ANFIS Technique to Estimate Daily Global Solar Radiation by Day in Southern Algeria

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Abstract. In this paper, the performance and accuracy of the adaptive neuro-fuzzy inference system (ANFIS) technique is assessed for estimating the daily horizontal global solar radiation H in South Algeria. 21 years of experimental data for three cities in South Algeria Adrar, Timimoun and Bordj Badji Mokhtar (BBM) were used to train and test the ANFIS model. The results verified that the ANFIS model provides accurate predictions based on statistical formulas such as: the root mean square error (RMSE), mean absolute percentage error (MAPE and the coefficient of determination (R). In a nutshell, the results highly encouraged the implementation of ANFIS to estimate the daily horizontal global solar radiation using only the number of the day of years n_d.

Keywords: Radiation · Daily global · ANFIS · Solar · Adrar · Timimoun · Bordj Badji Mokhtar

1 Introduction

Currently, Algeria has an intention for utilizing further alternative energy resources due to different economic reasons and more importantly other environmental protection goals. Solar radiation is considered as the most important renewable energy sources in the world [1]. Algeria South has a greatly advantageous from geographic position viewpoint; which is characterized by a large global sun-belt and important solar radiation. Estimation of the solar radiation using ANFIS is one of such the adopted techniques for Assessment solar energy at the interest site. The barriers in the measurement of solar radiation have resulted in the evolution of so many models and algorithms for its estimation from some routinely measured meteorological parameters such as; sunshine hour, minimum, maximum and average air temperatures, relative humidity, and cloud factor [2]. According to that, many empirical models for prediction

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and estimating daily global solar radiation has been developed [3, 4]. In the last years, Artificial intelligence is an alternative to the old statistical methods, which have the ability to track complicated dependencies between different variables, where conventional methods have their limits [6]. Among the best techniques is the Adaptive Neuro-Fuzzy Inference System (ANFIS). It is a hybrid smart system that merges methodologies of the learning power of the artificial neural networks with the knowledge representation of fuzzy logic [5]. Computationally adaptability and efficiency are the most two main advantages of the ANFIS [8], which can be used as a tool for estimating solar radiation data [9]. Mellit et al. [6] used ANFIS for predicting the global solar radiation based on sunshine duration and air temperature in Algeria. Tymvios et al. [7] proposed a comparative study between the Angstrom-Prescott models and artificial neural network (ANN) in Athalassa for estimating daily global solar radiation. In Cyprus. They utilized the parameters of maximum possible sunshine hours, sunshine hours, the number of months and maximum air temperature and they developed five different ANN models; two models with 2 inputs and three models with 3 inputs. Benghanem et al. [8] developed six ANN-based models to estimate daily global solar radiation in Saudi Arabia. They used different combinations of the input variable of day number of the year, sunshine hours, relative humidity and ambient temperature. Their results demonstrated that the most significant element is the sunshine duration. Mohammadi et al. [9] developed a hybrid approach, which included generalized fuzzy models and hidden Markov models, to estimate solar irradiation in India. They considered 15 different sets of meteorological variables to assess their influence on solar radiation estimation. Their results displayed that the most appropriate model was dependent on sunshine duration. Other parameters such as air temperature, relative humidity, atmospheric pressure and wind speed were ranked in the next places. Mohammadi et al. [10] employed the adaptive neuro-fuzzy inference system (ANFIS) to chosen the most significant input parameters for estimation of daily H_d in Iran. In this study, an used of adaptive neuro-fuzzy inferences system (ANFIS) is suggested to develop a program computing-based model for estimation of daily global solar radiation by day of the year. The prime aim is evaluating the sufficiency of the ANFIS scheme to provide a convenient way for accurately predicting the daily global solar radiation using only one simple input. The potential of developed ANFIS model is verified by providing statistical comparisons between its estimation with those of three DYB models established by Aouna and Bouchouicha [11].

2 Data and Methodology

2.1 Study Area

Algeria is the big largest country in Africa with a total area of 2,381.741 km^2 of which 87″ are desert. Algeria extends between the longitudes 9° W and 12° E and the latitudes 19° and 37° N, as shown in Fig. 1. Figure 1 shows the location of the three selected cities, the Algeria frontier.

The National Aeronautical and Space Administration (NASA) is considered as one of the best important data sources through its earth science research program [13].

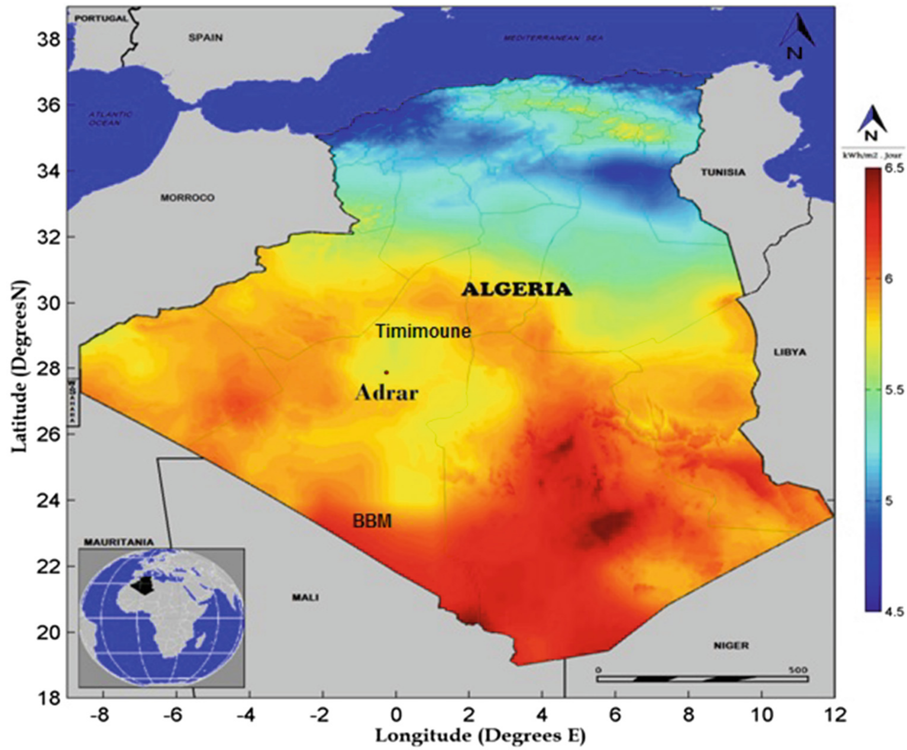

Fig. 1. The Annual average of the daily GHI (1983–2005) [12]

NASA has long supported both satellite systems and research providing data that is important for the study of weather and climate processes [14]. This data includes a large archive of over 200 satellite-derived meteorology and solar energy parameters for more than 21 years, from 1 July, 1983 to 30 June, 2005. The data is available on a 1° longitude by 1° latitude equal-angle grid covering the entire glob. Bouchouicha et al. [12] are validated the NASA-SSE solar data against historical ground measurements made in four Algerian National Office of Meteorology stations (Algiers, Tamanrasset, Oran, and Bechar) for over 10 years and another two radiometric stations (Adrar and Ghardaia) for more than 18 years. Regression analysis of this data with the monthly mean values of global solar irradiation shows a relative root mean square error of 12.4% and a relative mean bias error of (−4.6%). These results indicate that NASA's solar radiation data is acceptable for the development of the empirical models. 50% of the collected data were used for training and the subsequent 50% served for testing.

The geographical locations (latitude, longitude, elevation) for each of the three selected cities are showed in Table 1.

Table 1. Geographical locations of the selected cities

N	Location	Latitude	Longitude	Elevation (m)
1	Adrar	27.88	−0.28	263
2	Timimoun	29.25	0.28	312
3	BBM	21.33	0.95	398

2.2 Aadaptive Neuro-Fuzzy Inference System (ANFIS)

The fuzzy system under consideration in ANFIS is the first order Sugeno type fuzzy model [15]. A common rule set with two fuzzy if-then rules is the following:

$$\text{Rule 1 : If } x \text{ is } A1 \text{ and } y \text{ is } B1, \text{then} f_1 = c_{11}x + c_{12}y + c_{10} \tag{1}$$

$$\text{Rule 2 : If } x \text{ is } A2 \text{ and } y \text{ is } B2, \text{then} f_2 = c_{21}x + c_{22}y + c_{20} \tag{2}$$

The Sugeno Model could also be represented in a different but equivalent way as shown in Fig. 3. The architecture of it is summarized below [5]:

Layer 1. Every node i in this layer is a square node with a node function

$$O_{l,i} = \mu_{A,i}(x), \text{ for i} = 1, 2 \tag{3}$$

Where $\mu_{A,i}(x)$, is the membership function of the fuzzy concept A_i. The usual choice of the membership function is of bell-shaped with maximum equal to 1 and minimum equal to 0, such as the generalized bell function or the Gaussian function

$$\mu_{A,i}(x) = \frac{1}{1 + \left[\left(\frac{x-c_i}{a}\right)^2\right]^{b_i}} \tag{4}$$

$$\mu_{A,i}(x) = exp\left[-\left(\frac{x - c_i}{a}\right)^2\right] \tag{5}$$

Where {a_i, b_i, ci} (or {a_i, c_i} in the latter case) is called the premise parameter set. The generalized bell function type is chosen for the present application.

Layer 2. Every node in this layer is a circle node labeled π which multiplies the incoming signals and sends the product out [16, 17]. For example,

$$\bar{w}_i = \mu_{A,i}(x) \times \mu_{B,i}(x) \; i = 1, 2 \tag{6}$$

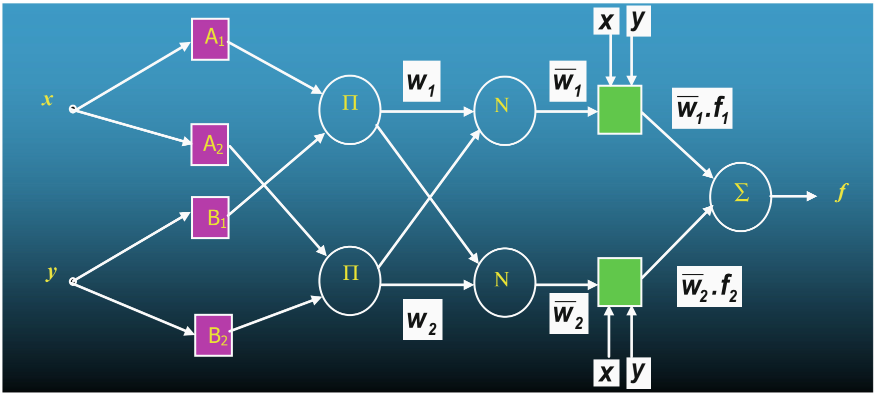

Fig. 2. ANFIS structure with two inputs

Layer 3. Every node in this layer is a circle node labeled N. The i^{th} node calculates the ratio of the i^{th} rule's firing strength to the sum of all rules' firing strengths (Fig. 2):

$$\bar{w}_i = \frac{w_i}{w_1 + w_2} \quad i = 1, 2. \tag{7}$$

Layer 4. Every node i in this layer is a square node with a node function

$$o_1^4 = \bar{w}_i f_i = \bar{w}_i (p_i x + q_i y + r_i). \tag{8}$$

Where $\bar{w}_i$ is the output of layer 3 and $\{p_i, q_i, r_i\}$ is called the consequent parameter set.

Layer 5. The single node in this layer is a circle node labeled Σ. It computes the overall output as the summation of all incoming signals [18], i.e.

$$o_1^5 = \sum\nolimits_i \bar{w}_i f_i \tag{9}$$

$$f_i = (\bar{w}_1 x)p_1 + (\bar{w}_1 y)q_1 + (\bar{w}_1)r_1 + (\bar{w}_2 x)p_2 + (\bar{w}_2 y)q_2 + (\bar{w}_2)r_2 \tag{10}$$

The learning method of ANFIS is a hybrid learning algorithm which consists of two passes, namely the forward pass and the backward pass. In the forward pass (the first pass), the premise parameters will be fixed and the consequent parameters are identified by the least square estimate. In the backward pass (the second pass), the consequent parameters will be fixed and the premise parameters will be updated by the gradient descent which is a supervised learning [19].

Table 2. The established DYB empirical models for Adrar, Timimoun and BBM [11]

N	Equation	Location
1	$H = 3.2847 + 267.86n_d + 2.67E - 4n_d^2 - 2.08\text{E} - 6n_d^3 + 3.14\text{E} - 9n_d^4$	Adrar
2	$H = 3.2950 + 2.66\sin\left(\frac{1.668\pi}{365}n_d - 0.8598\right) - 0.25cos\left(\frac{5.22\pi}{365}n_d - 1.127\right)$	Timimoun
3	$H = 6.17 + 1.907\sin\left(\frac{2.15\pi}{365}n_d - 1.558\right) - 0.7041cos\left(\frac{3.535\pi}{365}n_d + 0.8983\right)$	BBM

2.3 Statistical Error Analysis of Model ANFIS

The performance of the selected models are analyzed and evaluated with three statistical parameters. These are root mean square error (RMSE), mean absolute percentage error (MAPE) and coefficient of determination (R) test indicators. The mathematical formulae of the two statistical parameters are described below [20]:

$$RMSE = \left\lfloor \frac{1}{N}\sum\nolimits_{i=1}^{N}\left(\bar{H}_{i,c} - \bar{H}_{i,m}\right)^2 \right\rfloor^{\frac{1}{2}} \tag{11}$$

$$MAPE = \frac{1}{N}\sum\nolimits_{i=1}^{N}\left|\frac{\bar{H}_{i,m} - \bar{H}_{i,c}}{\bar{H}_{i,m}}\right| \times 100 \tag{12}$$

$$R = \frac{\sum_{i=1}^{N}\left(\bar{H}_{i,c} - \bar{\mathrm{H}}_{c,av}\right).\left(\bar{H}_{i,m} - \bar{\mathrm{H}}_{m,av}\right)}{\sqrt{\sum_{i=1}^{N}\left(\bar{\mathrm{H}}_{i,m} - \bar{\mathrm{H}}_{m,av}\right)^2 \cdot \sum_{i=1}^{N}\left(\bar{\mathrm{H}}_{i,c} - \bar{\mathrm{H}}_{c,av}\right)^2}} \tag{13}$$

Where N is the total number of available data points, $H_{m,av}$, $H_{c,av}$ are the average of measured and estimated values of solar radiation (KWh/m^2) and $H_{i,c}$, $H_{i,m}$ are i^{th} estimated and measured daily global solar radiation (KWh/m^2) respectively.

Table 3. Statistical indicators obtained for the established DYB models for Adrar, Timimoun and BBM [11]

Model number	MAPE	RMSE (KWh/m^2)	R	Location
1	3.2034	0.2391	0.9892	Adrar
2	2.8499	0.2108	0.9924	Timimoun
3	2.6647	0.1998	0.9877	BBM

3 Results and Discussion

In this study, the potential of ANFIS technique to estimate the daily horizontal global solar radiation by day of the year as a single input 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 DYB empirical models. Following offers the most significant results obtained in this research work. Figures 3, 4 and 5 show the scatter plots between the measured and computed global solar radiation values via the developed ANFIS model for Adrar, timmimoun and BBM respectively. At the beginning, the ANFIS networks were trained with the long-term averaged measured data. Three bell-shaped membership Functions were used to fuzzily the ANFIS input. Various types of membership function and also number of membership function were tested to recognize the most favorable type and number of membership functions. After training process the ANFIS networks were tested to calculate the daily horizontal global solar radiation (H) based on days of the year (n_d). Long-term measured daily global solar radiation (H) as the output parameter and the number of days (n_d) as the input parameter were collected and defined for the learning techniques. For this aim, one year averaged global radiation data achieved from the period of 10 years from January 1985 to December 1994 was used to train the samples and the one year averaged daily data set obtained from the remaining period of January 1995 to December 2004 was served to test the samples.

Table 4. Performance of the proposed ANFIS model based upon different statistical indicators

Location	Phase	MAPE	RMSE (KWh/m^2)	R
Adrar	Training	2.7593	0.2011	0.99558
	Testing	2.9584	0.2051	0.99396
Timimoun	Training	2.0879	0.1904	0.99341
	Testing	2.3478	0.1932	0.99301
BBM	Training	2.1493	0.1795	0.98993
	Testing	2.3986	0.1803	0.98983

The superiority of the developed ANFIS model can be justified by providing some comparisons with DYB empirical models. To achieve this, the performance of the ANFIS-based model is verified against the DYB empirical models previously established by Aouna and Bouchouicha [11] for Adrar, Timimoun and BBM. Table 2 shows these DYB models established based upon the long-term measured daily data set for three sites. The values RMSE, MAPE and R obtained by the study of Aouna and Bouchouicha [11] to evaluate the performance of three established DYB models are presented in Table 3. Nevertheless, by making a comparison between the statistical results listed in Table 3 with those of Table 4 it is apparently found that the ANFIS model enjoys greater performance compared to calibrated DYB empirical models. Thus, the developed ANFIS model can be introduced as the superior model to estimate the daily horizontal global solar radiation by the day of the year, from the results presented in Table 3 [11] and the obtained in this manuscript, it's clearly obvious that the better in terms of statistical indicators especially for the coefficient of determination (R) which was better compared to the empirical model for the 3 different locations (Adrar, Timmimoun, BBM) and the results for the comparison taken for the testing phase.

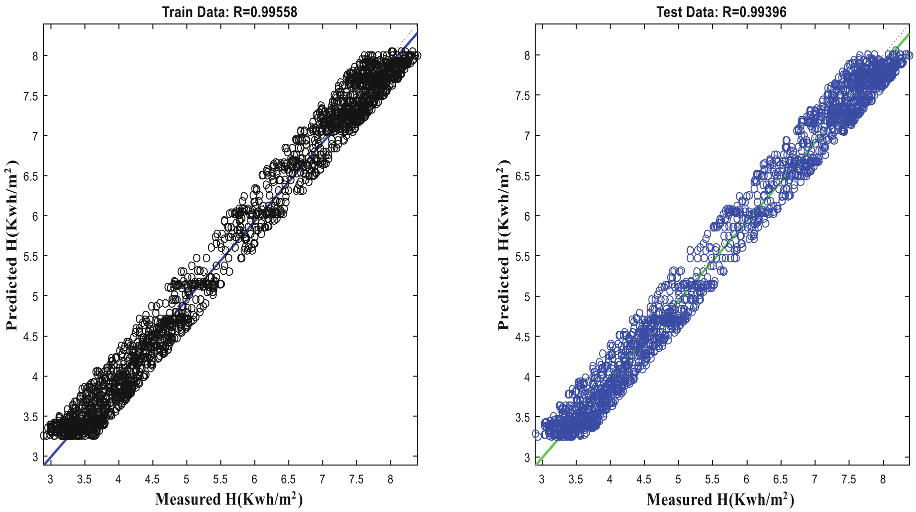

Fig. 3. Scatter plots of the measured data against the predicted daily global solar radiation by ANFIS model for Adrar

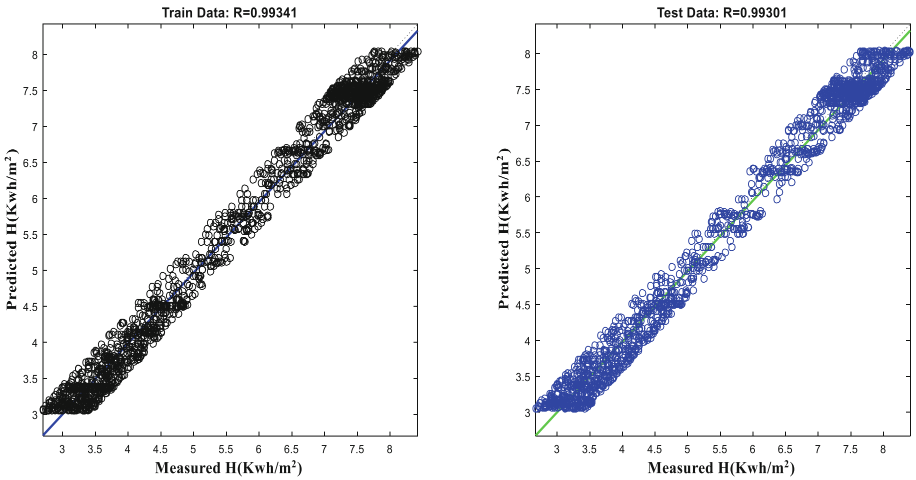

Fig. 4. Scatter plots of the measured data against the predicted daily global solar radiation by ANFIS model for Timimoun

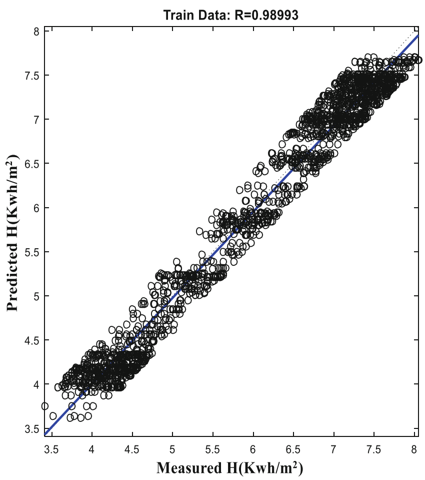

Fig. 5. Scatter plots of the measured data against the predicted daily global solar radiation by ANFIS model for BBM

4 Conclusions

In this work, an adaptive neuro-fuzzy inference system (ANFIS) was utilized to estimate the daily horizontal global solar radiation by day of the year. Basically, the prediction of global solar radiation based upon day of the year offers 2 advantages. First, there is no dependency to any specific input element such as meteorological data. Second, there is no need to any pre-calculation analysis. As a matter of fact, this study aimed at identifying the potential of ANFIS technique to predict the global solar radiation by day of the year. The predictions accuracy of the developed ANFIS model was evaluated using three statistical indicators such RMSE, MAPE and R. Thereafter to validate the adequacy of the developed ANFIS model its performance was compared against the DYB empirical models previously established by Aouna and Bouchouicha [11]. As a conclusion, the utilized ANFIS model can be used to estimate the horizontal global solar radiation with favorable level of reliability and precision. Generally, the developed ANFIS model in this study enjoys a series of merits including the simplicity, easy usage as well as high accuracy. As a result, the suggested ANFIS model would play a notable role in various applications such as designing, simulating and monitoring the solar energy technologies, particularly in isolated areas.

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