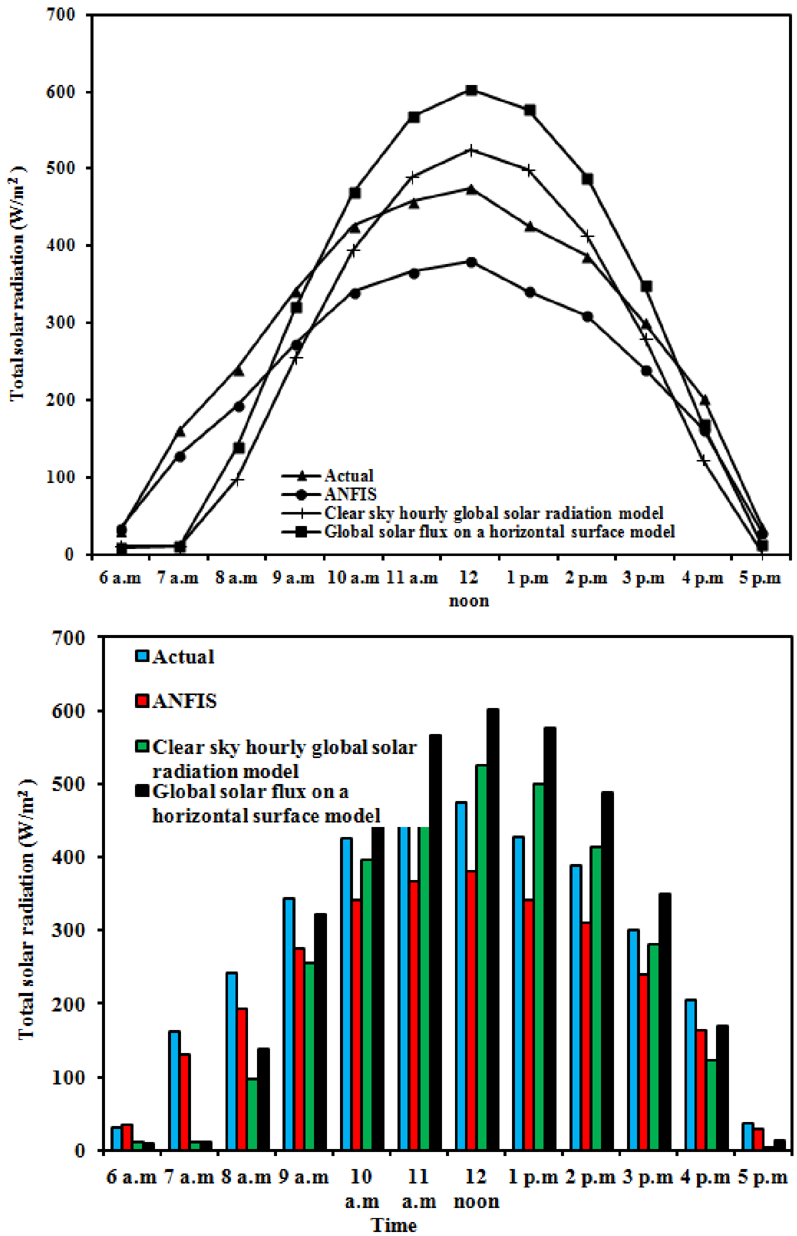

Fig. 11. Behavior of the proposed models during prediction of hourly total solar radiation on horizontal surface during January month

3.4 Graphical Representation of the Rules for Hourly Total Solar Radiation on Horizontal Surface Prediction

A graphical depiction of the all rules generated to map the input data (antecedent) with the output (consequent) for hourly total solar radiation on horizontal surface in the ANFIS is shown in Fig. 12. This figure shows that each rule is represented by an individual row, while variables are represented by individual columns. The first five columns depict the membership functions for the five input variables (Time, JD, AT, RH and SH), referenced by the antecedent or the "if-part" of each rule. The sixth column shows the membership functions used by the consequent or the "then-part" of each rule.

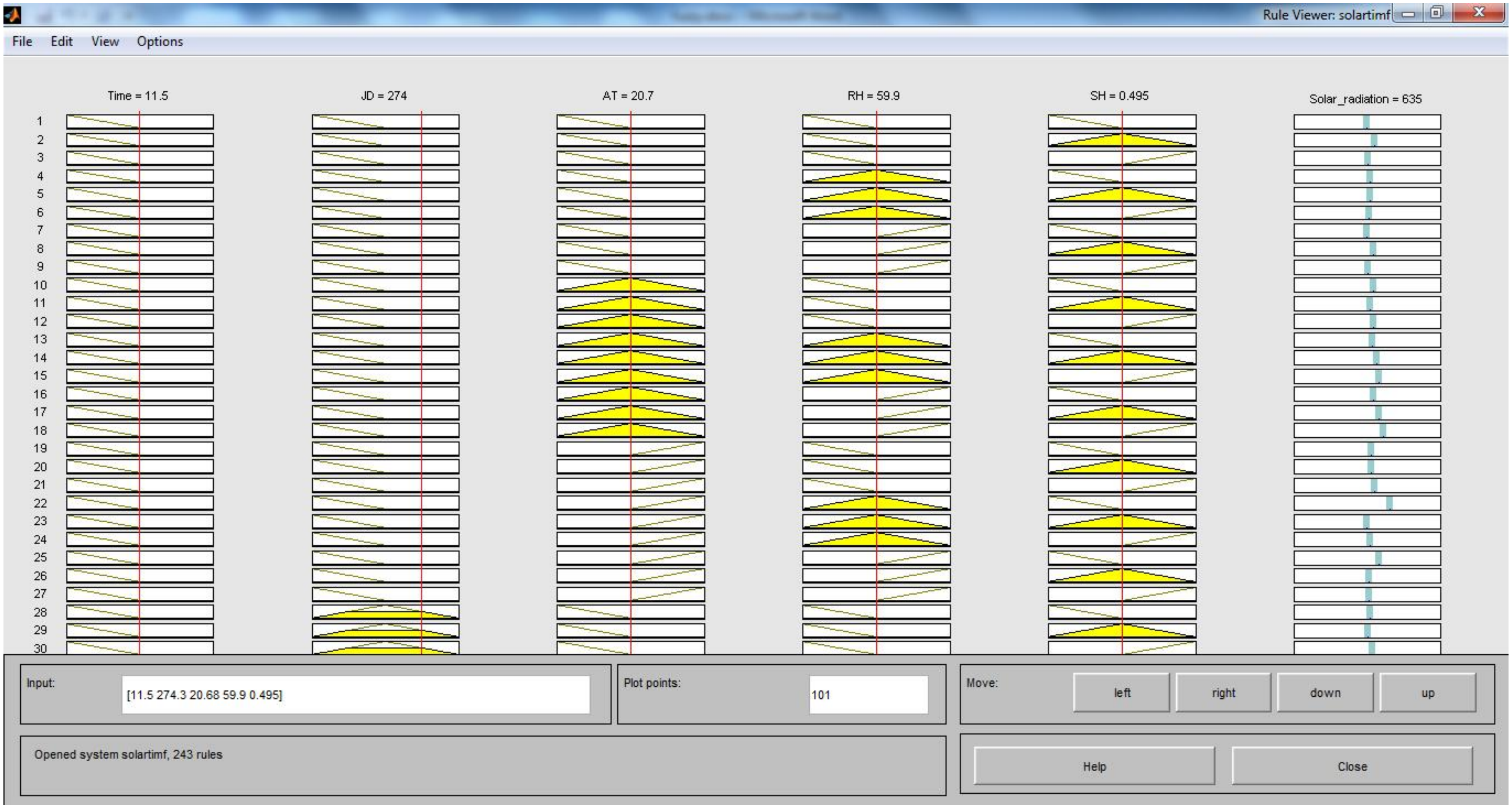

Fig. 12. Graphical representation of the rules for solar radiation ANFIS model

Table 2. Values of coefficient of determination, mean absolute error and root mean square error between observed and estimated values of solar radiation using testing data for the investigated models

Investigated model	Root mean square error (W/m^2)	Mean absolute error (W/m^2)	Coefficient of determination
Clear sky hourly global solar radiation model	165.42	109.32	0.6428
Global solar flux on a horizontal surface model	168.37	111.36	0.6355
ANFIS total hourly solar radiation on horizontal surface model	82.28	52.73	0.8949

The vertical lines in the first five columns (Fig. 12) indicate the current data inputs for local time, Julian day, air temperature, relative humidity and relative sunshine duration to be 11.5, 274, 20.7, 59.9 and 0.495, respectively. The bottom plot in the right column represents the aggregate of each consequent. Whereas, the defuzzified output value was represented by a thick line passing through the aggregate fuzzy set. For system inputs of local time of 11.5, JD of 207, AT of 20.7, RH of 59.9 and SH of 0.495, the defuzzified output (solar radiation) was shown to be 635 W/m^2 (Fig. 12).

4. CONCLUSION

In this research work, the adaptive neuro-fuzzy inference system (ANFIS) was applied to estimate the hourly horizontal total solar radiation. The inputs were local time, Julian day, air temperature, relative humidity and relative sunshine duration. Basically, the prediction of total solar radiation based upon meteorological parameters offers advantages. One of these advantages that the inputs can be measured directly by simple tools. Furthermore, there is no need to any pre-calculation analysis. The predictions accuracy of the developed ANFIS model was evaluated using different statistical indicators such as MAE, RMSE and R^2. The results demonstrated that ANFIS would be an efficient technique to provide the highly accurate predictions of hourly horizontal total solar radiation using the selected inputs. The developed ANFIS model in this study had several intrinsic worth including the simplicity, easy usage as well as high accuracy. As a result, the suggested ANFIS model would play a notable role in various solar energy applications particularly in isolated areas with no access to specific meteorological elements.

COMPETING INTERESTS

Authors have declared that no competing interests exist.

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