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NEW MODEL FOR SOLAR RADIATION ESTIMATION FROM MEASURED AIR TEMPERATURE AND RELATIVE HUMIDITY IN NIGERIA

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ABSTRACT
Solar radiation prediction is essential for effective and reliable solar power project, predicted solar radiation can be used for accurate solar energy prediction. Solar radiation measurement is not sufficient in Nigeria for various reasons such as maintenance and repair cost, calibration of instrument, and expansive of measuring device. In this paper, adaptive neuro-fuzzy inference system (ANFIS) model was developed to predict the monthly average solar radiation in Nigeria. Air temperature of monthly mean minimum temperature, maximum temperature and relative humidity obtained from Nigerian Meteorological Agency (NIMET) were used as inputs to the ANFIS model and monthly mean global solar radiation was used as out of the model. Statistical evaluation of the model was done based on root mean square error (RMSE) and correlation coefficient R to examine the accuracy of the developed model. The values of RMSE and R for the training data are 0.91315MJ/m^2 and 0.91264MJ/m^2 respectively. The obtained result showed a good correlation between the predicted and measured solar radiation which proves ANFIS to be a good model for solar radiation prediction.

Key words: *Solar radiation, prediction, temperature, relative humidity, ANFIS. Nigeria*

1. INTRODUCTION

Solar energy is one of the most harnessed renewable energy source in the world due to its availability and cleanliness. Its feasibility and ease of accessibility makes it the most used across the globe [1, 2]. Several technologies have been harnessed for solar power projects especially in the sun rich regions. Solar radiation data estimation is necessary especially in developing countries due to the unavailability of measured data in place [3-5]. Solar radiation measurement is not sufficient in Nigeria for various reasons such as maintenance and repair cost, calibration of instrument, and expansive of measuring device, for this reason meteorological parameters were used to predict the solar radiation using different methodologies. Several models have been developed for global solar radiation estimation using the meteorological data such as temperature (minimum, maximum and average), sunshine hours, relative humidity, longitude, latitude, altitude, sea level pressure, etc. [6-11].

Several works have been carried out to predict solar radiation in Nigeria and over the world. Empirical models were used to predict solar radiation in Nigeria by [12-15]. However, due to the need of precise and reliable solar radiation data, the use of artificial intelligence for solar radiation predicting using meteorological data are employed by [16, 17]. Further researches [18-24] have also been carried out across the globe using artificial intelligence technique for solar radiation prediction. The works carried out proved the efficiency and accuracy of solar radiation prediction using artificial intelligence.

Although various researches have been carried out for solar radiation prediction, different models have been developed over the years, different algorithm have also been developed using artificial intelligence techniques. There is still need to explore other methods for better accuracy and reliability. ANFIS is a robust and frequently used hybrid intelligent system that combines the learning power of neural network and representation of fuzzy logic, it has the advantage of computational efficiency and reliability over neural network and fuzzy logic. ANFIS has been widely utilized for solar radiation prediction across the globe and has shown good results in various engineering systems [3, 16, 25-27]. In this paper, adaptive neuro-fuzzy inference system soft computing technology is used for solar radiation prediction in Nigeria. Monthly mean minimum temperature, maximum temperature and relative humidity from Kano meteorological data are used as the input to the ANFIS model while global solar radiation is used as the output model. The main objective is to investigate the feasibility of using only air temperature

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and relative humidity for global solar radiation in Nigeria using ANFIS soft computing technique.

2. STUDY LOCATION

In this study, long term monthly average temperature (minimum, maximum and average),monthly mean relative humidity and monthly mean solar radiation on horizontal surface for the period of 11 years (2002-2012) were obtained from Nigerian Meteorological agency (NIMET), Kano, Nigeria [28]. The data were recorded at meteorological station in Kano, North West Nigeria with 12.0022°N latitude and 8.952°E longitude and at an altitude of 456m. The monthly average solar radiation of the site was obtained from National Aeronautics and Space Administration (NASA) website [29]. The monthly average data used for the work were divided into two sets, one set which is 70% of the data (2002-2008) were used for training while the other set which is 30% of the data (2009-2012) were used for testing.

3. ADAPTIVE NEURO-FUZZY APPROACH

3.1 Neuro Fuzzy Computing

The term soft computing can be termed as recent technologies such as Fuzzy Logic genetic Algorithms, Neural Network, Adaptive Neuro Fuzzy Inference system that are used in solving problems. The technologies involved have their complementary reasoning and searching methods in solving real-world complex problems [18]. In real-life computing problems, it is better and more beneficial to employ different computing methods in a symbiotic way than relying on only one soft computing technique. Combining two soft computing techniques like neural network and fuzzy logic, which termed as Adaptive neuro fuzzy computing is termed hybrid intelligent system [30]. Neural network recognizes patterns and adapt to cope with the evolving environment while Fuzzy logic implements decision-making and differentiation by the use of human knowledge [31].

3.2 Adaptive Neuro-fuzzy Inference System (ANFIS)

J .S Roger first developed ANFIS in 1993 by the combination of neural networks and fuzzy logic systems [32]. It has an adaptive network functionality that is considered equivalent to the fuzzy inference system. ANFIS is a network based structure which uses the Sugueno-type "IF…THEN" rules and Neural networks that is capable of matching inputs with their corresponding outputs [33]. The fuzzy inference system used in this study has four inputs, *x, y, z* and *s* and one output, *f*. The first order Sugueno-type if-then rules with only two inputs is discussed as follows. Figure1 below shows the typical ANFIS structure. Nodes that are on the same layer have the same functions and the output of layer j is denoted as $O_{j,i}$.

1. If x is A and y is B, then:

$$f_1 = p_1 x + q_1 y + r_1 \quad (1)$$

2. If x is A_2 and y is B_2, then:

$$f_2 = p_2 x + q_2 y + r_2 \quad (2)$$

Where $p_i, q_i \; and \; r_1$ are consequent parameters

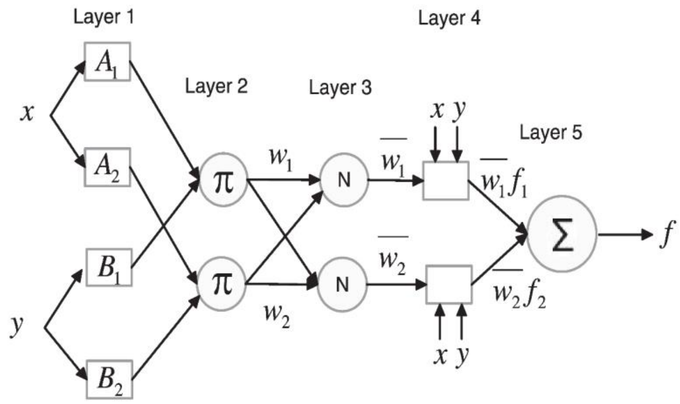

Figure 1: ANFIS architecture with two inputs, two rules and one output

Layer 1: This layer comprises of all the input membership functions and provides them to the next layer. The nodes in this layer are all adaptive nodes. The output for node is given by

$$O_{j,i} = \mu_{A_i}(X_i) for \; i = 1, 2 \quad (3)$$

Or

$$O_{j,i} = \mu_{B_{i-2}}(y), for \; i = 3, 4 \quad (4)$$

Where $\mu_{A_i}(X_i)$ and $\mu_{B_{i-2}}(y)$, are the membership functions of node A, x or y is the input to node *i*, and A_i or B_{i-2} is an associated linguistic label. $O_{j,i}$ Is the membership grade of a fuzzy set A and B. the generalized function of the nonlinear parameters is represented below [23] and [20].

$$\mu_{A_i}(X) = \frac{1}{1 + \left(\frac{x - c_i}{a_i}\right)^{2b_i}} \quad (5)$$

Where (a_i, b_i, c_i) are the variable sets. The function varies with change in the variable values, hence manifesting different types of membership functions for fuzzy set A.

Layer 2: the output of the second layer is the consequence of all the signals that are coming from the previous layer. This output is considered to be AND or OR operation of the membership functions coming from the previous layer [34]. Thus;

$$O_{2,i} = w_i = \mu_{Ai}(x) \times \mu_{Bi}(y), i = 1{,}2 \quad (6)$$

Where $\mu_{Ai} \; and \; \mu_{Bi}$ are the membership functions of node A and node B input layer respectfully.

Layer 3: The third layer makes the rule, this is where normalization takes place and it is also a non-adaptive layer. The output of each node in this layer gives the ration of the node's firing strength to the sum of all the firing strengths entering the node [35].

$$O_{3,i} = w_i = \frac{w_i}{w_i + w_2}, i = 1,2 \qquad (7)$$

w_i Is the firing strength of node i

Layer 4: in this layer every node is and adaptive node with node function, which means every node I is the product of the normalized signal from the previous node [36] and [35].

$$O_{4,i} = \overline{w_i} f = \overline{w_i}(p_1 x + q_1 y + r_1) \qquad (8)$$

Where $\overline{w_i}$ is the normalized signal of node i or rather normalized firing strength from the third layer and p_1, q_1 *and* r_1 are the consequent parameters.

Layer 5: layer five has a single node, which is called the fixed node and it is a non-adaptive node. It sums up all the signals that are incoming from the previous layer and calculate them as total output [32] and [34].

$$O_{5,i} = \sum_i \overline{w_i} f_i = \frac{\sum_i w_i f}{\sum_i w_i} \qquad (9)$$

Where f_i is the linear combination of the consequent parameters of the fourth layer.

3.2.1 ANFIS Training/Learning

Two default training algorithms used in ANFIS are Least Squares Estimation (LSE) in the forward pass and Gradient Decent (GD) in the backward pass. In the forward pass LSE is used to determine the consequent parameters(p_i, q_i and r_i) In the backward pass GD is used to update the premise parameters (membership function parameters). According to[34], LSE is used in hybrid with GD because GD is generally slow, and may be trapped in local minima.

3.3 Model Performance Evaluation

The performance of the ANFIS model is analyzed using the following statistical indicators

(1) Root mean square error (RMSE)

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(O_i - \overline{P_i})^2}{n}} \qquad (10)$$

(2) Correlation coefficient(R)

$$R = \frac{\sum_{i=1}^{n}(O_i - \overline{O_i}) \; .(P_i - \overline{P_i})}{\sqrt{\sum_{i=1}^{n}(O_i - \overline{O_i}) . \sum_{i=1}^{n}(P_i - \overline{P_i})}} \qquad (11)$$

Where O_i *and* P_i are predicted and experimental values respectfully, and $\bar{O}_i$ *and* $\bar{P}_i$ are mean values of O_i *and* $P_i$respectively. Also n is the total number of the test data. When higher value of R is obtained, it shows that the model has a better performance while RMSE with smaller value indicates better performance of the model.

4. MODEL DEVELOPMENT

This section explains the step by step procedure of model development as presented in Figure 2. The time series data were used for the prediction during the ANFIS modeling. The original data were obtained from NIMET Nigeria. The obtained data were fed into the model as inputs and outputs, the ANFIS model form the predicted output of solar radiation at the end of the process.

At the beginning the data is presented in its matrix form on an excel sheet arranged in columns, with four input data on the first four columns and the output on the last column (column five). The number of columns of the input data is thereby selected to represent the real inputs. The time series data were fed into the ANFIS structure for training purpose. The ANFIS is then trained with the data obtained, during this training, we adjust the ANFIS parameters until they satisfy the outputs submitted. The testing process undergoes the same procedure but with the data that has not been used during the training process. The final output obtained from the ANFIS structure gives the prediction of solar radiation by ANFIS approach. The step by step process is presented in Figure 2 using flow chart.

To evaluate the performance of the system RMSE and R^2 presented in equations (10) and (11) respectively were used. From the ANFIS output and targeted output a correlation graph is presented in Figure (3) and (4).

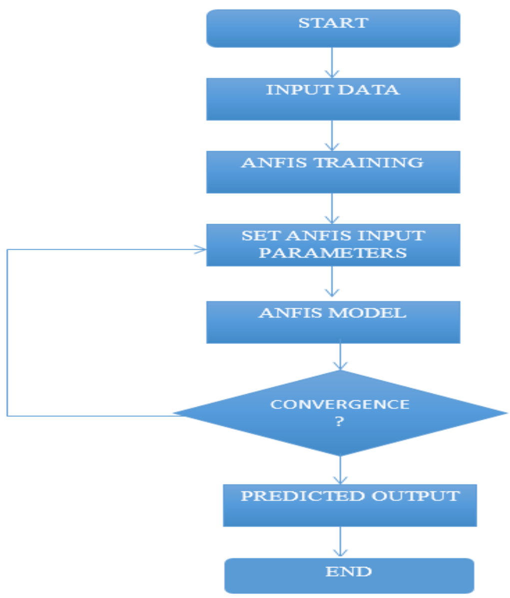

Figure 2: Flow chart of the developed ANFIS model

4. RESULTS AND DISCUSSION

In this paper, the potential of air temperature and relative humidity for solar radiation prediction using ANFIS technique was employed. The developed ANFIS model was trained and tested with the data obtained from NIMET, 70% of the data was used for training and 30% was used for testing. The combination of minimum temperature, maximum temperature and relative humidity serve as the input parameter and solar radiation as the output parameter. The precision of the developed ANFIS model is assessed using two statistical indicators, the root mean square error (RMSE) and correlation coefficient(R). lower values of RMSE signifies good correlation, though the ideal value is 0. R ranges between -1 and +1, the value of R near -1 or +1 signifies accuracy and perfect linear relationship between the target and measured values. If R nears 0 it illustrates non-linear relationship between estimated and target output. The obtained values of RMSE and Rare presented in table 1.

Table 1. Statistical evaluation of the developed model.

	RMSE (MJ/m^2)	R (MJ/m^2)
Training result	0.91315	0.91264
Testing result	1.497	0.87212

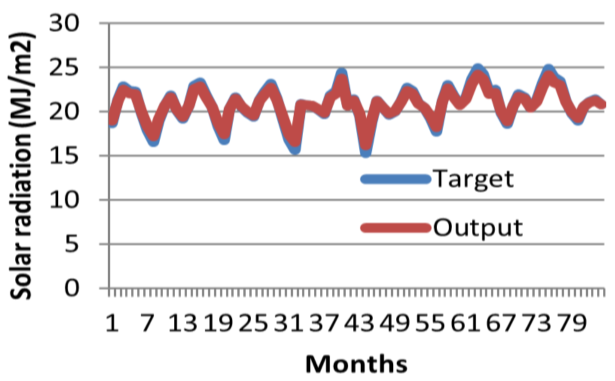

Figure 3: Training data (target and predicted output)

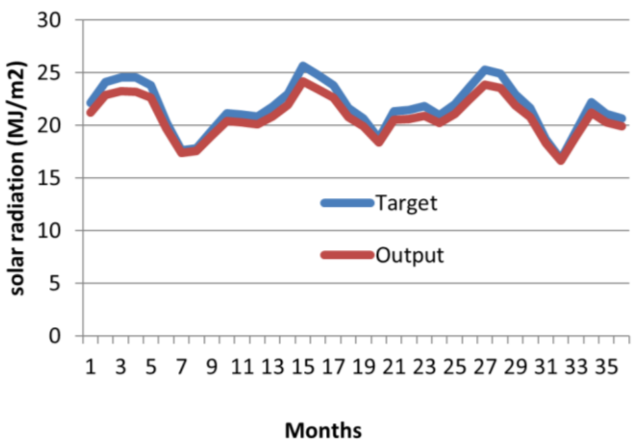

Figure 4: Testing data (target and predicted output)

To analyse the performance of the model graphically, Figure 3 which shows the relation between the target of the trained data and its output. It is clear that there is a strong correlation between the predicted solar radiation and the measured solar radiation. Figure 4 also proves a strong correlation between the measured and the predicted solar radiation. Moreover, the statistical indicators used to evaluate the results prove a very good correlation with RMSE of the trained data as 0.91315 and R=0.91264, and that of the testing data to be RMSE=1.497 and R=0.87212 as shown in Table 1.Based on the obtained values of RMSE and R, there is strong relationship between the predicted and the measured parameters.

5. CONCLUSION

In this study, adaptive neuro-fuzzy inference system was used to estimate the global horizontal solar radiation in Nigeria. Meteorological data used as input to the developed model was obtained from NIMET. Data set of 2002-2012 of minimum temperature, maximum temperature and relative humidity were used as the input data and solar radiation as the output data. Statistical evaluation was done based on RMSE and R to examine the accuracy of the developed model. The values of RMSE and R for the training phase are 0.91315MJ/m^2 and 0.91264MJ/m^2 respectively. From the results obtained, it is clear that the developed model is efficient and reliable for effective solar radiation prediction in Nigeria, and also prove strong correlation between the predicted output and the target. Moreover, based on the meteorological parameters chosen as input parameters to the developed model, it proves that the choice of air temperature and relative humidity is efficient for solar radiation prediction in Nigeria.

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