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SOFT COMPUTING BASED ON AR-ANFIS AND AR-ANN FOR MODELING AND PREDICTING HALF HOUR GLOBAL SOLAR RADIATION

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ABSTRACT
In this paper, we are interested in the exploration of the possibility to develop models for predicting the half hour global solar radiation. For this purpose, we applied a method which combines the artificial neural networks (ANN) based on the multilayer perceptron (MLP) and the adaptive neuro fuzzy inference system (ANFIS) with an autoregressive process (AR). In this basis, two models called AR-ANN and AR-ANFIS are developed to analyze and predict half hour global solar radiation time series measured during three years in the area of Agdal at Marrakesh, Morocco. To evaluate the performance of the developed models, a comparison with real measurements is achieved. In term of some statistical criteria, the developed models are able to generate half-hour global solar radiation time series with a variance accounting around 97% and an MSE around 0.25%. Consequently they can successfully be an excellent tool for the management of daily global solar radiation in case of lack of measurements in a given region having similar climate as Marrakesh. Deep comparison shows that AR-ANFIS model is slightly more accurate than the AR-ANN model.

Keywords: Adaptive Neuro-Fuzzy Inference System (ANFIS); Artificial Neural Networks (ANN); Autoregressive Process; time series; Global solar Radiation; Prediction.

INTRODUCTION
Renewable energy sources such as solar energy were advocated even before the energy crisis in 1973. Indeed, Solar energy has attracted a great deal of attention because it is not only sustainable, but it is also renewable and this means that we will never run out of it. It has been one of the most studied and researched topics in recent years [1]. Solar energy has many different applications: analysis of the thermal load on building, solar energy collecting systems, atmospheric energy balance studies, ... [2], [3]. The global solar radiation (GSR) data are the most important parameter to know for the solar energy applications [2], [3] for what, the solar radiation data should be measured continuously and accurately over the long-term. Unfortunately, GSR measurements are sparse and inaccurate in the most of the area of the world. Indeed, there is no doubt that the real GSR measurements are the best, but these measurements are not easily available due to the cost of equipment, technical or institutional limitations like maintenance and continuous calibration process [4]-[8].

The high variability and unpredictability of the GSR makes it difficult to manage. But for understanding the behavior and improving the performance of the solar systems, it is essential to know precisely GSR variations at low scale [9]. Indeed, it is inadequate to develop fine, accurate and precise models to describe the solar system output if the input data are approximate. So, an accurate solar radiation prediction is important and can help to optimize the solar system production by reducing additional costs with a setting up of an appropriate strategy [5], [10]

Over the past decades, various empirical and theoretical models have been used to compute the components of the solar radiation [11], [12]. Recently, there has been an interest in modeling, analyzing and estimating solar radiation using soft computing techniques, such as: Artificial Neural Network, Fuzzy-logic, Adaptive-Network-Based Fuzzy Inference System, etc.. Several researchers have used these techniques to predict solar radiation as a function of meteorological data and they have developed many predictive methods around the world. H. citakoglo developed an ANN, ANFIS, and MLR models to estimate solar radiation in turkey on a monthly basis as a function of month number (M), extraterrestrial radiation (Ra), average temperature (Tmean), and average relative humidity (RHmean) using measured data including solar radiation gauged at 163 meteorological stations in Turkey [13]. Z. Ramedani applied radial basis SVR to predict global solar radiation based on some simple meteorological data [14]. H. El Badaoui et all applied the artificial neural networks method based on the multilayer perceptron (MLP) to find the most effective model to predict the average daily global solar radiation in the region of sebt El Guerdane at agadir, Morocco [15]. R. Iqdour et all studied the possibilities and the difficulties in the application of the MLP neural networks for predicting half hour solar radiation data [16].

In this paper, we are interested in applying a method which combines the adaptive neuro-fuzzy inference system and the artificial neural networks techniques with the autoregresive process to analyze half hour global solar radiation times series, gauged at Agdal Marrakesh meteorological station in Morocco.

MATERIALS AND METHODS

Artificial neural network

Artificial neural network (ANN) is considered as one of the most realistic models of the biological brain functions and as an efficient way for solving complex problems [17,18]. Indeed, ANN has been inspired from both the biological nervous system and mathematical theories of learning, information processing and control. ANN was started in 1890 but its application has really become solid in the last fifteen years and it is still developing rapidly. Also, it presents different advantages as the classification ability, examination, simulation and decision-making what gives ANN a wide application in the engineering field, and even in other fields.

Technically artificial neural network is a computing system made up of a number of samples and highly interconnected processing elements, which process information by their dynamic state response to external inputs [19, 20].

Neural networks can provide fundamentally different approaches to material modeling and processing control techniques than numerical or statistical methods [21]. Indeed, ANN has the ability to solve nonlinear complex relations among input variables without the need of any previous assumption about these relations [22]. Garrett said in his interesting engineering definition of the ANN that: "A computational mechanism is able to acquire, compute and represent mapping from one multivariate space of information to another, given a set of data representing that mapping" [23]. Furthermore, artificial neural networks can be used as a black box approach to create models of systems profiting of the facility to model non-linear (as well as linear) phenomena. The high computational rates, robustness and ability to learn of ANNs allow them to identify models of complex systems [24]. Their ability is related to the quality of the signals used for training and the performance of the training algorithms and their parameters do not contain information that can be directly understood by the human operator or that can easily be related to the physical properties of the system to be modeled [25].

ANN is divided in three layers, interconnected by weighted connection lines, input Pi, middle Wi (hidden) and an output a (Fig. 1). Each neuron of an individual layer is connected with each neuron of the next layer, giving rise to a large number of connections [26]. Firstly, ANN model must be trained by using cases with known outcomes and then it will adjust its weighting of various input variables over time to refine output data [27]. In the literature, various architectures of neural systems are studied. Feed forward, recurrent neural network, Gaussian radial basis function neural networks and dynamic neural networks constitute typical structurally different approaches [28]. Among the various NN-based models, the most popular and commonly used is the feed forward neural network, which is known as the Multi Layer Perceptron (MLP) type neural network. It has been applied to solve many difficult and diverse problems such as the prediction, the simulation, the control and the decision making that has helped to use them in the engineering field [29-33]. In this work, we use the back-propagation based Multi-Layer Perceptron neural networks as it will be presented in the following section.

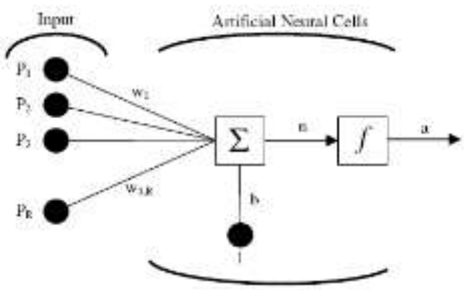

Figure 1: Neural network model

Where, the neuron has a biais b. To form the net input n, the biais is summed with the weighted inputs.

Two types of stages are required to identify the MLP neural networks. The first stage is the network structure determination. Different networks with one hidden layer have been tried and the activation function used in this case is the sigmoid function defined as:

$$f(x) = \frac{1}{1+e^{-x}} \qquad (1)$$

The second stage is the identification of parameters, which represents the learning phase of the neural networks. In this study, we use the most commonly optimization algorithm of Levenberg Marquardt (LM) to adjust the parameters of the MLP neural networks. It is an iterative technique that locates the minimum of a multivariant function that is expressed as the sum of squares of non-linear real valued functions [34-36]. The LM is the first algorithm exposed to combine the steepest gradient descent and Gauss-Newton iterations. It provides a solution for non-linear least square minimization problems. This implies that the cost function to be minimized has the following special form: $J(\theta) = \frac{1}{2}\sum_{t=1}^{N}(\hat{y}_m - y_m)^2$ (2)

Where, y_m and $\hat{y}_m$ represent respectively real and estimated data and N represents the sample size. The gradient of the cost function $J(\theta)$ is given by:

$$\nabla J = \begin{pmatrix} \frac{\partial J}{\partial \theta_1} \\ \cdots \\ \cdots \\ \frac{\partial J}{\partial \theta_m} \end{pmatrix} \qquad (3)$$

Where, m is the number of unknown parameters.

The LM algorithm is based on the parameter's updating formula defined as follows:

$$\theta^k = \theta^{k-1} \pm \left[H\left(\theta^{k-1}\right) + \mu_k I\right]^{-1} \nabla J\left(\theta^{k-1}\right) \qquad (4)$$

where $H\left(\theta^{k-1}\right)$ and μ_k are respectively the Hessian and the step of the cost function.

Adaptive Neuro-Fuzzy Inference System (ANFIS)

ANN is an important tool for modeling and identifying various real world problems. If the input data are less accurate or ambiguous, ANN would be struggling to handle them and a fuzzy system such as ANFIS may be the adequate solution [37].

The ANFIS can simulate, model and analyze the mapping relation between the input and the output data through a learning algorithm to optimize the parameters of a given fuzzy inference system [38-40]. The ANFIS is realized by an appropriate hybrid combination of the powerful features of fuzzy systems with those of neural networks, which enables the use of verbal and numeric power of intelligent systems [41]. Commonly, from the fuzzy system theory, fuzzification and defuzzification mechanisms, with different rule-based structures, can lead to various solutions of a given task. Fundamentally, ANFIS is a network representation of Sugeno-type fuzzy systems using neural learning capabilities [37, 42, 43].

Jang proposed first the ANFIS method [42] and applied its principle successfully to resolve many problems [42, 44]. It can be applied in different domains such as the modelisation of nonlinear functions [42,45], the prediction of time series [42,46], the identification of control system parameters [47] and the fuzzy controller design [48].

Without loss of generality, we assume that the fuzzy inference system under consideration has two inputs x and y and one output f. We assume that, for now a first-order Sugeno fuzzy model [49, 50] is a base of two fuzzy if-then rules. It can be expressed as:

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

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

Where x and y are the inputs, f is the output, A_1, A_2, B_1, B_2 are the input membership functions. Figure 2 illustrates the reasoning mechanism for this Sugeno model [51, 52], where w_1, w_2 are the rule firing strengths and { p_i, q_i, r_i } are the parameter set

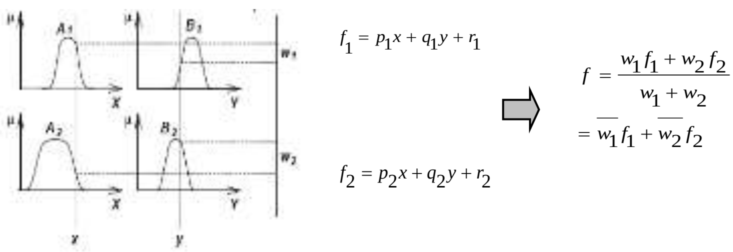

Figure 2: Two-input first order Sugeno fuzzy model with two rules

The fuzzy reasoning steps (inference operations upon fuzzy if-then rules) performed by the fuzzy inference systems are:

The premise part: in the fuzzification step, the input variables are compared with the membership functions to obtain the membership values of each linguistic label. The membership functions are combined to get firing strength (weights) of each rule.

The consequent part: in the deffuzzification step, the qualified consequent is generated of each rule depending on the firing strength. Finally, the qualified consequents are aggregated to produce a crisp output.

The corresponding equivalent ANFIS architecture is given by figure 3 [53]. Nodes of the same layer have the same function as described subsequently. We note that $O_{l,i}$ represents the output of the i^{th} node in layer l.

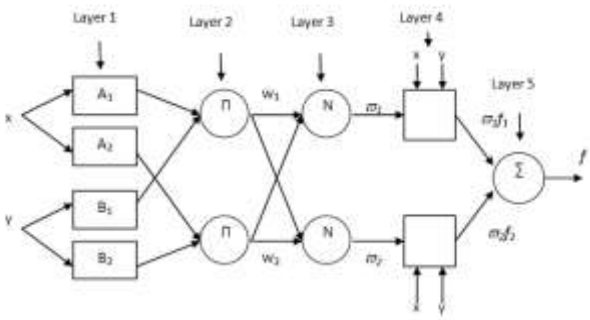

Figure 3: ANFIS architecture

Layer 1:

These nodes represent the input nodes, and are also termed as adaptive nodes. Each node of this layer corresponds to one linguistic label of one of the input variables, and it generates a membership grade, which corresponds to the membership function to obtain the grade of the linguistic label [54, 27].

$O_{1,i} = \mu_{Ai}(x)$ for i = 1, 2 (5)

or $O_{1,j} = \mu_{Bj}(y)$ for j = 3, 4

Where: x and y are crisp inputs, $O_{1,i}$ and $O_{1,j}$ are the linguistic labels (small, large, etc.) characterized by an appropriate membership functions μ_{Ai} and μ_{Bj} respectively, i and j represent the nodes. The outputs of this layer are the membership values of the premise part. The membership function can be any suitable parameterized membership function, for example: triangular, trapezoidal, Gaussian functions or other shapes. In this study, we use a Gaussian membership function described by:

$$\mu_{ij}(\mu_j) = \exp\left[-\left(\frac{\mu_j - c_{ij}}{\sigma_{ij}}\right)^2\right] \qquad (6)$$

c_{ij} and σ_{ij} characterize the center and the width of the i[th] rule of the j[th] membership function respectively. These parameters, which are so-called nonlinear parameters, are termed the premise part parameters.

Layer 2:
The nodes of the second layer correspond to the fixed nodes labeled as Π, which apply the AND operation to obtain the output results of firing strength. The firing strength means the weight degree of if–then rules in the premise part. The weight degrees w_i of this layer are the products of the corresponding degrees from the first layer, and can be expressed as:

$$O_{2,i} = w_i = \mu_{A_i}(x) \times \mu_{B_i}(y),\ i = 1, 2 \qquad (7)$$

Layer 3:
Each node in this layer is a fixed node labeled N which indicates that it plays a normalization role of the firing strengths from the previous layer [55]. The i[th] node calculates the ratio of the i[th] rule's firing strengths to the sum of all rule's firing strengths:

$$O_{3,i} = \overline{w_i} = \frac{w_i}{w_1 + w_2},\ i = 1, 2. \qquad (8)$$

For convenience, the output of the layer will be called normalized firing strengths or normalized weights.

Layer 4:
Every node in this layer is an adaptive node. The output of each node is a simple product of the normalized firing strength and a first-order polynomial (for a first-order Sugeno model). Thus, the outputs of this layer can be given by:

$$O_{4,i} = \overline{w_i}\, f_i = \overline{w_i}\,(p_i x + q_i y + r_i) \qquad (9)$$

where, $\{p_i, q_i, r_i\}$ are the linear parameters or so-called consequent parameters and $\overline{w_i}$ is the output of layer 3.

Layer 5:
There is only one single fixed node in the fifth layer labeled Σ. The node performs the summation of all the incoming nodes, and represents the defuzzification procedure. Therefore, the single output of the ANFIS model is:

$$O_{5,1} = \text{overall output} = \sum_i \overline{w}_i f_i = \frac{\sum_i w_i f_i}{\sum_i w_i} \qquad (10)$$

Using this method, a fuzzy inference system is based on system specifications. This initial model is changed firstly to a neuro fuzzy network and secondly it trained by experimental measured data from the real system.

ANN and ANFIS based on the autoregressive process
The main aim of this work is to offer a convenient way to predict accurately the half hour global solar radiation characterized by a large variation and fast transient periods. For this raison, we have focused on the combination of the ANN and the ANFIS methods presented previously with an autoregressive (AR) process to handle these difficulties and predict the target without using any exogenous meteorological-based inputs (Fig. 4) [56] - [58].

The predictive autoregressive process output $\hat{y}_m$ at time m from n output previous values is defined by the following expression:

$$\hat{y}_m = f\,(y_{m-1}, y_{m-2}, \dots, y_{m-n}) \qquad (11)$$

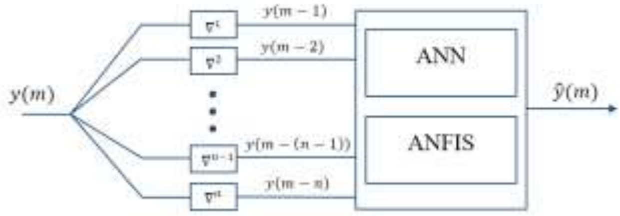

Figure 4: Autoregressive process architecture

Where: y(m) is the reel output, n is also called the order of the AR process, and ∇ is the delay.

Model performance evaluation

To assess the performance of the developed models, several statistical criteria are used in this study:

Root Mean Square Error (RMSE)

It evaluates the residual between estimated and observed data. This index assumes that larger estimated errors are of greater importance than smaller ones; hence it gives a more proportionate penalty. The RMSE is known to be descriptive when the prediction capability among predictors is compared [59] - [62]. this index is defined by:

$$\mathrm{RMSE} = \sqrt{\frac{1}{N}\sum_{m=1}^{N}(y_m - \hat{y}_m)^2} \qquad (12)$$

We note that, low RMSE value means a perfect fit.

Mean Squared Error (MSE)

The MSE define how close a regression line to a set of points and can be considered as a signal fidelity measure. Its goal is to compare two signals by providing a quantitative score describing the degree of similarity or, conversely, the level of error between them. It does this by taking the distances, errors, from the points to the regression line and squaring them. The squaring is necessary to eliminate any negative signs. It also gives more weight to larger differences. Usually, MSE assume that one of the signals is a pristine original, while the other is distorted or contaminated by errors. So, the smaller the Mean Squared Error, the closer the fit is to data. It is calculated by:

$$\mathrm{MSE} = \frac{1}{\mathrm{N}}\sum_{\mathrm{i}=1}^{\mathrm{N}}(\mathrm{y_m} - \hat{\mathrm{y}}_\mathrm{m})^2 \qquad (13)$$

Mean Absolute Percentage Error (MAPE)

MAPE is an important tool to measure the accuracy of the predicted signal. It calculate the size of the error in percentage terms as the average error of the unsigned percentage. When a point is close to zero the error can be extremely large, producing a distortion of the overall error rate [52].

$$\mathrm{MAPE} = \frac{1}{\mathrm{N}}\sum_{\mathrm{i}=1}^{\mathrm{N}}\left(\frac{\mathrm{y_m} - \hat{\mathrm{y}}_\mathrm{m}}{\mathrm{y_m}}\right).100\ \ (\%) \qquad (14)$$

Correlation coefficient (R)

R quantify the relation between estimated and observed data in unit-free terms. When all points of a scatter plot fall directly on a line with an upward incline, R = +1, and when all points fall directly on a downward incline, R = -1. Indeed, the closer R is to +1, the stronger the positive correlation, and the closer R is to -1, the stronger the negative correlation.

$$R = \sqrt{\frac{\sum_{i=1}^{N}(\hat{y}_m - \bar{y}_m)^2}{\sum_{i=1}^{N}(y_m - \bar{y}_m)^2}} \qquad (15)$$

Where $\bar{y}_m$ is the mean values of real data and N represents the sample size.

Variance Accounting For (VAF)

The VAF was introduced by Babuska et al. [63]. This criterion allows to evaluate the quality of a model as a percentage by measuring the standard deviation of the variance between two signals. Its optimum value is 100%

when the both signals are equal, if they differ, the VAF will be low. The VAF criterion is given by the following expression :

$$\mathrm{VAF}=100\%\left[1-\frac{\mathrm{var}(y_m-\hat{y}_m)}{\mathrm{var}(y_m)}\right] \qquad (16)$$

where, var(.) is the variance.

Database description

In this study, the used data is measured along three years from 2012 till 2014, in the area of Agdal at Marrakesh, Morocco (Fig. 5). The station of Agdal Marrakesh was installed by the international mixed laboratory "Remote Sensing and Water Resources in the Semi-Arid Mediterranean" (TREMA) at the Faculty of Sciences Semlalia Marrakesh.

Figure 5: Geographical situation of the Agdal Marrakesh station

The used time serie is constructed from the half hour global solar radiation measurements $\{y_m\}$, recorded over three years. Therefore, the database is defined as follows:

$G = \{(x_m, y_m)\}$, m = 1 ... 1095.

Where x_m is the input of the AR-ANN and the AR-ANFIS models y_m is the output of the both models.

The real data evolution of half hour global solar radiation measurements is represented in figure 6.

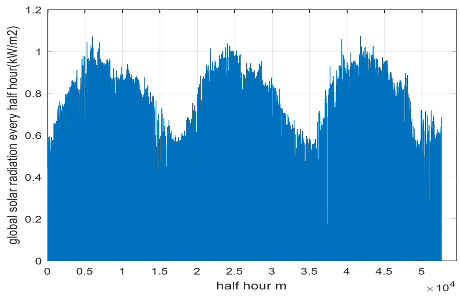

Figure 6: Evolution of half hour global solar radiation measurements

RESULTS AND DISCUSSION

Overall, soft computing models such as ANN and ANFIS are very robust to analyze and predict times series for different reasons. In one hand, it is not necessary to make an analysis of a problem or of an internal structure of a system based on the in-depth knowledge. In the other hand, they can handle a huge agreement of data. For this reasons, we applied the artificial neural networks ANNs based on the MLP and the ANFIS modeling approaches combined with an Autoregressive process (AR) for developing two models to predict the ahead global solar radiation data based on the historical data measured previously in m, m-1, m-2, …, m-n times, where n is the AR process order as described previously. The data set was randomly divided into two subsets: the training and the testing data subsets. Where, the training subset was used to train the AR-ANN and the AR-ANFIS models, whereas the testing data subset was used to verify the accuracy and the effectiveness of the trained ANN and ANFIS models.

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Autoregressive Artificial neural networks application and results

To create the Autoregressive Artificial neural networks (AR-ANN) model, the determination of the data sets repartition, the ANN structure, the training algorithm and the transfer function, is necessary. The good choice of these parameters, the better and the adequate results we get. For this reason and for justifying our choice, different trying and simulations have been done:

- The data set repartition used in our study is 75% for the training phase and 25% for the testing phase;
- The suitable structure of our developed model is [4 - 5 -1-1] (Fig. 7).

As cited and demonstrated previously:

- The most appropriate transfer function is the sigmoid function;
- The performed training algorithm is the Levenberg Marquardt.
- The best autoregressive order is 4.

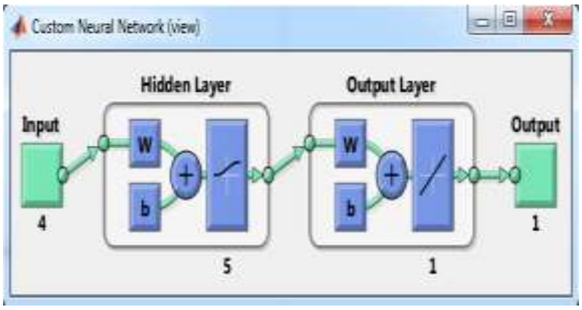

Figure 7: Structure of the AR-ANN developed model

For studying the effectiveness of the developed model to predict the half hour global solar radiation time series, we draft firstly the scattering diagram for the training (Fig. 8) and testing (Fig. 9) data, which presents a comparison between measured and predicted data. From these figures, we can note a strong concentration of the points $(y_m, \hat{y}_m)$ around the first bisectrix. Secondly, the evolution of measured and predicted values is presented in Figure 10. The obtained results demonstrate that there is almost a complete agreement between measured and predicted data.

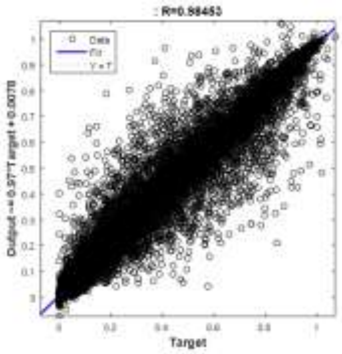

Figure 8: Scattering diagram of AR-ANN model of measured and predicted data for training phase

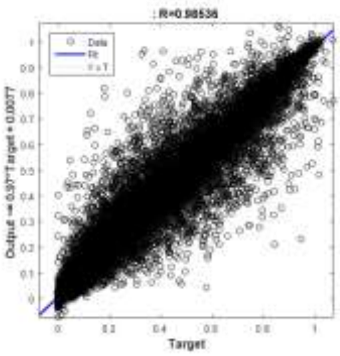

Figure 9: Scattering diagram of AR-ANN model of measured and predicted data for testing phase

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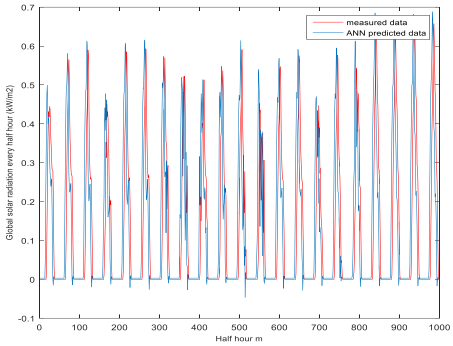


Figure 10: Evolution of measured and predicted data by AR-ANN model

Autoregressive Adaptive neuro-fuzzy inference systems applications and results

In this part, the same input and output variables are used to develop the Autoregressive Adaptive neuro-fuzzy inference systems (AR-ANFIS) model. In order to obtain the best performance results, various combinations are designed for one output value. The membership function number and the most suitable transfer function are defined after different simulations.

In other hand, we take in consideration that it is not favorable to increase the number of the membership functions in an ANFIS model because too many parameters must be predicted [64]. As a result, the number of membership functions and the number of iterations must be respectively between 2 and 4 and between 1 and 5 .
The variation of the membership functions and the iterations lead to the realization of many combinations, which are all executed and their results are compared to select the optimal result. In our case, the Gaussian function is used as a membership function to create the model (Fig. 11).

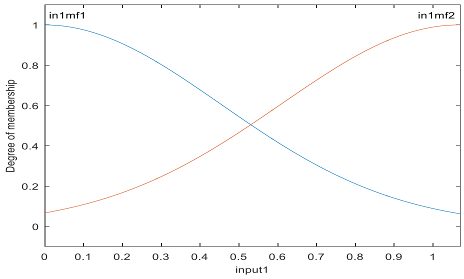
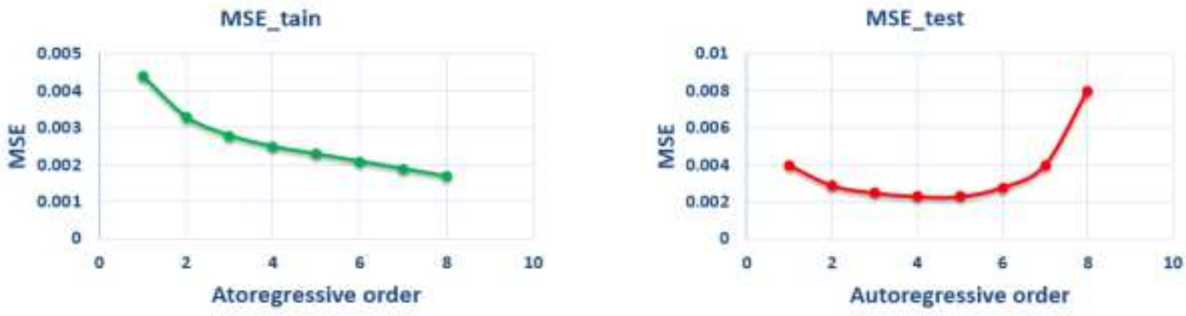


Figure 11: Gaussian membership functions

Finally, the autoregressive order must be determined carefully to ensure a good performance of the developed model.

Figure 12 represents the effect of the autoregressive order variation versus MSE in the training phase (Figure 12.a) and in the testing phase (Figure 12.b).



(a) *(b)*

Figure 12: Effect of autoregressive order variation versus MSE: (a): Training phase (b) Testing phase

From these graphs, we remark that when the autoregressive order increased, the prediction performance increased too but when this order exceeds 5 the performance of the proposed model kept increasing in the training phase without improving the accuracy in the testing phase. This is due to the large size of the used data into the model during the training phase. We notice also that, increasing the autoregressive order heavily penalizes the training time and the accuracy of the prediction during the testing phase.

In the figures 13 and 14, we represent the scattering diagrams of the measured and the predicted data for the training and the testing phases wile in figure 15 the evolution of measured and predicted data by AR-ANFIS model is illustrated. Consequently, the obtained results of this second used approach to predict the half hour global solar radiation demonstrate the high correlation between measured and predicted values and the good accuracy of the developed model.

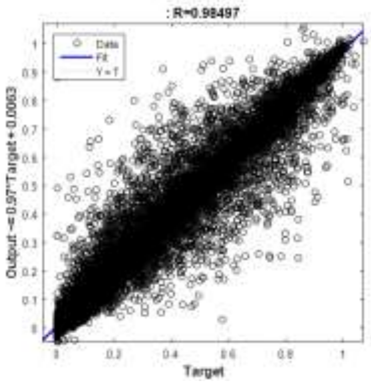


Figure 13: Scattering diagram of AR-ANFIS model of measured and predicted data for training phase

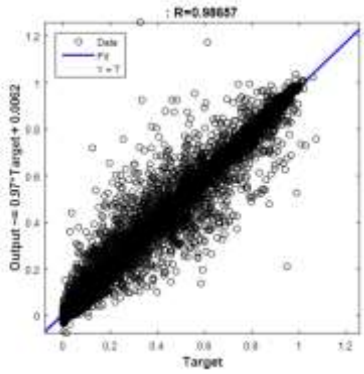


Figure 14: Scattering diagram of AR-ANFIS model of measured and predicted data for testing phase

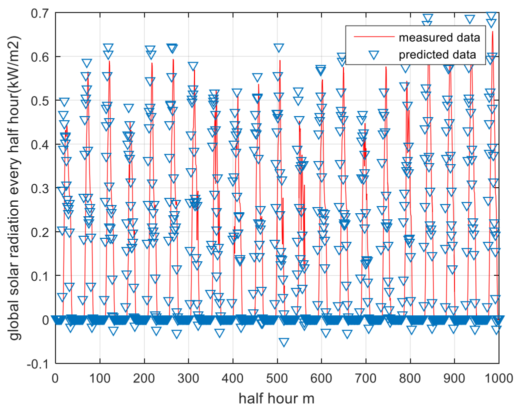


Figure 15: Evolution of measured and predicted data by AR-ANFIS model

Comparison study

The previous statistical indicators (RMSE, MSE, MAPE, R and VAF) are used to compare the measured and the predicted values by each model (Table I). From table I, we remark the advantages of the two developed models with a variance accounting around 97% and an MSE around 0.25% to predict the half hour global solar radiation.

Table 1: Values of statistical indicators for ANFIS and ANN models

Statistical indicators	AR-ANN	AR-ANFIS
RMSE	0.0500	0.0495
MSE	0.002500	0.002449
MAPE	2.23%	2.17%
VAF	97.0600%	97.1227%
R	0.98522	0.98551

To appreciate the quality of both models, to generate data having the same frequency distribution as the real measurements, we perform another test (Fig. 16). It is important to note that the frequency distribution presents an accurate comparison between the two models. It demonstrates a slight advantage of the AR-ANFIS model.

Consequently, we note that AR-ANFIS model presents a good performance to predict half hour global solar radiation data with a considerable accuracy.

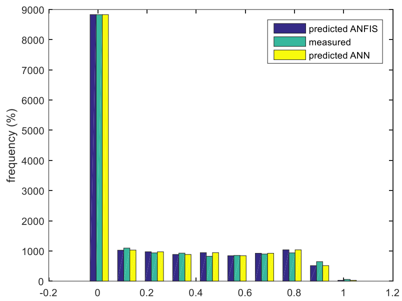


Figure 16: Frequency distributions of measured and predicted data using AR-ANN and AR-ANFIS models

CONCLUSION

In this paper, we developed two models based on the artificial intelligence methodology such as the autoregressive artificial neural network (AR-ANN) and the autoregressive adaptive neuro-fuzzy inference systems (AR-ANFIS). These models are applied for modeling and predicting the half hour global solar radiation data in Marrakesh, Morocco. The performance of the developed models, AR-ANFIS and AR-ANN, is investigated. Several statistical criteria were used to achieve a comparison between predicted and measured values. The obtained results demonstrate that both models are able to generate half-hour global solar radiation time series with a variance accounting around 97% and an MSE around 0.25%. Consequently they can both be successfully used as an excellent tool for the management of daily global solar radiation in case of lack of measurements in a given region having similar climate as Marrakesh. The precise comparison performed between the two techniques shows that the AR-ANFIS model is slightly more accurate than the AR-ANN model.

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