ANFIS based Prediction of Monthly Average Global Solar Radiation over Bhubaneswar (State of Odisha)

Sthitapragyan Mohanty

Research Scholar, Department of Computer Science & Engineering, CET Bhubaneswar

Email-msthitapragyan@gmail.com

Abstract -- **The paper presents an adaptive neuro-fuzzy inference system (ANFIS) based modeling approach to predict the monthly global solar radiation (MGSR) in Bhubaneswar. Comparisons of the predicted and measured value of monthly global solar radiation (GSR) on a horizontal surface are presented. The input parameters of the model used in this paper are sunshine duration, temperature, humidity, clearness index and the Global solar radiation is taken as the output. An adaptive neuro-fuzzy inference system based modeling is used to predict the monthly Global solar radiation for Bhubaneswar for five years 2000-2004.The solar radiation data for forty months are used for training the ANFIS and the data for twelve months is used for testing. The purpose of the study is to compare the accuracy of ANFIS with the measured value Calculated by using Angstrom's equation and some intelligent techniques (Neural Network & SVM)**

Index Terms-- **Global Solar radiation, Sunshine duration, ANFIS**

I. INTRODUCTION

Among all Renewable energy sources, solar radiation is considered as the most important parameter in the design and evaluation of solar energy devices. Many developing nations solar radiation measurements data are not easily available.

Therefore it is important to elaborate methods to estimate the solar radiation on the basis of meteorological data. Global solar radiation (H_G) is the most important component of solar radiation since it gives the total solar availability at a given place. Global radiation is measured only at a few locations due to the high cost involved in the purchase of various equipments and maintenance thereof**.** The amount of solar radiation potential in the particular location is important for solar energy system design such as stand-alone PV and hybrid systems. Global solar radiation data is taken as the most important factor for sizing of PV system. The total solar radiation received at any points on earth of the PV panel in the form of direct and diffuse radiation.

Diffuse solar radiation is not observed experimentally in any meteorological station. For this some climatological parameters are needed to develop and estimate the global &diffuse solar radiation. To estimate the amount of solar energy incident on a horizontal surface, many models were developed to relate the global solar radiation (H_G) with various parameters such as relative humidity, sunshine duration, temperature, latitude, longitude etc.**M**any models have been proposed to predict the amount of solar radiation in some cities using various meteorological / climatologically parameter [1-6].

Application of Neuro -Fuzzy Techniques for Solar Radiation W.A. Rahoma , U Ali Rahama and A.H Hassan Journal of Computer Science ,7 (10): 1605-1611, 2011 ANFIS neuro-fuzzy system was discussed as because it combines fuzzy logic and neural network techniques to gain more efficiency. The structure of the TS fuzzy model [10] is identified using a method which permits to determine the optimal structure on automatic manner. Hargreaves et al.'s Model [8, 9, and 15]. Hargreaves et al. were the first to propose a procedure to estimate the global solar radiation by using the difference between daily maximum and daily minimum air temperature and extraterrestrial radiation. A clear review of ANN applications for renewable energy systems has been reported by Kalogirous [18, 19] and Mellit et al. [20] for photovoltaic systems. M. Rizwan, M. jamil and D. P. Kothari [21] used GNN, a modified approach of artificial neural network (ANN), is proposed to estimate solar energy to overcome the problems of ANN such as a large number of neurons and layers required for complex function approximation . Benghanem & A.Mellit[22] used four RBF models for predicting the DGSR using meteorological data at AI-madinah(Saudi Arabia).

In this present work we applied the Takagi-Sugeno fuzzy systems for modelling the daily solar radiation data [26-27]. The Anfis model is used to estimate the global solar radiation at Bhubaneswar with availalable climatic parameters of sunshine hour, temperature, humidity and compare the result with the measured value calculated by using Angstrom equation and neural network.

2. METHODOLOGY:-

2.1**. Data collection:**

The meteorological parameter sunshine duration measured by Bhubaneswar from 2000 to 2004, were applied for predicting monthly GSR using different Neuro-

Fuzzy techniques. Here we have applied the data of 40 months for training and the data of 12 months for testing.

2.2. Anfis Model:-

The main objective of this work is to predict the Global solar radiation by using attributes such as temperature, relative humidity, sunshine duration, clearness index by using ANFIS model and compare with other models.

.   The basic structure of a FIS consists of three conceptual components: a rule base, which contains a selection of fuzzy rules; a database, which defines the membership functions (MF) used in the fuzzy rules; and a reasoning mechanism, which performs the inference procedure upon the rules to derive an output. The ANFIS uses a hybrid-learning rule combining back-propagation, gradient-descent, and a least-squares algorithm to identify and optimize the Sugeno system's parameters.

As it is difficult to mathematically define the relationship among different climatological parameters used for prediction of global solar radiation. ANFIS can be used to map nonlinear relationship for prediction of output (Jang 1991; 1993). ANFIS neuro-fuzzy system was considered, as it combines fuzzy logic and neural network techniques that are used to gain more efficiency. A neural network can learn from both the data and feedback without understanding the pattern involved in the data. But, the fuzzy logic models are easy to compare the pattern because they use linguistic terms in the form of IF-THEN rules. A neural network with their learning capabilities can be used to learn the fuzzy decision rules; thus creating a hybrid intelligent system.

A fuzzy inference system consists of three components. These are (a) rule base, contains a selection of fuzzy rules. (b) data base, defines the membership functions used in the rules and, (c) reasoning mechanism, to carry out the inference procedure on the rules and given facts. This combination merges the advantages of fuzzy system and a neural network. Jang (1991) proposed a combination of a neural network and fuzzy logic popularly known as called an adaptive neuro-fuzzy inference system.

ANFIS Architecture:-

A typical adaptive network shown in Figure 1 is a network structure consisting of a number of nodes connected through directional links. Each node is characterized by a node function with fixed or adjustable parameters. Learning or training phase of a neural network is a process to determine parameter values to sufficiently fit the training data. The basic learning rule method is the back propagation method, which seeks to minimize some error, usually sum of squared differences between network's outputs and desired outputs. Generally, the model performance is checked by the means of distinct test data, and relatively good fitting is expected in the testing phase. Considering a first order (Takagi and Sugeno,

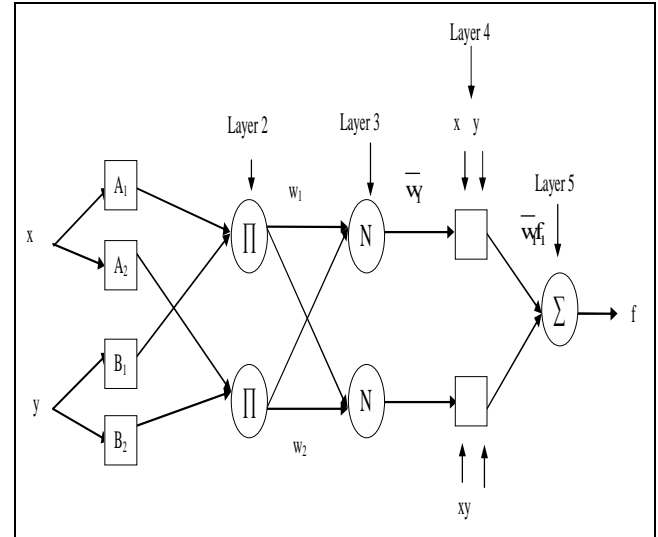1985; Sugeno and Kang, 1988) fuzzy interface system, a fuzzy model consists of two rules.

Fig 1-ANFIS Architecture

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)

If f_1 and f_2 are constants instead of linear equations, we have zero order TSK fuzzy-model. Node functions in the same layer are of the same function family as described below. It is to be noted that O_i^j denotes the output of the ith node in layer j.

Layer 1: Each node in this layer generates a membership grade of a linguistic label. For instance, the node function of the ith node might be

$$O_i^j = \mu A_i(x) = \frac{1}{1+\left[\left(\frac{x-c_i}{a_i}\right)^2\right]^{b_i}}$$

(3)

where x is the input to the node I, and A_i is the linguistic label (small, large) associated with this node; and $\{a_i, b_i, c_i\}$ is the parameter set that changes the shapes of the membership function. Parameters in this layer are referred to as the "Premise Parameters".

Layer 2: Each node in this layer calculates the firing strength of each rule via multiplication:

$$O_i^2 = w_i = \mu A_i(x) \times \mu B_i(y), \ i=1,2 \quad (4)$$

Layer 3: The ith node of this layer calculates the ratio of the ith rule's firing strength to the sum of all rule's firing strengths:

$$O_i^3 = \overline{w_i} = \frac{w_i}{w_1+w_2}, \ i=1,2 \quad (5)$$

For convenience outputs of this layer will be called normalized firing strengths.

Layer 4: Every node i in this layer is a squared node with a node function

$$O_i^4 = \overline{w_i} f_i = \overline{w_i}(p_i + q_i y + r_i) \qquad (6)$$

where, W is the output of layer 3, and is the parameter set. Parameters in this layer will be referred as "Consequent Parameters ".

Layer 5: The single circle node computes the overall output as the summation of all incoming signals i.e.

$$O_i^5 = \text{Overall output} = \sum_i^n \overline{w_i} f_i = \frac{\sum_i w_i f_i}{\sum_i w_i} \qquad (7)$$

Thus, an adaptive network is presented in Figure 2 is functionally equivalent to a fuzzy interface system. The basic learning rule of ANFIS is the back propagation gradient decent which calculates error signals (defined as the derivative of the squared error with respect to each nodes output) recursively from the output layer backward to the input nodes. This learning rule is exactly the same as the beck-propagation learning rule used in the common feed-forward neural networks by Jang (1993). From ANFIS architecture (Figure 1), it is observed that the given values of the of premise parameters, the overall output can be expressed as a linear combination of the consequent parameters. Based on this observation, a hybrid learning rule is employed here, which combines a gradient decent and the least squares method to find a feasible of antecedent and consequent parameters. The details of the hybrid rule are given by Jang (1993) where it is also claimed to be significantly faster than the classical back propagation method.

From the ANFIS architecture shown in Figure 1, we observe that when the values of the premise parameters are fixed and the overall output can be expressed as a linear combination. The output f can be rewritten as:

$$f = \frac{w_1}{w_1 + w_2} f_2 + \frac{w_1}{w_1 + w_2} f_2 = \overline{w} f_1 + \overline{w} f_2$$

$$= (\overline{w}x)p_1 + (\overline{w}y)q_1 + (\overline{w_1})r_1 + (\overline{w_2}x)p_2 + (\overline{w_2}y)q_2 + (\overline{w_2})r_2 \qquad (8)$$

which is linear in the consequent parameters p_1, q_1, r_1, p_2, q_2, r_2. Therefore, the hybrid learning algorithm developed can be applied directly. More specifically, in the forward pass of the hybrid learning algorithm, node outputs go forward until layer 4 and the consequent parameters are identified by the least squares method. In the backward pass, the error signal propagates backward and the premise parameters are updated by gradient descent.

Accordingly, the hybrid approach converges much faster since it reduces the dimension of the search space of the original back-propagation method. For this network created fixes the membership functions and adapt only the consequent part; then ANFIS can be viewed as a functional-linked network where the enhanced representation, which take advantage of human knowledge and express more insight. By fine-tuning the membership functions, we actually make this enhanced representation.
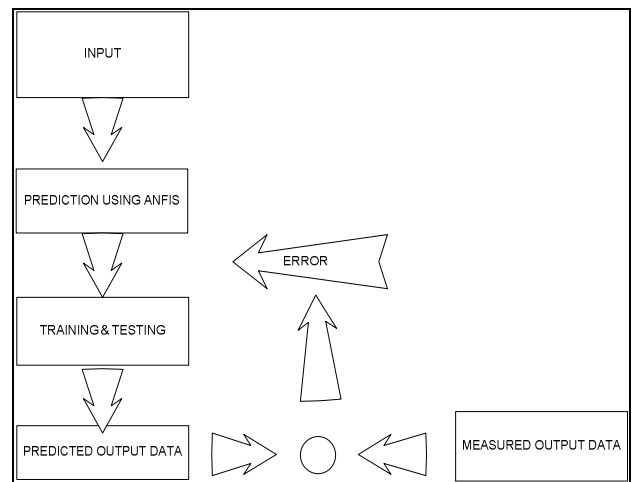
Prediction Model:-

Fig 2 -ANFIS prediction Model

The data set is available from the A renewable energy resource laboratory,NASA .A complete data set of five years of data (2000-2004) are used for prediction of global solar radiation by using different Meteorological parameters. A total of sixty months (2000-2004) datasets are used in ANFIS model. Forty months are considered as training and twenty months are considered under testing. During training, a five layered ANFIS structure is constructed having one input, three hidden and one output. The Gaussian type of membership function (gaussmf) is used for input and linear type function is used for output. The number of correct outputs is noted till the error is minimized

3. RESULT AND DISCUSSION:-

To design and develop an ANFIS model in MATLAB 12.0 software version is used in this study. The proposed ANFIS network has adapted the training data groups to form best membership function so as to deduce the desired output for testing data with minimum epochs.
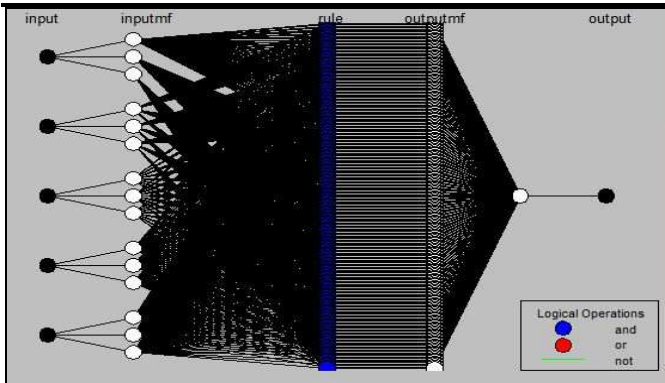
Figure3. ANFIS model structure for proposed work

The ANFIS architecture for proposed model is shown in Figure 3. Input membership function is described with Gaussian membership function. Hybrid learning algorithm is used and ANFIS model is run till the error is minimized. Error is minimized in two epochs during training. Then, testing of data is carried out.
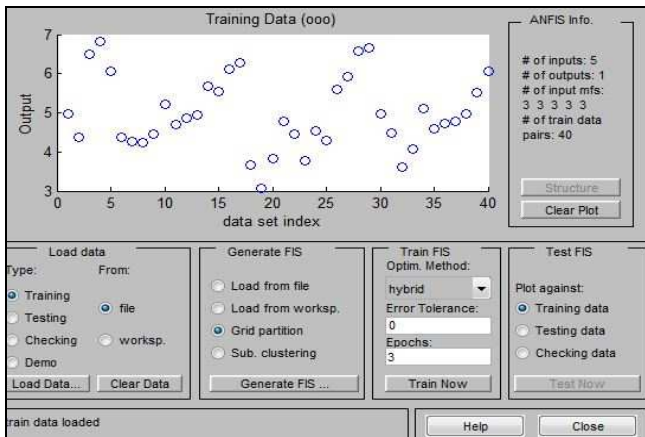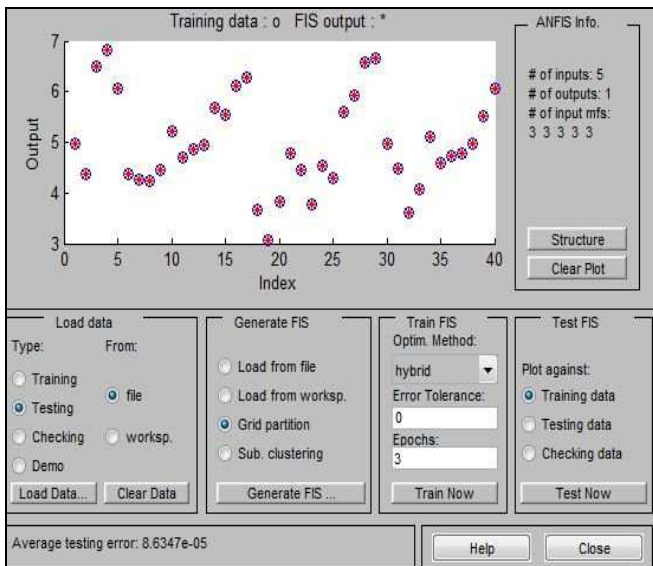

Figurer4.Training data for proposed work

Figure5.Distribution of predicted and actual response during testing the proposed work

The pattern of variation of actual and predicted response is shown for training and testing dataset for proposed model Figures 4 and 5 show that actual (blue dot) and predicted (red dot) values are uniformly distributed respectively for training and testing data
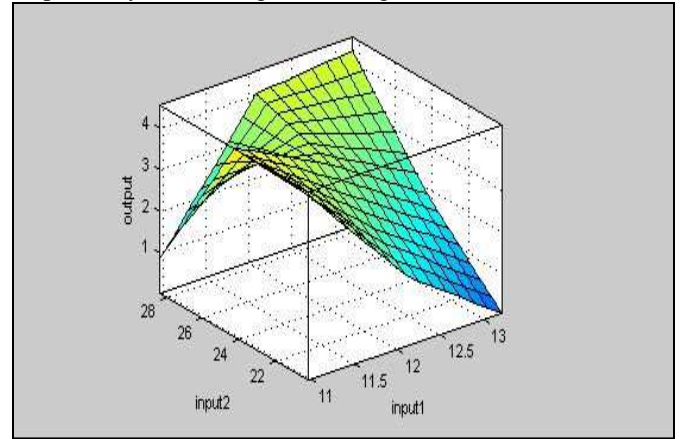

Figure6. Surface plot for the proposed work

The surface plot shown in Figure 6 indicates that the total landscape of decision space is covered by the ANFIS model for proposed model. The residual analysis is carried out for the predicted values of the model by calculating the difference of actual and predicted values for training and testing data. It is observed that the residuals are distributed uniformly along the center line. The absolute percentage relative error in training phase is 0.000574and in testing phase 0.485126.

Table -1

month	Measured	prediction using nn	prediction using anfis	prediction using SVM
jan	0.799364	1.118864	0.7994	0.596619
feb	0.173063	0.498763	0.1731	0.273063
mar	0.494893	0.494893368	0.4949	0.511357
apr	0.211091	0.211090636	0.2111	0.30837
may	0.1	0.6463	0.1	0.264449
jun	0.9	1.1477	0.9	0.600349
jul	0.100851	0.100850894	0.1009	0.231094
aug	0.527772	0.527771897	0.5278	0.427772
sep	0.175781	0.175781346	0.1758	0.253708
oct	0.5983	0.5983	0.5983	0.335363
Nov	0.4616	0.4616	0.4616	0.52927
Dec	0.1119	0.1119	0.1119	0.299211

Estimated monthly global solar radiation in comparison
With measured data for Bhubaneswar from 2000-2004
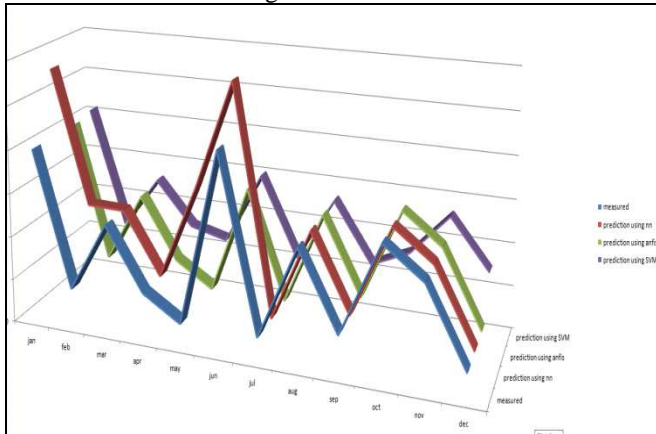Using different model

Fig 7.Measured & predicted values of different model

4. CONCLUSIONS:

The proposed ANFIS model has successfully predicted the global solar radiation for various domains and it becomes suitable for any design of Isolated solar energy conversion application. The ANFIS model shows better results in comparision with other models . The evaluation results of solar radiation shows a significant improvement in statistical parameters and depicts better accuracy than other models. The comparative results demonstrate the predicting capability of ANFIS model and its compatibility for any region with varying climatic conditions. This prediction of solar radiation makes it suitable for installation of a monitoring station for a remote place and it can be extended for the sizing of standalone PV systems in future.

REFERENCES

[1]. Mellit A , Kalogirou SA."Artificial intelligence techniques for photovoltaic applications": *a review. prog Energy comb sci* 2008; 34:574-632.

[2]. J. P. Duffie and W. A. Beckman, "Solar Engineering of Thermal Process", *John Wiley & Sons*, New York, NY, USA, 1991.

[3]. M. Iqbal, "an Introduction to Solar Radiation", *Academic Press*, Toronto, Canada, 1983.

[4]. International Energy Agency (IEA), "Validation of models for estimating solar radiation on horizontal surfaces," *Atmosphere & Environment service*, Canada, 1988.

[5]. J. A. Prescott, "Evaporation from a water surface in relation to solar radiation," *Philosophical Transactions of the Royal Society*, vol. 64, pp. 114–120, 1990.

[6]. Angstrom A. "solar and terrestrial radiation "*J R Meteorolog Soc* 1924; 50(210); 121-5.

[7]. Prescott JA. "Evaporation from a water surface in relation to solar radiation".*Trans R Soc* Aug 1940; 64:114-25.

[8]. Mellit A, Benghanem M, Salhi H. "An Adaptive Artificial Neural Network for Modelling and Simulation of a Stand-Alone Photovoltaic Power System". *In: Proceedings of the 3th conference on systems, signals, and devices*. IEEE 2005; 4:257.

[9]. Mellit A, Benghanem M. "Modelling and simulation of stand-alone power system using artificial neural network". *Solar world congress*. ISES/ASES 2005.

[10].R. Iqdour† and A. Zeroual," A rule based fuzzy model for the prediction of solar radiation "*Revue des Energies Renouvelables* Vol. 9 (2) 2006 113 – 120.

[11]. Farzad Fathian BEPLS, "Predicting Global Solar Radiation using Genetic Algorithm",(*GA*) Vol. 2 (6) May 2013: 54- 63

[12].E.O. Falayi, J.O. Adepitan, and A.B. Rabiu, "Empirical Models for the Correlation of Global Solar Radiation with Meteorological Data for Iseyin", *Nigeria*, Vol. 9.(2). Nov 2008

[13].V Sivamadhavi1*, and* R Samuel Selvaraj2, **"**Prediction of monthly mean daily global solar Radiation using Artificial Neural Network". *Earth Syst. Sci.* **121**. (6). Dec 2012, pp. 1501–1510

[14]. J. O. Ojosu and L. K. Komolafe, "Models for estimating solar radiation availability in South Western Nigeria," *Solar Energy, vol*. 16, pp. 69–77, 1987.

[15].G. H .Hargreaves and Z. A. Samani, "Reference crop evapotran spiration from temperature," *Transactions of the ASAE*, vol. 1, pp.96–99, 1985.

[16].Reddy K. "Solar resource estimation using artificial neural networks and comparison with other correlation models". *Energy Conversion and Management 2003*; 44(15):2519e30.

[17].Jiang Y. "Computation of monthly mean daily global solar radiation in China using artificial neural networks and comparison with other empirical models". *Energy* 2009; 34(9):1276e83.

[18].Kalogerirou SA. "Artificial neural networks in renewable energy systems applications": a review. *Renewable and Sustainable Energy Reviews* 2001; 5: 373e401.

[19].Kalogirou SA. "Applications of artificial neural networks for energy systems". *Applied Energy* 2000; 67:17e35.

[20].Mellit A, Kalogirou S. "Artificial intelligence techniques for photovoltaic applications": a review. *Progress in Energy and Combustion Science* 2008; 34(5):574e632.

[21].M.Rizwan, M.jamil and D.P.Kothari,"Generalized Neural Network Approach for Global solar energy estimation in India,"*IEEE Transactions on Sustainable Energy*, vol.3 (3), July 2012.

[22].Benghanem M & Mellit. A, "Radial basis function network-based prediction of Global solar radiation data: application for sizing of a stand-alone photovoltaic system AI-Madinah", *Saudi Arabia, Energy* 2010; 35:3751-62.

[23].Dorvio ASS, Jervase, AI-lawati A, "Solar radiation estimation using artificial neural networks". *APPL energy* 2002; 74:307-19.

[24]. M. Jamil Ahmad and G.N. Tiwari**, "Study** of Models for Predicting the Mean Hourly Global Radiation from Daily Summations", *Open Environmental Sciences*, 2008, 2, 6-14.

[25].paul A.Lynn ,"Electricity from sunlight: an introduction to photovoltaics .United kingdom " :*john Wiley & Sons, Ltd*, 2010.

[26].R. Iqdour and A. Zeroual, '*Modelling Daily Global Solar Radiation Using Fuzzy Systems*', International Conference on Modelling & Simulation - ICMS'04, Valladolid, Spain, 2004.

[27].R. Iqdour and A. Zeroual, '*Modelling Solar Data Using the Takagi-Sugeno Fuzzy Systems*', International Conference on Modelling & Simulation - MS'04, Lyon, France, 2004.