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Fuzzy Model, Neural Network and Empirical Model for the Estimation of Global Solar Radiation for Port-Harcourt, Nigeria

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Authors' contributions

This work was carried out in collaboration between all authors. All authors read and approved the final manuscript.

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ABSTRACT

The invaluable role of the estimation of global solar radiation in solar engineering systems provides very useful direction for various solar applications. This paper employs the Adaptive Neuro Fuzzy Inference System (ANFIS), Artificial Neural Network (ANN) and regressive technique for the prediction of global solar radiation(GSR) on horizontal surface using temperature swing and relative humidity as input parameters covering years 1981 to 2005. The performance of the models was tested using statistical indicators such as mean bias error (MBE), root mean square error (RMSE), and correlation coefficient (CC). The results with ANFIS and ANN method provide a relatively better prediction with ANFIS the more preferable.

Keywords: Angstrom model; fuzzy logic system; neural network; solar radiation; temperature.

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1. INTRODUCTION

The invaluable role of the estimation of global solar radiation in solar engineering systems provides very useful direction for various solar applications. The data acquire for modeling GSR are also useful for obtaining various indices of heat stress and thermal comfort and are usually insufficient to cover many areas, for some reasons which have been discussed extensively [1,2]. Therefore, it is imperative to be able to estimate GSR for many locations having similar geographical features.

Various models were utilized for estimating GSR and compared for the different climates of the world [3]. The Angstrom type model as one of these models is found to be very important for estimating GSR in tropical climate. Nigeria is a region with untapped enormous solar potential. This alternative source of energy can help to boost its acute shortage of electricity. The use of a combination of two or more meteorological data in the estimation of solar radiation will improve the accuracy of the estimation. This will provide solar data needed for optimizing the design of solar equipment specific to the region [4,5].

Soft computing techniques like ANFIS and ANN are computationally efficient techniques for determining nonlinear relationship between input and target output parameters. They possess learning capability and give outputs which compare reasonably well with observed measurement [6,7].

In ANN, the Levenberg-Marquardt backpropagation has become a standard techniques implored in a wide spectrum of disciplines because of its robustness [8,9]. ANN can take several input parameters unlike the traditional Angstrom equation that considers only sunshine duration for its prediction. ANN and other artificial intelligence systems have been found as better and quicker prediction methods for producing the sizing curve of photovoltaic systems [10].

This study aims to develop Angstrom type model, ANFIS and ANN models using temperature swing and relative humidity as input parameters in the estimation of GSR for Port-Harcourt, Nigeria, and to then compare the results from the models by statistical indicators.

2. DATA AND METHODS OF ESTIMATION

The data used in the study were obtained from the Nigerian Meteorological Agency (NIMET), Lagos, for Port-Harcourt (4.78° N, 7.01° E). Temperature swing and relative humidity were used as the input parameters covering years 1981 to 2005. The study considered three different methods for the estimation of GSR.

2.1 Empirical Model

The empirical model of the Angstrom type which relates the monthly average daily global radiation to the maximum temperature [11] was first considered given by:

$$\frac{\bar{H}}{H_0} = a + b\bar{T}_m \tag{1}$$

where, $\bar{H}$ is the monthly average global radiation on the horizontal surface ($MJm^{-2}day^{-1}$), while H_0 is the monthly average daily extraterrestrial radiation on a horizontal surface ($MJm^{-2}day^{-1}$), $\bar{T}_m$ is the monthly mean maximum temperature and *a* and *b* are the regression constants.

2.2 Fuzzy Model Estimation

The second approach of estimating the GSR considers the ANFIS neuro-fuzzy system which combines artificial neural network and fuzzy logic techniques [12]. The Sugeno system of the Matlab© toolbox was used for the ANFIS. ANFIS Editor is used for training, checking and testing of the data set made up of one input and one output variables (ANFIS1) and two inputs and one output variables (ANFIS2). The fuzzy input sets in this case are the maximum temperature for ANFIS1 and relative humidity and maximum temperature as input fuzzy sets for ANFIS2.

This method of estimation comprises three basic steps. The first step is the fuzzification of the input data sets which uses a single spike for representing the membership function of the rule consequent. The trapezium type membership function is used for the prediction as shown in Fig. 3.

The second step involves the setting of the rule base linking the input and output variables. The rules are a type of “if-then” rules that are expressed in natural language. The format of the Sugeno style fuzzy rule for the input and output is considered for all possible combinations of the rule construct as shown in Fig. 3. The form of these rules respectively for ANFIS1 and ANFIS2 are given as:

If the maximum temperature is LOW
THEN GSR is LOW

and

If the relative humidity is LOW AND the maximum temperature is LOW
THEN GSR is LOW.

In this case, one can view detailed behavior of the FIS to changing input variables and rule consequent.

The final step is called defuzzification which uses weighted average techniques for the output [13].

2.3 Neural Network Estimation

The final approach of estimating the GSR considers the multi-layer perceptron (MLP) feed forward neural network which consist of input layer, hidden layer and output layer respectively. These layers are complex interconnections of biological neurons that mimic the human brain with the ability to learn and store experiential knowledge of the processed information. Information flows from the input layer down to the output layer in a unidirectional manner. The hidden and output layers used the sigmoid activation function which constrains the output to between 0 and 1 given as [11]:

$$Z_k = (1 + e^{-v_k})^{-1} = f(V_k) \qquad (2)$$

The weighted sum of the input is then added to the bias to obtain the net input and the output is then calculated as:

$$Y_k = f(\sum_{k=1}^{n} W_k I_k + b_k) \qquad (3)$$

where W_k and I_k are the weight and input vectors respectively.

Several ANN algorithms were investigated in order to obtain the optimal ANN network used for the training process in the estimation of the GSR. This kind of network having an output, in this case which is the measured GSR is known as the supervised network. Two ANN architectures were considered, NN1 with only one input parameter of maximum temperature and NN2 with both relative humidity and maximum temperature as the inputs. ANN has been applied extensively in various fields for modeling, identification, optimization, prediction, forecasting and control of complex systems.

Statistical performance of the results from the different models compared with the measured value is carried out using the following indicators such as: mean bias error (MBE), root mean square error (RMSE) and correlation coefficient (CC).

$$MBE = \sum_{i=1}^{N} \frac{(H_{cal} - H_{obs})}{N} \qquad (4)$$

$$RMSE = \left\{\frac{\sum_{i=1}^{N}(H_{obs} - H_{cal})^2}{N}\right\}^{1/2} \qquad (5)$$

$$\mathrm{CC} = \frac{\sum_{i=1}^{N}(H_{cal} - \bar{H}_{cal})(H_{obs} - \bar{H}_{obs})}{\{[\sum_{i=1}^{N}(H_{cal} - \bar{H}_{cal})^2][\sum_{i=1}^{N}(H_{obs} - \bar{H}_{obs})^2]\}^{1/2}} \qquad (6)$$

where, H_{cal} and H_{obs} stand for the predicted and measured values respectively, and n is the total number of observations. The RMSE is always positive and has ideal value equal to zero while the ideal values for the MBE and correlation coefficient should be zero and one respectively [14].

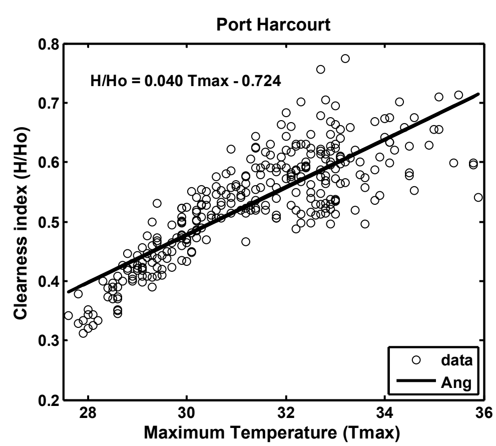

Fig. 1. Correlation between H/Ho and maximum temperature using mean monthly values

3. RESULTS AND DISCUSSION

Fig. 1, is a plot of the clearness index H/Ho against maximum temperature for the years 1981-2005. The regression coefficients determined from the plot give values of $a =$

-0.724 and $b = 0.040$ for Port Harcourt. These values of (a) and (b) are closely related to those obtained using maximum temperature by [15]. The correlation coefficent between the clearness index and the maximum temperature is 0.8263. This implies that 82.63% of clearness index can be accounted for by the maximum temperature. Hence the GSR in Port Harcourt can be predicted by:

$$\frac{\bar{H}}{H_0} = -0.724 + 0.040\bar{T}_m \quad (7)$$

On the other hand, Fig. 2 are plots of the Correlation of GSR obtained by different models for years 1981 – 1984. In these plots the five different models were compared with the measured GSR. The statistical performance using CC, RMSE and MBE were calculated as shown in Tables 1-3. Close observation of Table 1, shows that the correlation coefficient of 0.861, 0.888, 0.974, 0.837 and 0.957 were obtained respectively using the Angstrom type model; ANFIS1; ANFIS2; NN1 and NN2 for estimation of global solar radiation for year 1981. Also, the RMSE and MBE (having ideal value of zero) values for the various models clearly show that the ANFIS and NN models give a better fit with respect to the measured GSR.

Close observation of Table 2 and 3 also show the same trend as observed for Table 1. Figs. 5 and 6 show the regression plots between the actual and predicted GSR for NN1 and NN2

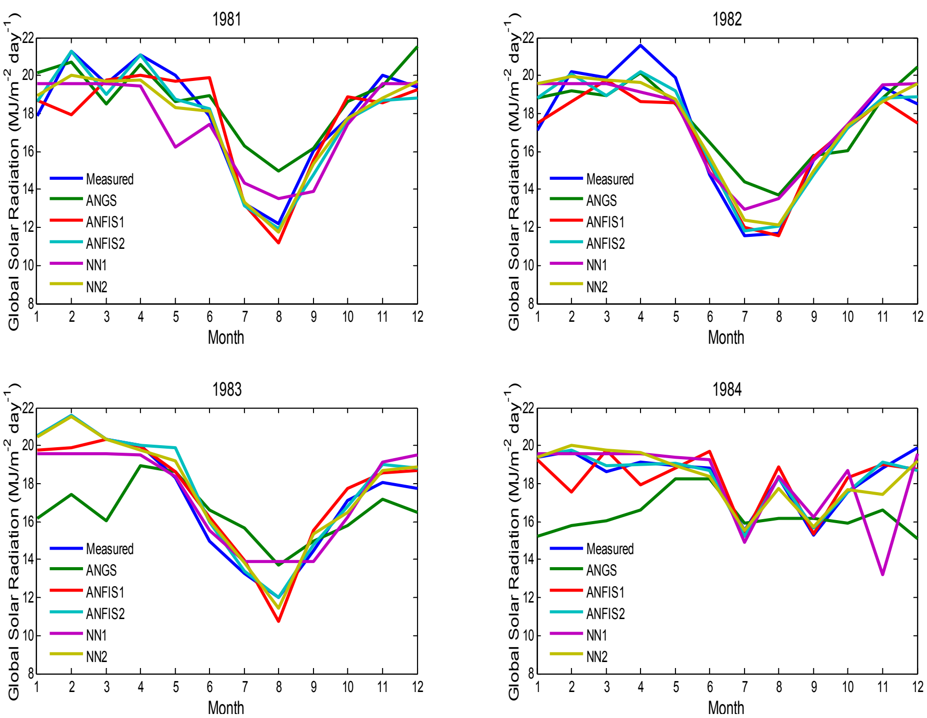

Fig. 2. Correlation of GSR obtained by different models 1981 - 1984

Table 1. Analysis of GSRs for year 1981 using various models

Year 1981	GSR	EQUATION 1	ANFIS 1	ANFIS 2	NN1	NN2
Months	**MJm^{-2}day^{-1}**	**MJm^{-2}day^{-1}**	**MJm^{-2}day^{-1}**	**MJm^{-2}day^{-1}**	**MJm^{-2}day^{-1}**	**MJm^{-2}day^{-1}**
Jan	17.873	20.157	18.692	18.611	19.596	18.955
Feb	21.263	20.705	17.917	21.281	19.596	20.015
Mar	19.568	18.515	19.736	19.027	19.545	19.727
Apr	21.109	20.568	19.999	21.108	19.442	19.789
May	20.030	18.652	19.698	18.777	16.209	18.293
Jun	17.873	18.925	19.874	18.269	17.452	18.100
Jul	13.251	16.324	13.183	13.129	14.352	13.327

Year 1981	GSR	EQUATION 1	ANFIS 1	ANFIS 2	NN1	NN2
Months	**$MJm^{-2}day^{-1}$**	**$MJm^{-2}day^{-1}$**	**$MJm^{-2}day^{-1}$**	**$MJm^{-2}day^{-1}$**	**$MJm^{-2}day^{-1}$**	**$MJm^{-2}day^{-1}$**
Aug	12.172	14.955	11.169	11.945	13.495	11.769
Sep	16.024	16.187	15.559	14.752	13.876	15.340
Oct	17.719	18.652	18.875	17.684	17.452	17.755
Nov	20.030	19.473	18.575	18.692	19.591	18.838
Dec	19.414	21.526	19.283	18.831	19.596	19.720
	CC	0.861	0.888	0.974	0.837	0.957
	RMSE	2.660	2.503	2.557	2.622	2.544
	MBE	-0.693	0.314	0.352	0.511	0.392

Table 2. Analysis of GSRs for year 1982 using various models

Year 1982	GSR	EQUATION 1	ANFIS 1	ANFIS 2	NN1	NN2
Months	**$MJm^{-2}day^{-1}$**	**$MJm^{-2}day^{-1}$**	**$MJm^{-2}day^{-1}$**	**$MJm^{-2}day^{-1}$**	**$MJm^{-2}day^{-1}$**	**$MJm^{-2}day^{-1}$**
Jan	17.103	18.788	17.463	18.835	19.594	19.591
Feb	20.184	19.199	18.623	20.102	19.596	19.965
Mar	19.876	18.925	19.736	18.926	19.585	19.736
Apr	21.571	20.157	18.645	20.209	19.148	19.634
May	19.876	18.515	18.575	19.187	18.715	18.765
Jun	14.792	16.461	15.346	15.443	14.916	15.717
Jul	11.556	14.408	11.976	11.805	12.979	12.375
Aug	11.710	13.723	11.573	12.059	13.495	12.100
Sep	15.562	15.777	15.715	14.767	15.547	14.995
Oct	17.257	16.050	17.221	17.224	17.452	17.361
Nov	19.414	18.788	18.702	18.788	19.489	18.636
Dec	18.490	20.431	17.463	18.855	19.591	19.585
	CC	0.904	0.964	0.969	0.925	0.937
	RMSE	3.017	2.925	2.921	2.960	2.922
	MBE	-0.319	0.529	0.099	-0.226	-0.089

Table 3. Analysis of GSRs for year 1983 using various models

Year 1983	GSR	EQUATION 1	ANFIS 1	ANFIS 2	NN1	NN2
Months	**$MJm^{-2}day^{-1}$**	**$MJm^{-2}day^{-1}$**	**$MJm^{-2}day^{-1}$**	**$MJm^{-2}day^{-1}$**	**$MJm^{-2}day^{-1}$**	**$MJm^{-2}day^{-1}$**
Jan	20.493	16.187	19.736	20.493	19.596	20.466
Feb	21.571	17.419	19.864	21.584	19.596	21.556
Mar	20.339	16.050	20.340	20.324	19.596	20.339
Apr	20.030	18.925	19.969	20.034	19.522	19.760
May	18.336	18.652	18.657	19.891	18.386	19.176
Jun	14.946	16.598	16.200	16.007	15.547	16.050
Jul	13.251	15.640	13.983	13.390	13.876	13.830
Aug	12.018	13.723	10.765	12.015	13.876	11.448
Sep	14.484	14.955	15.559	14.752	13.876	15.340
Oct	17.103	15.777	17.764	16.809	16.209	16.493
Nov	18.027	17.146	18.547	18.994	19.148	18.696
Dec	17.719	16.461	18.692	18.836	19.522	18.878
	CC	0.673	0.952	0.981	0.931	0.979
	RMSE	2.885	2.780	2.801	2.844	2.804
	MBE	0.899	-0.147	-0.401	-0.036	-0.310

respectively. It is obvious from the plots the NN2 gives a better prediction as compared to NN1. Generally, the soft computing techniques of ANFIS2, NN2, ANFIS1 and NN1 respectively give a reasonably high performance in the estimation of the monthly average global solar radiation with respect to the regression method.

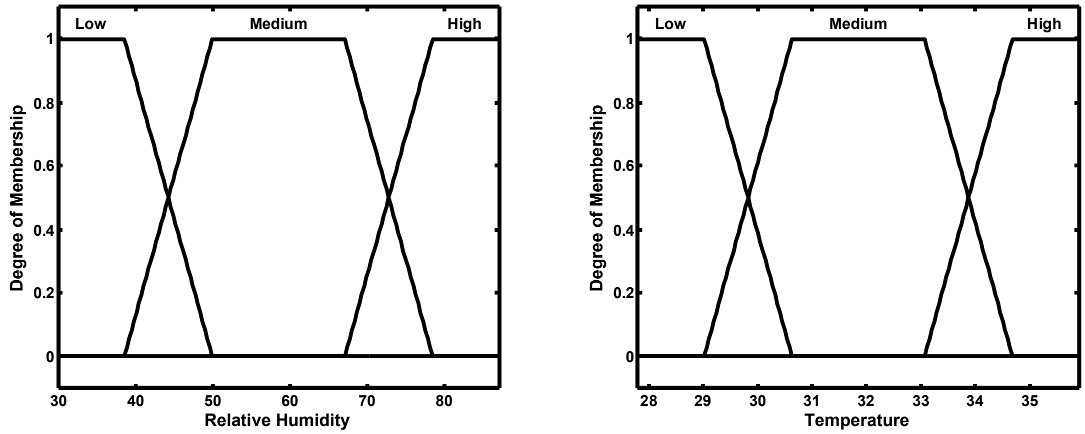

Fig. 3. ANFIS2 Fuzzy input sets using trapezium membership functions representing relative humidy and maximum temperature as inputs

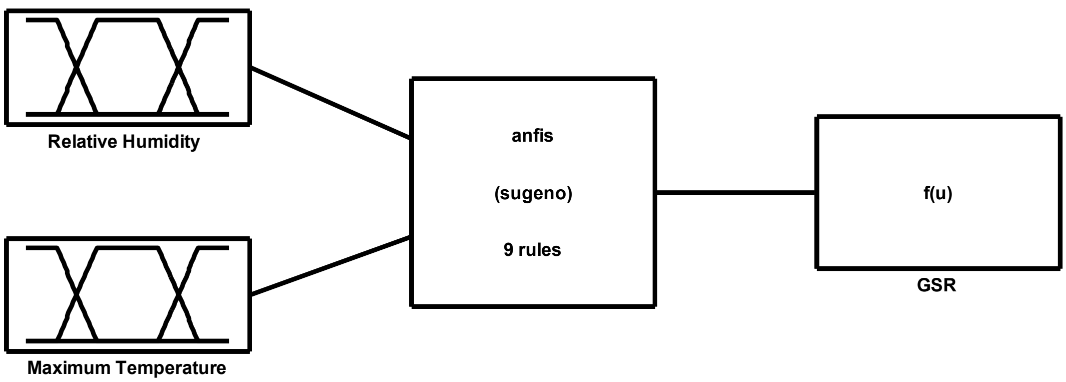

Fig. 4. ANFIS 2, using 2 inputs, 1 output and 9 rules

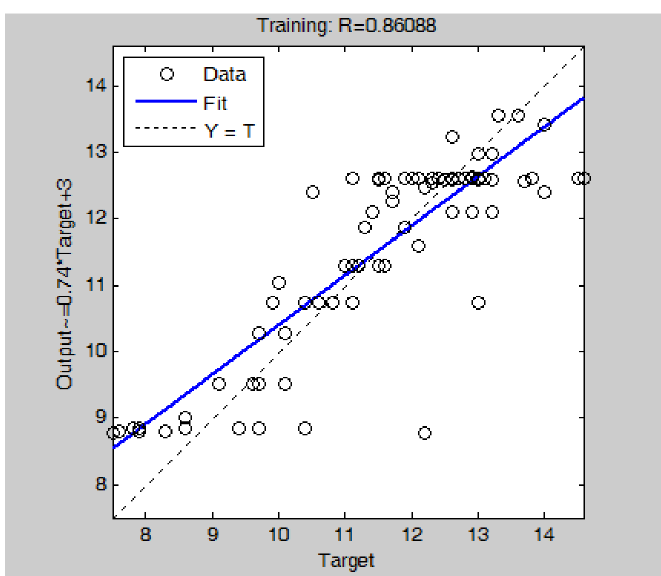

Fig. 5. Best fit lines between actual and predicted GSR for NN1

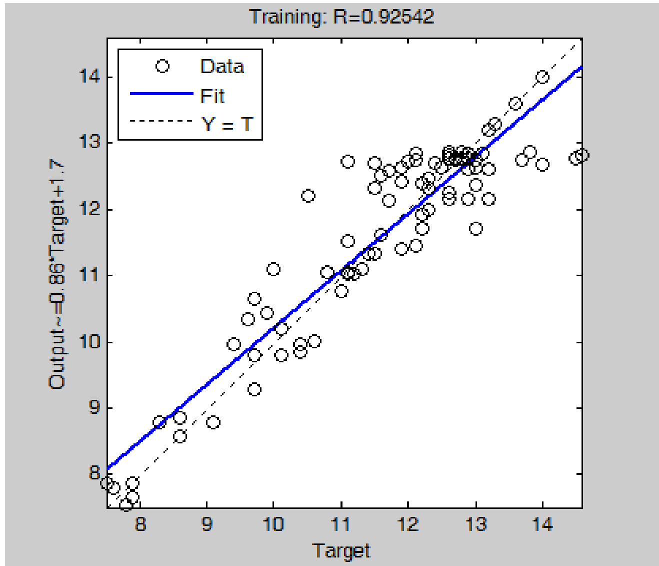

Fig. 6. Best fit lines between actual and predicted GSR for NN2

4. CONCLUSION

The Angstrom type, ANFIS and NN models were used for the estimation of monthly average global solar radiation for Port Harcourt, Nigeria using maximum temperature, relative humidity and daily global radiation. The models showed very good result with respect to widely used statistical indicators of Correlation Coefficient (CC), Mean Bias Error (MBE) and Root Mean Square Error (RMSE). It was found that the models provided reasonably high degree of precision in the estimation of monthly average global solar radiation on horizontal surfaces. Our result indicates that the ANFIS and NN models give better results and may be used satisfactorily for the estimation of global radiation in Port Harcourt and regions having similar climatic features.

COMPETING INTERESTS

Authors have declared that no competing interests exist.

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