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Estimation of Global Solar Radiation at Onitsha with Regression Analysis and Artificial Neural Network Models

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Abstract

Energy plays an important role in determining the conditions in which living matter can exist and continuous steering power for social, economic and technological prospective development. This study is aimed at estimating the global solar radiation on horizontal surface using meteorological parameters of average temperature and relative humidity for a period of eleven years (1996-2006) at Onitsha, Anambra State of Nigeria. Regression analysis and artificial neural network models were employed in the analysis. Validation of the results using error analysis show that one-variable model of relative humidity has MBE=0.0032, RMSE=0.0109, MPE=-0.753 and one-variable of average temperature has MBE=0.087, RMSE=0.3025, MPE=-0.778. Two-variable model of relative humidity and average temperature has MBE=0.350, RMSE=1.214 and MPE=-3.928. While artificial neural network has MBE=0.00024, RMSE=0.0134 and MPE=0.203. Based on the above validation results, it therefore become clear that artificial neural network has better agreement with measured global solar radiation. Hence, should be used for estimation of global solar radiation of Onitsha and other locations with similar climatic factors

Key words: Troposphere, global solar radiation, artificial neural network, regression analysis

Introduction

The troposphere is the lower layer of the earth atmosphere. Most of the weather phenomena, systems, convection, turbulence and clouds occur in this layer, although some may extend into the lower portion of the stratosphere[1]. The troposphere contains almost all the atmospheric water vapour, it contains about 70 to 80 percent of the total mass of the earth atmosphere and 99 percent of the water vapour[1]. The resulting solar interaction on the atmosphere leads to changes in weather as well as so called climate change.

This study is aimed at estimating the global solar radiation with regression analysis and artificial neural network at Onitsha, Anambra State.

A number of correlation with meteorological parameters such as ambient temperature, the total precipitation, relative and specific humidity, total cloud cover etc have been developed by different researchers[2] to estimate global solar radiation in different locations. Empirical model for the estimation of global solar radiation with meteorological parameters were first developed by[3] and the model was put into convenient form by[4] as:

$$\frac{H}{Ho} = a + b\left(\frac{n}{N}\right) \quad (1)$$

Where H is the measured global solar radiations
Ho is the monthly extraterrestrial solar radiation on horizontal surface, n is the bright sunshine hours, N is the maximum possible sunshine Hour, $\frac{H}{Ho}$ is the clearness index, n/N is the fraction of sunshine hours, a and b are regression constants.

Material and Methods

The data used for this study were obtained from the Nigeria Meteorological Agency, Federal Ministry of Aviation Oshodi, Lagos and Renewable Energy for Rural Industrialization and Development in Nigeria.

The data collected cover a period of eleven years (1996 – 2006) at Onitsha (Latitude 5^0N, Longitude 6^0 and altitude 56 meters above sea level). The model were developed by converting solar radiation data for Onitsha measured in millimeters to useful form (MJ/M^2/day) with a conversion factor of 1.1364 proposed by 5.

The two methods involves in this work are regression analyses and artificial neural network models which is discussed as follows.

Regression Analysis: In regression analysis, the first and second order regressions of normal equations were employed to estimate global solar radiation 6 as follows

$$aN + bx = y$$
$$aN + bx + cr^2 = y \quad (2) \text{ and } (3)$$

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.

To execute the regression analysis of the first order, both sides of equation (2) were multiply by '1' and equation (3) by x, the summation of both sides of the equations gave

$$aN + b\sum x = \sum y \quad (4)$$

$$aN\sum x + b\sum x^2 = \sum xy \quad (5)$$

Applying our variables (T_{av} and R) as the independent variable in equation 2 for first order we obtained.

$$a_1 N + b_1 Tav = H_1 \quad (6)$$

$$a_2 N + b_2 R = H_2 \quad (7)$$

Second order regression analysis: To obtain second order regression equation, we multiple equation (3) by 1, x and x^2 successively and summing we obtained the following equations.

$$a_1 N + b_2 \sum x + C_3 \sum x^2 = \sum y \quad (8)$$

$$a N\sum x + b_2 \sum x^2 + C_3\sum x^2 = \sum xy \quad (9)$$

$$a_1 N\sum x^2 + b_2\sum x^3 + C_3\sum x^4 = \sum x^2 y \quad (10)$$

Applying these equations by using our independent variables, such as average temperature and relative humidity we have.

$$H_3 = a_3 + b_3 Tav + C_3 Tav \quad (11)$$

$$H_4 = a_4 + b_4 R + C_4 R^2 \quad (12)$$

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 [7].

The weighed sum of the inputs,

$$v_k = \sum_{J=0}^{N} \mathrm{X_j W_{kj}} + \mathrm{b_k} \quad (13)$$

is calculated at kth hidden node.

wkj is the weight on connection from the jth to the kth node; xj is an input data from input node; N is the total number of input (N=17); and bk denotes a bias on the kth hidden node.

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

$$Z_k = [\,1 + e^{(-v_k)}]^{-1} \quad (14)$$

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,

$$y_k = \sum_{k=1}^{N} \mathrm{V_k}\, Z_k + \mathrm{b_k} \quad (15)$$

Where N is the total number of hidden nodes; and vk is the weight from the kth hidden node to the sigmoid transfer function of the output node.

Results and Discussion

Table-1 shows the measured atmospheric parameters and solar radiation. Where, T_{av} = monthly average daily temperature, H= measured values of average daily solar radiation on the horizontal surface, R = Relative Humidity. Equation 6 and 7 were used to estimate solar radiation of first order, while equation 11 and 12 were used to estimate global solar radiation with second order.

The graphs comparing the results between results from the regression analysis, (first and second order), artificial neural network and the measured values of global solar radiation is shown in table -2. In the table below, H = measured value of global solar radiation, H_1 and H_2 = estimation from first order, H_3 and H_4 = estimation from second order, while H_5 = estimation from artificial neural network.

Figure-2 to 3 shows the graph comparing the results from the regression analysis, artificial neural network and measured values of global solar radiation.

From the graph it is clear that results from artificial neural network estimation has a closer agreement with measured values compared with results from regression analysis.

Table-2 shows the differences between estimation from regression analysis both first and second order and measured values of global solar radiation, and the differences between estimation from artificial neural network and measured. The results of the differences between artificial neural network artificial neural network for February, July, October and November is zero, this indicates that the estimation of ANN and measured values are of the same values, while the other months ANN also have a small values indicating close range with the measured values compare to the values from regression analysis.

The total value of the differences between artificial neural network is small than the total values of regression analysis both first and second order.

Validation of the results using error analysis show that one – variable model of relative humidity has MBE = 0.0032, RMSE = 0.0109, MPE = -0.753 and one variable model of average temperature has MBE = 0.087, RMSE = 0.3025, MPE = -0.778. Two – variable model of relative humidity and average temperature has MBE = 0.350, while artificial neural network has MEE = 0.350, artificial neural network has MBE = 0.00024 respectively.

Conclusion

Solar energy has an important role in economic development of our country, since energy plays an important role in determining the conditions in which living matter can exist. From the results, this study has show that atmospheric parameters can be used to estimate global solar radiation. Based on the validation results, it therefore becomes clear that artificial neural network has better agreement with measured global solar radiation, but both have estimating capacity. Hence, artificial neural network model should be used for estimation of global solar radiation at Onitsha and other locations with similar climatic conditions.

Acknowledgment

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Table -1
Monthly mean values of climatic parameters for Onitsha (1996 – 2006)

S/N	Month	T_{av} (^{0}C)	R(%)	H (MJ/M2/day)
1	January	34.336	67.546	14.25
2	February	35.527	69.727	15.65
3	March	34.809	75.182	14.77
4	April	33.555	79.182	14.27
5	May	32.236	81.127	12.85
6	June	31.027	84.546	12.61
7	July	29.545	87.000	11.65
8	August	30.436	88.182	10.80
9	September	31.364	85636	12.26
10	October	33.364	82.818	15.18
11	November	33.500	75.909	16.51
12	December	33.836	71273	15.42
	$\sum$ =	389.535	948.91	169.22

Table -2
Difference 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	1.085	1.861	-0.186	0.181	0.0449
2	Feb	0.467	0.082	-1.599	- 1.045	0.0000
3	March	1.876	-0.019	-0.711	0.307	-0.0804
4	April	0.553	-0.184	- 0.196	1.142	0.2177
5	May	- 0.892	- 1. 207	- 0.761	0.0793	-0.0602
6	June	- 0.445	-0.457	0.493	2.296	0.0105
7	July	0.543	1.076	2.469	4.491	0.0000
8	Aug	1.274	1.720	3.322	5.456	- 0.0203
9	Sept	0.517	0.703	1.850	3.749	- 0.0204
10	Oct	-1.723	- 1.726	- 1.081	0.564	0.0000
11	Nov	- 1.723	- 1854	- 1.436	- 0.864	0.0000
12	Dec	- 0.48	0.038	-0.186	16.379	0.0028
	Total $\sum$	1.048	0.038	-0.186	16.379	0.00288

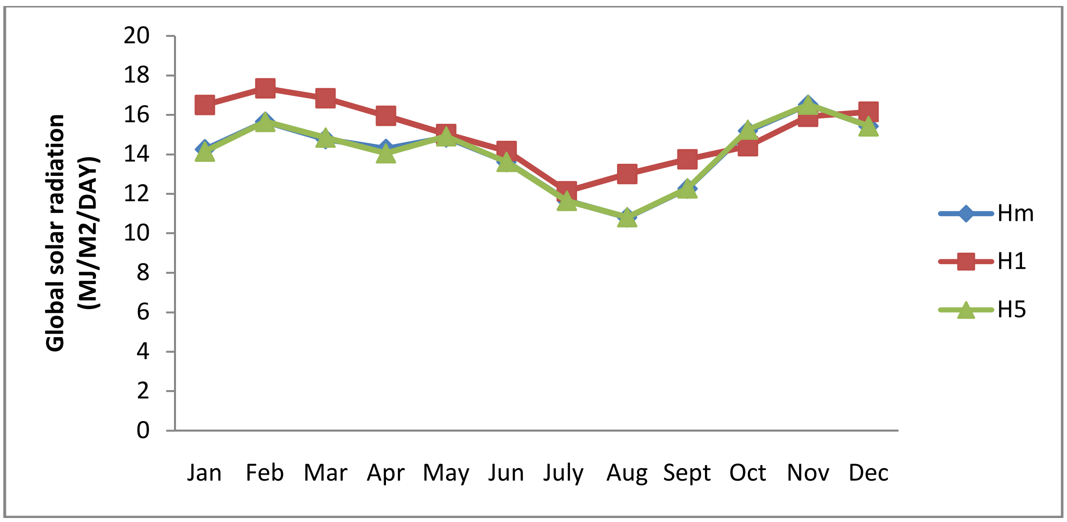

Figure 1
Measured, estimation of first order (Tav) and artificial neural network

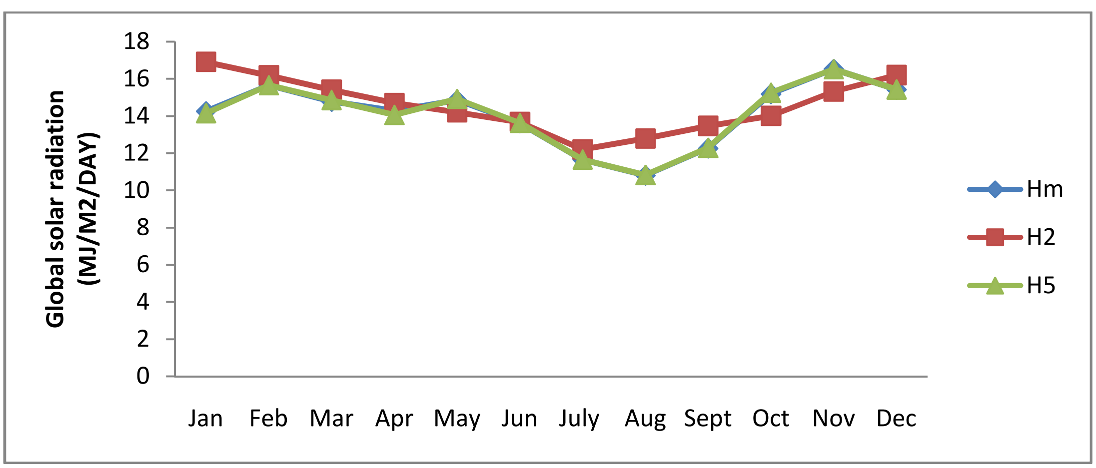

Figure-2
Measured, estimation of first order ® and artificial neural network

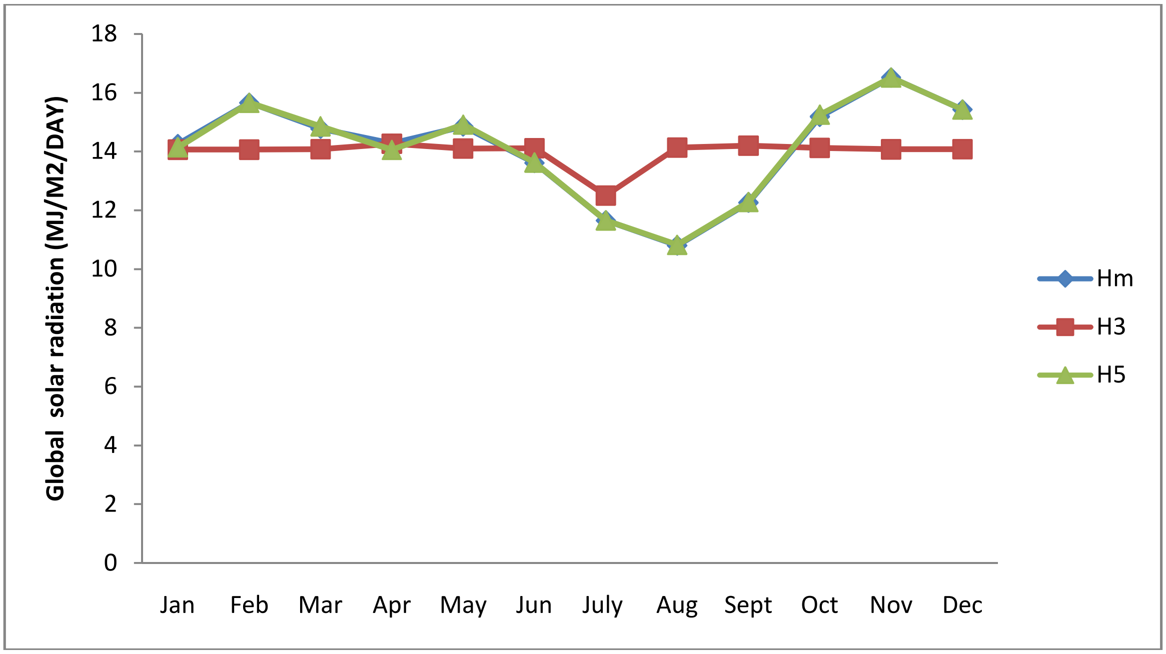

Figure-3
Measured, estimation of second (Tav) and artificial neural network

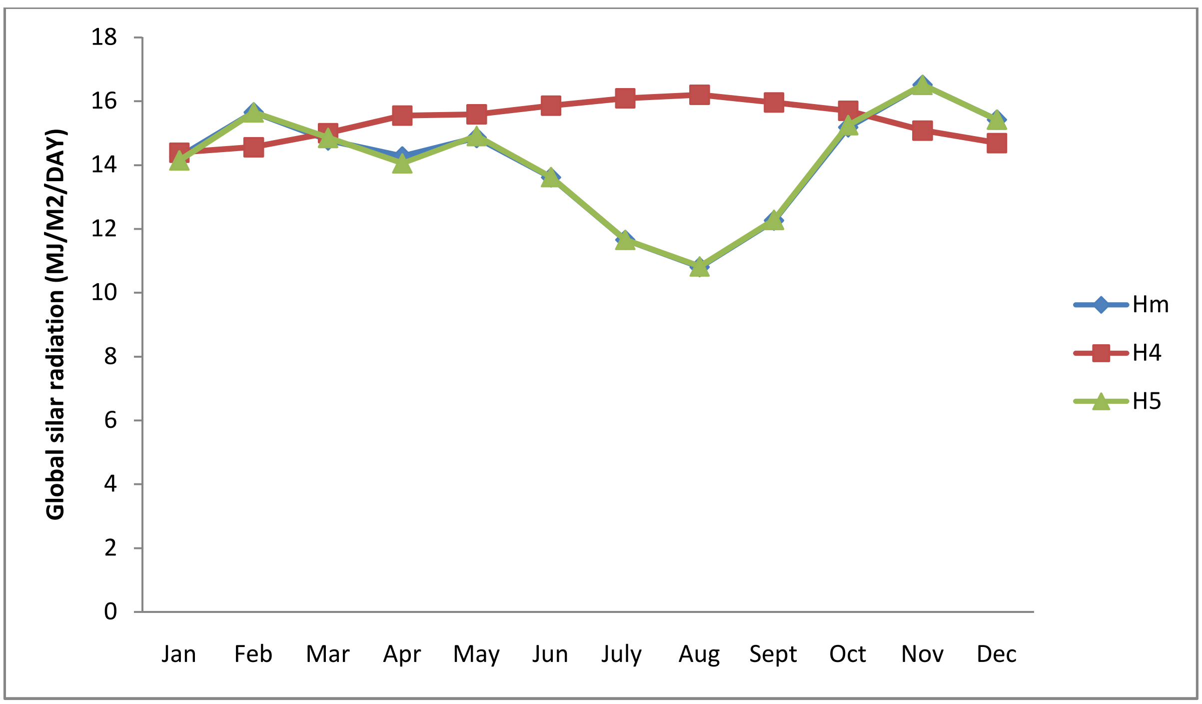

Figure-4
Measured, estimation of second order (R) and artificial neural network