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Strictly as per the compliance and regulations of:

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I. Introduction

The troposphere is the lower layer of the Earth's 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. The troposphere contains almost all the atmospheric water vapour. It contains about 70 to 80 percent of the total mass of the earth's atmosphere and 99 per cent of the water vapour. Temperature and water vapour content in the troposphere decrease rapidly with altitude and thus most of the water vapour in the troposphere is concentrated in the lower, warmer zone. Water vapor concentrations vary with latitude. The condition of the atmosphere as dictated by the sun is very dynamic both in space and time scales. The resulting solar interactions on the atmosphere leads to changes in weather as well as the so called climate change.

The objective of this study is to model the relevant data provided by the Nigerian Meteorological Agency, Federal Ministry of Aviation, Oshodi, Lagos, Nigeria as shown in Table 1 and the global solar radiation data collected from Renewable Energy for Rural Industrialization and Development in Nigeria using the Angstrom-Prescott, statistical technique (multiple regression model) and the artificial neural networks (ANN), and then comparing the results of these three models along with the measured solar radiation data. The table below (Table1) shows the atmospheric parameters in preparation of the prediction.

Table 1 : Meteorological Data for Warri

Month	$\bar{n}$ Hour	T_m °C	$\bar{H}_M$ (MJm^{2}day^{-1})
JAN	4.72	33.00	12.52
FEB	4.80	33.68	14.26
MAR	4.61	33.45	15.64.
APR	4.92	32.86	18.11
MAY	4.89	31.93	12.84
JUN	3.86	30.53	13.99
JUL	2.27	28.77	14.67
AUG	2.31	28.89	13.85
SEPT	2.57	29.99	15.40
OCT	4.15	31.28	16.55
NOV	5.23	32.74	15.81
DEC	5.66	32.66	18.16

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II. Methods and Procedures

Multiple Regressions

Regression method is one of the most widely used statistical techniques Mendenhall and Beaver (1994) and Sharda, and Patil (1990). Multiple regression analysis is a multivariate statistical technique used to examine the relationship between a single dependent variable and a set of independent variables. The objective of the multiple regression analysis is to use independent variables whose values are known to predict the single dependent variable (Olaniyi, 2011). The effect of independent variables on the response is expressed mathematically by the regression or response function f:

$$y = f(x_1, x_2, \ldots, x_n; \beta_1, \beta_2, \ldots, \beta_n) \quad (1)$$

where y is the dependent variable.

$\beta_1, \beta_2, \ldots, \beta_n$ in the regression parameters which will be determined

The regression model for the observed response variable is written as

$$z = y + \varepsilon = f\left(x_1, x_2, \ldots, x_n; \beta_1, \beta_2, \ldots \beta_n\right) + \varepsilon \quad (2)$$

Where ε is the error in observed value z (Olaniyi, 2011).

To find *unknown regression parameters* $\{\beta_1, \beta_2, \ldots \beta_n\}$, *the method of least squares (*Beenstock, 1992) can be applied:

$$E\,(\beta_1, \beta_2, \ldots \beta_n) = \sum_{j=i}^{n} (z_j - y_j)^2 = \sum_{j=i}^{n} (z_j - f\,(x_1\, x_2, \ldots, x_n; \beta_1, \beta_2, \ldots \beta_n)\,)^2 \quad (3)$$

Where $E\ (\beta_1, \beta_2, \ldots \beta_n)$ is the error function or sum of squares of the deviations.

To estimate $\beta_1, \beta_2, \ldots n$ we minimize, *E*, by solving the system of equations:

$$\frac{\partial E}{\partial \beta_1} = 0, \; i = 1,2, \ldots, n \quad (4)$$

a) Model Specification and Analysis

The regression model to consider in this study takes the maximum temperature (Tm) and sunshine hour ($\bar{n}$) as the explanatory variables and measured values (H_m) as dependent variable. This is used to obtain a reliable parameter estimates in the regression. The model to be used can be specified as

$$H_M = f\,(T_M, \bar{n}) \quad (5)$$

More precisely;

$$H_M = \beta_0 + \beta_1 T_M + \beta_2 \bar{n} \quad (6)$$

$\beta_0, \beta_1, \beta_2 > 0$

III. Angstrom-Prescott Model

There are several types of empirical formulae for predicting the monthly mean daily global solar radiation as a function of readily measured climatic data (Iqbal, 1977; and Klien, 1977). Among the existing correlations, the one used in this paper is the Angstrom–Prescott regression equation, which relates the monthly mean daily global solar radiation to the number of hours of bright sunshine as follows

$$\frac{\bar{H}_M}{H_O} = a + b\frac{\bar{n}}{\bar{N}} \quad (7)$$

Where,

$\bar{H}_M$ = measured monthly mean daily global solar radiation on a horizontal sunshine.

$\bar{n}$ =monthly mean daily bright sunshine hour, $\bar{N}$ = Maximum possible monthly mean daily sunshine,

a and b = regression constant.

The monthly mean daily extraterrestrial radiation $\bar{H}_o$ and monthly mean day length $\bar{N}$ was derived from the formulae:

$$\bar{H}_O = \frac{24}{\pi} I_{SC}\, E_O\, [W_S \sin\Phi \sin\Phi + \cos\Phi \cos\delta\, \cos W_S] \quad (8)$$

$$\bar{N} = \frac{2}{25}\,\mathrm{COS}\text{-}1\ (-\tan\Phi \tan\delta) \quad (9)$$

$$\delta = 23.45 \sin\left[\frac{N+284}{365}\right] \quad (10)$$

$$W_S = \mathrm{COS}\ \text{-}1\ (-\tan\Phi \tan\delta) \quad (11)$$

I_{SC} = solar constant (4.921 $\mathrm{MJM^{-2}\ day^{-1}}$)

N = characteristic day number

Φ = latitude angle

δ = angle of declination

$$a = -0.110 + 0.235 \cos\Phi + 0.323\ (n/N) \quad (12)$$

$$b = 1.449 - 0.553 \cos\Phi - 0.694\ (n/N) \quad (13)$$

IV. Artificial Neural Network Model

Artificial neural network models are based on the neural structure of the brain (Ibeh et al, 2012). The brain learns from experience and so do artificial neural networks. Previous research has shown that artificial neural networks are suitable for pattern recognition, prediction and pattern classification tasks due to their nonlinear nonparametric adaptive-learning properties. As a useful analytical tool, ANN is widely applied in analyzing the data stored in database or data warehouse nowadays (Massie, 2001). One critical step in neural network application is network training. Generally, meteorological data is selected and refined to form training data sets. Artificial Neural Network is widely used in various branches of engineering and science and their unique proper of being able to approximate complex and nonlinear equations makes it a useful tool in quantitative analysis (Olaniyi, 2011).

The true power and advantage of neural networks lies in their ability to represent both linear and non-linear relationships and in their being modeled. Traditional linear models are simply inadequate when it comes to modeling data that contains non-linear characteristics. In this paper, one model of neural network is selected among the main network architectures used. The basis of the model is neural structure as shown in Fig. 1. These neurons act like parallel processing units.

a) Multi-Layer Perception

The most popular network architecture in use today is perhaps the Multilayer Perceptron network and it uses supervised network (Hair and Tatham, 1998). This type of neural network is known as a supervised network because it requires a desired output in order to learn. The goal of this type of network is to create a model that correctly maps the input to the output using historical data so that the model can then be used to produce the output when the desired output is unknown. Figure 1 show the block diagram of a double hidden layer multiplayer perceptron (MLP).

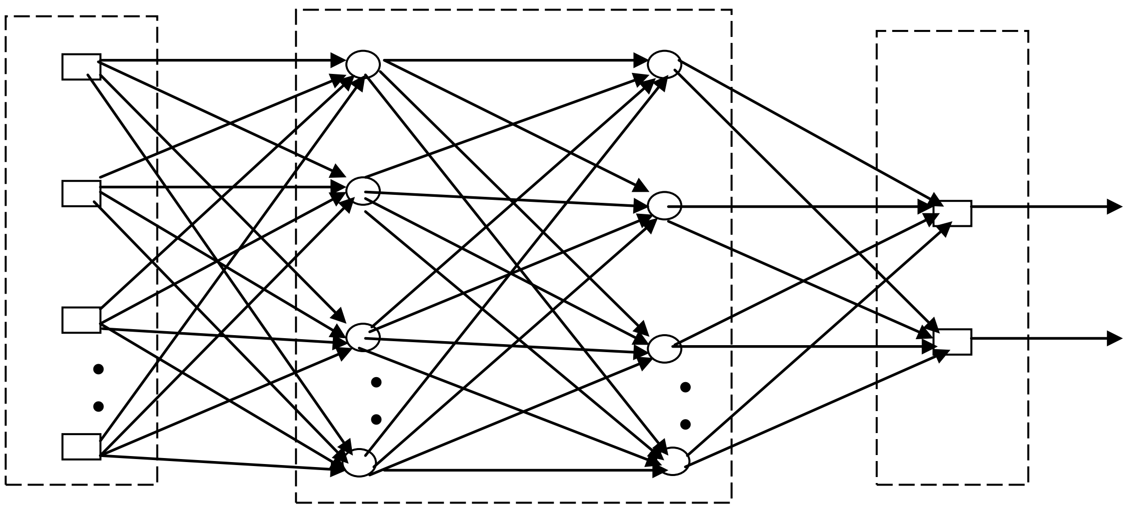

Figure 1: Structure of the artificial neural network with Double hidden layer

The inputs are fed into the input layer and get multiplied by interconnection weights as they are passed from the input layer to the hidden layer. Within the hidden layer, they get summed then processed by a nonlinear function (usually the hyperbolic tangent).

If more than a single hidden layer exists then, as the processed data leaves the first hidden layer, again it gets multiplied by interconnection weights, then summed and processed by the second hidden layer and so on. Finally the data is multiplied by interconnection weights then processed one last time within the output layer to produce the neural network output.

An artificial neuron is a unit that performs a simple mathematical operation on its inputs and imitates the function of biological neurons and their unique process of learning (Ibeh and Agbo, 2012). The weighted sum of the inputs are calculate using the following equation,

$$v_k = \sum_{j=1}^{m} x_j w_{kj} + b_k \qquad (7)$$

Where v_k is the weight sum from the *k*th 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; m is the total number of input (N=17); and b_k denotes a bias on the *k*th hidden node.

The mathematical structure of the normal method is as shown in fig.2

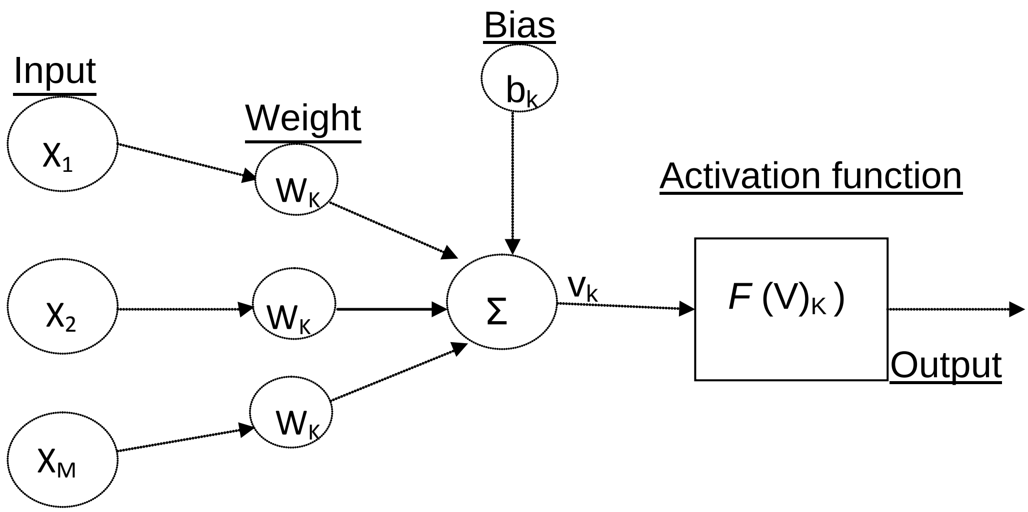

Fig. 2 : Mathematical structure of ANN (Ibeh et al, 2012)

V. Results and Discussions

Table 2 is obtained from the SPSS output for the analysis of the multiple linear regressions relating the measured values of global solar radiation as a function of the maximum temperature (Tm) and the sunshine hour (n). The standard error for each of the variables is indicated in the table 3. From figure 1, the highest value of solar radiation is 18.16 and 18.11MJ/M^2/Day respectively. These results suggest that there is peak dry season in Warri during December and April when the solar radiation is high. Again, the low values of solar radiation occur from May to August, which indicates peak rainfall Warri when the sky is cloudy and solar radiation is low.

Table 2 : Standard error of the models

Variable	Coefficient Std.	Std. Error	*t*-statistic	Prob.
Tm	-0.362	0.656	-0.461	0.785
$\bar{n}$	0.966	0.428	0.830	0.617
Constant	22.591	0.301	1.098	0.000

ERROR	ANN	REGRESSION	ANGSTROM-PRESCOTT
MBE	0.0085	0.2490	0.0352
RMSE	0.0004	0.0104	0.0251
MPE	-1.2580	-2.2116	-1.6230

Table 3 : Summary of error of the two models

VI. Conclusion

In this paper, three techniques for modeling and forecasting the solar radiation of Warri Nigeria: Neural Network, Angstrom-Prescott and Statistical Technique. The forecasting ability of these models is accessed on the basis of MBE, RMSE and MPE. We have discovered the fact that Neural Networks output perform better in forecasting from table 2 and 3 compare to other two models. Thus, ANN should be used for prediction of global solar radiation of the location and other location that has similar condition.

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