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ESTIMATION OF GLOBAL SOLAR RADIATION AT CALABAR USING TWO MODELS

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Abstract
In this study, the estimation of global solar radiation with Meteorological parameters at Calabar- Nigeria latitude 4^0N and longitude 8^0 E were carried out. The daily mean temperature and relative humidity for seventeen years (1991 to 2007) from Nigerian Meteorological Agency, Federal Ministry of Aviation, Oshodi, Lagos were used. The global solar radiation data were collected courtesy of Renewable Energy for Rural Industrialization and Development in Nigeria. Two models (multiple regression and artificial neural network) were used for the estimation. Comparing the graphs of correlation equation 4 and 5, and equation 6 and 7 of the first model, it is obvious that the first order correlation has better estimation power. Looking at the overview of all the Figures (1 -5A), is it is clear that the two models used in this study has estimation capacity, but Figure 5A shows better correlation with the measured values, which indicates that artificial neural network model is a better model for estimation. Therefore has been recommended for global solar radiation estimation at Calabar and its environs with similar weather condition. Alternatively, first order regression should be use for estimation in the absent of artificial neural network.
Keywords: artificial neural network, regression, model, global solar radiation

1. Introduction

In evaluating development and standard of living of any nation, energy plays a very vital role. It is the fundamental resources which give the ability to transform transport and manufacture any and all kind of goods. To this effect energy is vital to the development of any nation.

Without the sun, the earth would have been a frozen rock stranded in space (Ekpe, 2011). The sun warms the earth and makes life possible. Its energy generates clouds, cleanses our water, produces plants, keeps animal and humans warm, and drives ocean currents and thunderstorms. Despite the sun's importance, scientists have only begun to study it with high precision in recent decades (Sofia, 2008).

Energy is the motivating force behind the sustained technological development of any nation and Nigeria is blessed with reasonably high quantities of various energy resources. While Nigeria has adequate solar energy potential to support its energy demand, it is therefore important to harness that resource in view to finding solution to energy shortage in the country, and environmental degradation the country is facing. Solar energy is now considered to be most effective and economic alternative resource (Scheer and Ketley, 2002).

In developing countries, such as Nigeria, interest in solar energy applications has been growing in the provision of electricity and water supply in rural areas. Solar radiation is used directly to produce electricity and heat using photovoltaic (PV) systems and solar thermal systems respectively. Therefore, precise knowledge of historical global solar radiation at a location of study is required for the design and estimation of the performance of any solar energy system.

It is pertinent to note that many researchers who have done similar work (estimation of global solar radiation) in different locations concentrated on one model, either with artificial neural network or in most cases with empirical model of different modeling. But this work is aim at estimating global solar radiation with regression and artificial neural network, in other to recommend the best model for global solar radiation estimation.

Neural networks are adaptive statistical models based on an analogy with the structure of the brain. They are adaptive because they can learn to estimate the parameters of some population using a small number of exemplars (one or a few) at a time. Advance in the field of Artificial Neural Networks (ANN) in the late 1980s popularized non-linear regression techniques like Multi-layer Perceptons (MLP) and self-organizing maps (SOM). It is shown that Neural Networks (NN) can be trained to successfully approximate virtually any smooth, measurable function (Hornik, Stinchcombe and White, 1989). NN are highly adaptive to non-parametric data distributions and, whilst other statistical methodologies require a set of assumptions to be fulfilled, the former make no prior hypotheses about the relationships between the variables. NN are also less sensitive to error term assumptions and they can tolerate noise, chaotic components and heavy tails better than most of the other methods. Other advantages include greater fault tolerance, robustness, and adaptability especially compared to expert systems, due to the large number of interconnected processing elements that can be trained to learn new patterns (Lippman, 1987).

2. Regression Analysis

In regression analysis, the first and second order regressions of normal equations were employed to estimate global solar radiation as follows (Agbo et al, 2012)

$$aN + bx = y \qquad (2)$$

$$aN + bx + cr^2 = y \qquad (3)$$

Where a, b and c are constants which will be determined, y is the same as H (dependent variable), while x were used to replace any of the meteorological data like relative humidity, temperature (independent) etc.

Applying our variables (T_{av} and R) as the independent variable in equation 2 we obtain the first order regression as follows:

$$a_1 N + b_1 Tav = H_1 \qquad (4)$$

$$a_2 N + b_2 R = H_2 \qquad (5)$$

Where Tav = average temperature and R = relative humidity.

Similarly the second order regression using our independent variables, such as average temperature and relative humidity are as follows.

$$H_3 = a_3 + b_3 Tav + C_3 T_{av}^2 \qquad (6)$$

$$H_4 = a_4 + b_4 R + C R^2 \qquad (7)$$

3. Theory of artificial neural network

The neurons act like parallel processing units. An artificial neuron is a unit that performs a simple mathematical operation on its inputs and imitates the functions of biological neurons and their unique process of learning.

In order to compute the global solar radiation, 2-2-1 multilayer perceptron (MLP) neural networks were used, which include the input layer, a linear output layer and a sigmoid hidden function. That is two inputs (temperature and relative humidity), two hidden layer and one output layer. The weighed sum of the inputs

$$v_k = \sum_{j=0}^{N} X_j W_{kj} + b_k \qquad (8)$$

is calculated at kth hidden node.

w_{kj} is the weight on connection from the j_{th} to the k_{th} node; x_j is an input data from input node; N is the total number of input (N=12); and b_k denotes a bias on the kth hidden node.

Each hidden node then uses a sigmoid transfer function to generate an output

$$Z_k = [\,1 + e^{(-v_k)}\,]^{-1} \qquad (9)$$

between -1 and 1.

We then set the output from each of the hidden nodes, along with the bias b0 on the output node, to the output node and again calculated a weighted sum,

$$y_k = \sum_{k=1}^{N} V_k Z_k + b_k \qquad (10)$$

where *N* is the total number of hidden nodes; and v_k is the weight sum from the *k*th first hidden node to the sigmoid transfer function of the output node of the second hidden note, which sum up to give final output.

4. Source of data

The meteorological data of relative humidity and temperature were obtained from Nigerian Meteorological Agency, Federal Ministry of Aviation, Oshodi, Lagos, Nigeria as shown in and the global solar radiation data collected from Renewable Energy for Rural Industrialization and Development in Nigeria Table 2. The geographical location of the area Calabar is as shown in table 1.

Table 1: Geographical location of the station

Station	latitude	longitude	Attitude (m)
Abuja	**4^0 N**	**8^0 E**	**58**

Table 2 is the monthly average data of temperature, relative humidity and measured global solar radiation processed in preparation for the correlation and estimations.

Table 2: Monthly mean values of climatic parameters for Calabar (1996 – 2006)

S/N	Month	T_{av} (^{0}C)	R (%)	H (MJ/M2/day)
1	January	32.35	76.36	14.00
2	February	33.81	76.46	16.37
3	March	32.72	82.64	15.45
4	April	31.96	84.27	16.36
5	May	31.51	84.00	15.14
6	June	30.16	86.82	13.09
7	July	24.95	90.00	11.04
8	August	28.13	91.64	12.29
9	September	29.16	89.00	13.49
10	October	30.02	87.00	14.13
11	November	31.06	85.27	14.34
12	December	31.91	80.46	13.26
	$\sum$ =	371.711	1013.91	169.56

5. Results

Table 3 shows the differences between the results of the models estimation and the measured values of global solar radiation, while Figures 1 to 4, shows the result of each correlation with measured values, and Figure 5A and 5B, shows the graph of the artificial neural network estimation of global solar radiation of 2D and 3D respectively. Where H_1 = first order estimation with temperature, H_2 = first order estimation with relative humidity, H_3 = second order estimation with temperature, H_4 = second order estimation with relative humidity, H_5 = artificial neural network estimation and H = measured global solar radiation respectively.

Table 3: Differences between Calculated, Artificial neural network and Measured Global solar radiation

S/N	Month	H_1 –H	H_2 –H	H_3 –H	H_4 –H	H_5 -H
1	Jan	1.099	1.221	0.871	-2.498	0.0449
2	Feb	-0.239	-1.166	-1.516	-4.842	0.0000
3	Mar	0.088	-1.421	-0.583	-2.043	-0.0804
4	April	-1.536	-2.642	-1.485	-2.431	0.2177
5	May	-0.631	-1.370	-0.260	-1.299	-0.0602
6	June	0.472	0.145	1.805	1.671	0.0305
7	July	1.063	0.990	3.266	4.195	0.0000
8	Aug	-0.164	0.029	2.626	4.112	- 0.0103
9	Sept	-0.540	-0.670	1.415	2.003	- 0.0202
10	Oct	-0.671	-0.930	0.766	0.691	0.0000
11	Nov	-0.149	-0.912	0.545	-0.087	0.0002
12	Dec	0.048	0.048	1.616	-0.532	0.0028
	Total $\sum$	-1.160	-6.678	9.006	-1.060	0.125

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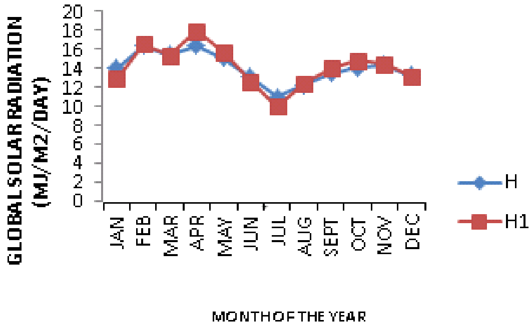

FIG. 1: Comparison between the measured and predicted values of Global solar radiation from correlation of equation 4

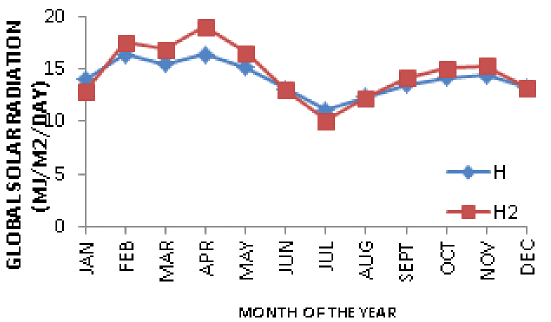

FIG.2: Comparison between the measured and predicted values of global solar radiation from correlation of equation 5

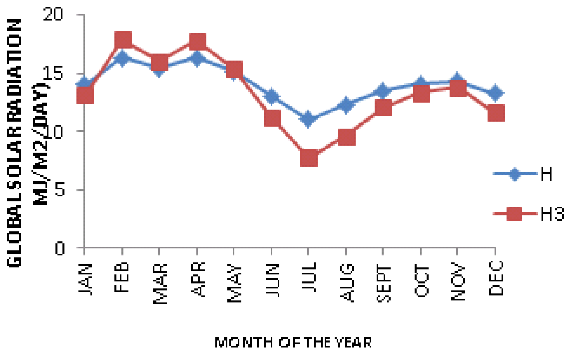

FIG. 3: Comparison between the measured and predicted values of global solar radiation from correlation of equation 6

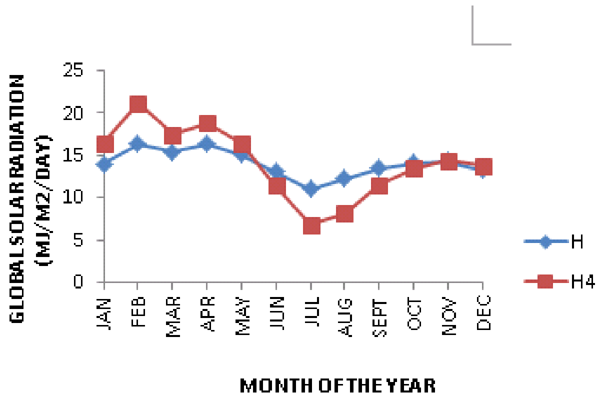

FIG.4: Comparison between the measured and predicted values of global solar radiation from correlation of equation 7

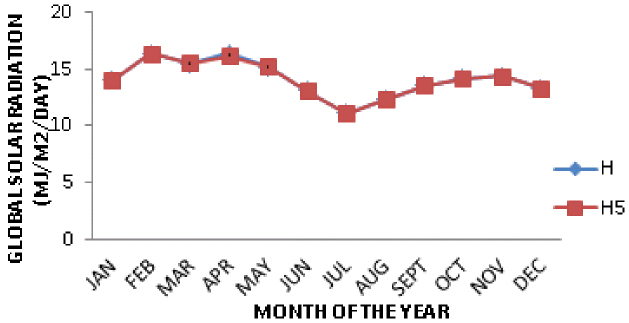

FIG. 5 A: Comparison between the measured and predicted values of global solar radiation with artificial neural network

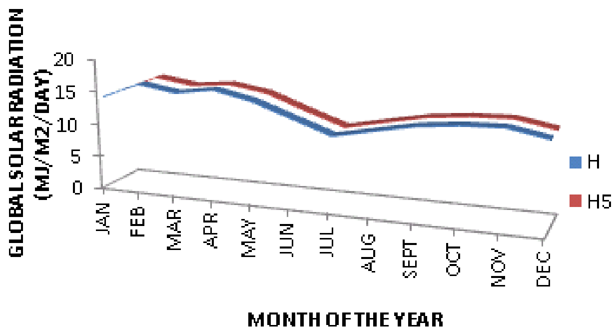

FIG. 5 B: Comparison between the measured and predicted values of global solar radiation with artificial neural network

6. Discussions

Figure 1, 2, 3, and 4 shows the estimation of global solar radiation at Calabar with correlation equation 4, 5, 6 and 7. While Figure 5A and 5B shows the 2-D and 3-D of the estimation with neural network. Close observation of the figures show that sharp crest occur in July in all the figures. This indicates heavy rainfall, high relative humidity, no or little solar flares effect in July. From Table 2 and Figures 1-5B, the weather conditions were grouped into four categories as follows:

Table 3: Classification of weather condition of Calabar according to measured and estimated values of globL solar radiation

VERY HIGH	HIGH	LOW	VERY LOW
February	**December**	**June**	**July**
March	**January**	**August**	
May		**September**	
October			
November			

"Very high" indicates those months that has high values of global solar radiation. "High" indicates the months whose values are not two high as the first group. "Low" refer to those months that has low values of solar radiation compared to first two groups, while "very low" is the month that has the lowest values of solar radiation.

The classification indicates that February, March, May, October, and November respectively have similar weather condition and the effect of solar flares is likely going to be very high since it has high solar radiation. In the month of December and January the values dropped. This indicates the presence of harmattan and the effect of solar flares is likely to be the cause of the also drop, but communication sector will experience some network failure. In June, August and September, the values of solar radiation dropped down drastically. This indicates a period of rainfall. This also shows high values of relative humidity. The very low value of solar radiation occurs in July. It shows the pick of rainfall at Calabar. From the observation and classifications, it is better to plant agricultural product in June, August and September respectively at Calabar. While the month of June is left for those crops that need heavy rainfall to germinate.

It is pertinent to note that comparing the graphs of correlation equation 4 and 5, and equation 6 and 7, it is obvious that equation 4 and 5 which is the first order correlation has better estimation power. This can be better understood from Figure 1 to 4. Looking at the overview of all the Figures (1 -5A), is it is clear that the two models has estimation capacity, but Figure 5A shows better correlation with the measured values. Thus is recommended for the estimation of global solar radiation. Figure 5B is the 3-D of graph of artificial neural network; this is to separate or stretch the graph of artificial neural network and measured values to show clear correlation between measured and its estimations and the trend of the graph.

7. Conclusion

Energy is the motivating force behind the sustained technological development of any nation and Nigeria is blessed with reasonably high quantities of various energy resources. In view of the above, this study use two models (multiple regression and artificial neural network) to estimate solar radiation. Comparing the graphs of correlation equation 4 and 5, and equation 6 and 7, it is obvious that the first order correlation has better estimating power. Looking at the overview of all the Figures (1 -5A), is it is clear that the two models used in this study has estimation capacity, but Figure 5A shows better correlation with the measured values, which indicates that artificial neural network model is a better model for estimation. Therefore has been recommended for global solar radiation estimation at Calabar and its environs with similar weather condition. Alternatively, first order regression should be use for estimation.

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