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Comparative Estimation of Global Solar Radiation over Two Nigerian Cities, Using Artificial Neural Network and Empirical Models

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ABSTRACT

The estimation of solar radiation intensity has been a focus of many researchers due to the cost of setting up its actual measurements. While many of them employed empirical models, this study utilizes the artificial neural network for the analysis and estimation of global solar radiation over two Nigerian cities. The model developed using sunshine hours, temperatures and relative humidity were compared with the existing empirical models. Model performance indicators comparing the measured data and the computed data for the derived and selected models, using the same number of input meteorological parameters showed that ANN having average values of RMSE, MBE, and MPE of 0.0744 $MJm^{-2}day^{-1}$, -0.0020 $MJm^{-2}day^{-1}$, and -0.0043%, respectively, performed slightly better. When different number of input meteorological parameters were used, the ANN gave the following error indicators for RMSE, MBE, MPE of 0.0394$MJm^{-2}day^{-1}$, -0.0023$MJm^{-2}day^{-1}$ and -0.0144% respectively. Also, in the result of solar radiation in Abuja, using the same number of meteorological parameters, the model with the best performance in the estimation of solar radiation is the ANN model with average values of RMSE, MBE, MPE of 0.1301$MJm^{-2}day^{-1}$, 0.0053$MJm^{-2}day^{-1}$ and 0.0441% respectively. Hence, the models are versatile for predicting global solar radiation in locations in the same climatic zones as locations studied in this study, where direct measurements of solar radiation is scarce and widely separated but there is availability of commonly measured meteorological parameters such as sunshine duration, minimum temperature, maximum temperature and relative humidity.

Keywords: Global Solar Radiation, Empirical, Prediction, Artificial Neural Network, Model.

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Introduction

The need for improving energy mix can not be over emphasized because many households in developing nations are not connected to the National grid. The alternative is small stand alone generators powered by fossil fuels. Apart from the cost of this fuels which in most cases is beyond the reach of average householders, is the environmental prolusion resulting from the incomplete combustion of such fuels. Thus, there has been an increase in the demand for renewable and clean energies according to [1].

One of the most viable renewable energy options, particularly in Nigeria, is the abundant solar energy falling on the Earth surface. Using solar energy necessitates an exact prediction of solar energy in the proposed location(s) according to [2]. The measurements of solar radiation are important due to increasing number of various applications of solar energy in design and installation of solar energy devices. Harnessing this radiant energy from the sun is essential, due to our reliance on hydrocarbon-based energy sources which cause negative impact on human health.

Since the trend of energy utilization has shifted to solar energy, knowledge about the amount of solar radiation at a location where solar energy is needed to be harnessed is essential, according to [3]. The amount of solar radiation is measured using an instrument called Pyrheliometer. However, the cost of setup could be very expensive and delicate, according to [4]. Hence, pyrheliometers setups are scarce and widely spaced in Nigeria. Thus, alternative means have to be developed to generate solar radiation data using commonly measured meteorological parameters for locations without instrument for measuring solar radiation, [5]. In order to circumvent this draw backs, modeling techniques had been used to significantly evaluate global solar radiation using more commonly measured meteorological data.

Empirical models for predicting global solar radiation have been proposed by [6-8]. The former estimates global solar radiation from sunshine hours while the latter did so from air temperature These models enable researchers or users of solar radiation data estimate the magnitude of the global radiation from meteorological parameters that are commonly measured at all meteorological stations because it is difficult and costly to set up instruments that measure global solar radiation directly. These models differ in the number of meteorological parameters used in correlating global solar radiation, accuracy and applicability. They can be categorized into empirical models, radiative transfer models and machine learning models. The radiative transfer models entail complex modeling of solar radiation using geographical and meteorological parameters. Hence, the aim of this study is to write an Artificial Neural Network soft code to estimate global solar radiation from commonly measured meteorological parameters, over the selected locations. The selected parameters shall be studied by ANN, which shall eventually lead to the development of a model to estimate the global solar radiation from routinely measured meteorological parameters. Such parameters include sunshine hours, minimum temperature, maximum temperature and relative humidity. The accuracy of the estimates shall be compared alongside estimates obtained from empirical models using firstly the same number of inputs and secondly with different number of inputs with measured data and the errors involved determined using error indicators.

With technological advancement, the use of artificial neural network is being acknowledged in various fields. Some previous studies have reported their assessment on the use of artificial neural network in some other studies, but it has not been fully utilized in estimating solar radiation in the locations under study and there is need to ascertain its accuracy in prediction of solar radiation. In a study, [9] used ANN to estimate monthly average daily global solar irradiation on a horizontal surface in Uganda based on weather station data (sunshine duration, maximum temperature, and cloud cover) and location parameters of (latitude, longitude, and altitude). Also, [10] who based their study on six years data, using back propagation method with tangent sigmoid as the transfer function to train the ANN model with daily values of measured sunshine duration and maximum temperature as input parameters.

Materials and Methods

The measured solar radiation, sunshine hour, minimum temperature, maximum temperature, and relative humidity data between (1999-2019) for Ibadan were obtained from the meteorological station of the International Institute of Tropical Agriculture Ibadan (IITA) while measured solar radiation, the minimum temperature and maximum temperature between (1990-1992) and (2012-2015) for Abuja were obtained from Nigerian Meteorological Agency (NIMET), Abuja. IITA is an international agricultural research institute with state-of-the-arts meteorological instrument used in measuring meteorological data while NIMET is a national agency saddled with measurement of meteorological data in the country. Data quality control was conducted on the data obtained from the meteorological stations mentioned above. The data were first examined for missing values and outliers. Missing values could be due to instrument failure or power surge. The missing values were replaced by the average of values from same week. Long arrays of missing data (a month for example) are replaced with the corresponding average of same days over the remaining years. The total number of missing data in the measured solar radiation, sunshine hour, minimum temperature, maximum temperature, and relative humidity columns did not exceed 3% of the total data points. The excessive days which are the (February 29) days in the leap years were removed, in order to have a 365-day for all the years considered in the study, to ensure uniformity of month comparison in the data.

The selected commonly measured meteorological parameters were analyzed using Mat Lab. The artificial neural network is a function in the Mat Lab tool box and it was used for the data analysis and prediction of solar radiation data. ANN is a soft computing tool and a data analysis method whose operation resembles a network of biological neurons that learn patterns which are eventually used to predict. Artificial Neural Network soft code was written and relationship between the selected parameters was studied by ANN, which eventually led to the development of a model. The model developed is capable of training and estimating the solar radiation for each month of the year as well as the mean solar radiation of each month.

The Angstrom, sunshine hour-based model is given by

$$\frac{\mathrm{H}}{\mathrm{H_o}} = a + b\,\frac{\mathrm{S}}{\mathrm{S_o}} \qquad (1)$$

where H and Ho are respectively global and extraterrestrial solar radiations, S and So are respectively the actual sunshine and maximum possible sunshine hours while a and b are geographical factors specific to the location.

On the other hand, the Hargreaves-Samani air temperature based model is given by

$$\mathrm{H} = \mathrm{Ho} \times K_r[(\Delta T)^n] \qquad (2).$$

where H and Ho are again global and extraterrestrial solar radiations respectively, ΔT is the difference between the maximum and minimum air temperature while Kr and n are geographical factors specific to the location.

[11] have determined a and b for the location under study and their modified Angstrom model is considered as model 1. [12] obtained 0.125 for Kr and their modified Hargreaves and Samani temperature is considered as model 2.

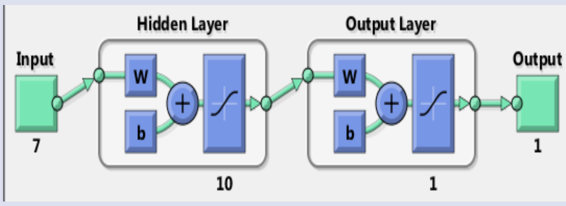

Figure 1. Pictorial representation of the artificial neural network employed in prediction of solar radiation in Ibadan.

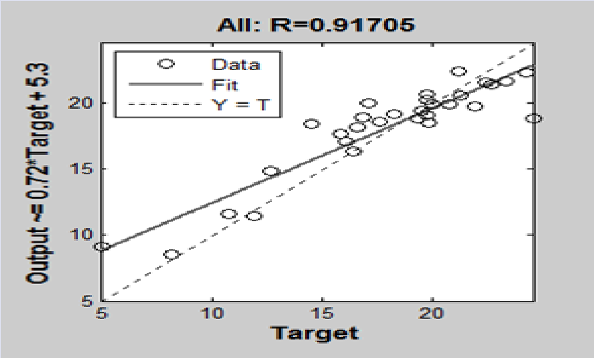

Figure 2. Post-Training regression analysis of the ANN (7-10-1) used for prediction of solar radiation in Ibadan.

The Artificial Neural Network generated model is model 3 and is given by

$$H = \Sigma\left[W_{oj}\left(\frac{2}{1-exp^{-2N}}-1\right)+b_o\right]$$

Where H is the computed solar global solar radiation, $\frac{2}{1-exp^{-2N}}-1$ is the activation function, N is the summed input and b_o is the bias of the output.

Hence, the three models are summarized in Table 1.

Table 1: Models used for the Comparative Estimation of Global Solar Radiation

Model Number and Name	Model Equation
1. Sunshine based model: [1]	$\frac{H}{H_o} = 0.24 + 0.35\frac{S}{S_o}$.........3
2. Temperature based model: [12]	$\frac{H}{H_o} = 0.125[(\Delta T)^{0.5}]$ … 4
3. Artificial Neural Network model	$(H) = \Sigma\left[W_{oj}\left(\frac{2}{1-exp^{-2N}}-1\right)+b_o\right]$ ... 5

Also, the model developed were tested by comparing its estimates derived from each model with measured data, using statistical error analysis tools such as Root Mean Squared Error (RMSE), Mean Bias Error (MBE), Mean Percentage Error (MPE).

RESULTS AND DISCUSSION

The results of the estimates of solar radiation in Ibadan when different number of meteorological parameters are employed, using the modified Angstrom-Prescott model, modified Hargreaves and Samani Model and the Artificial Neural Network model are displayed in Figure 3 below, while the Table 2 shows the results of error indicators.

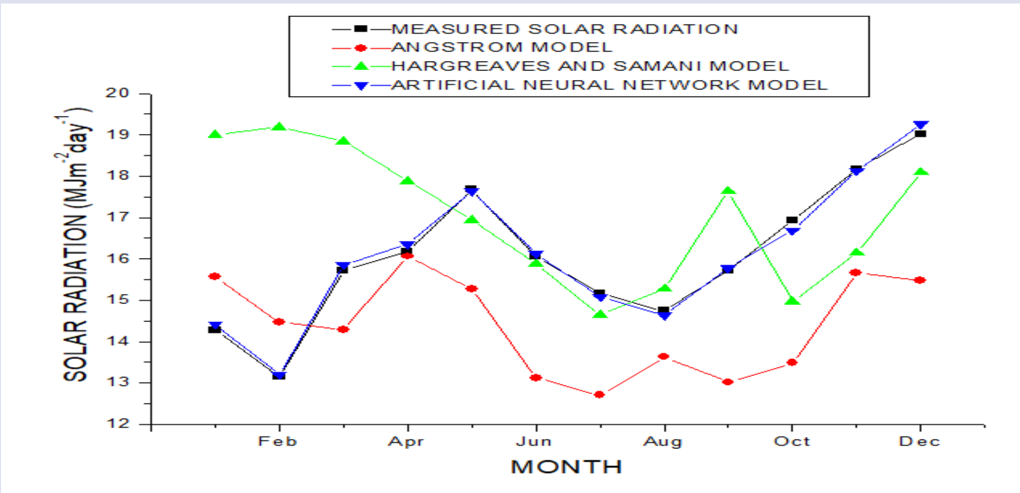

Figure 3. Comparison of the computed mean solar radiation with measured data.

Table 2: Error analysis of the result of the Prediction of solar radiation in Ibadan, when different numbers of meteorological parameters are employed.

MODEL PERFORMANCE INDICATOR			
MODELS	*RMSE*	*MBE*	*MPE (%)*
Angstrom-Prescott Model	0.6731	-0.1396	-0.8107
Hargreaves-Samani Model	0.7667	0.0801	0.6155
Artificial Neural Network Model	0.0394	-0.0023	-0.0144

It can be seen from Figure 3 that the ANN estimates matched the actual value more when compared with the estimates derived from the other two models. This might not be unconnected with more meteorological parameters used to trian the ANN because some other factors apart from sunshine hours and air temperature affect the global radiation.

Figure 3 also shows the comparison of the computed mean solar radiation with measured data. The maximum value of the solar radiation occurred in December (19.24 $MJm^{-2}day^{-1}$). The lowest solar radiation occurred in February (13.16 $MJm^{-2}day^{-1}$), this can be attributed to high turbidity of the atmosphere. This high turbidity is caused by accumulation of aerosol which arises from the prevalence of wind-blown dust of Saharan origin (north-easterly surface wind) known locally as harmattan dust, [12,13]. In addition, the low value of solar radiation recorded in February is due to prevalence of particulates such as aerosol that is being released from activities such as (bush burning) at this time of the year.

The result of the estimates of solar radiation in Ibadan when the same number of meteorological parameters are employed, using the modified Angstrom model, modified Hargreaves and Samani Model and the model derived from Artificial Neural Network model is displayed in Figure 4 below, while the error indicators are shown in Table 3.

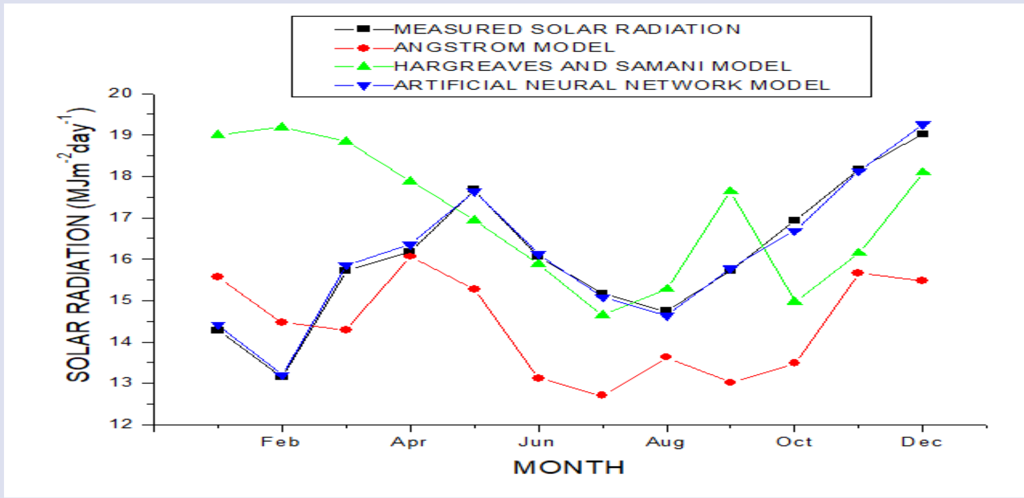

Figure 4. Comparison of the computed mean solar radiation with measured data.

Table 3: Error analysis of the result of the estimates of solar radiation in Ibadan, derived from the models, when the same numbers of meteorological parameters are employed.

MODEL PERFORMANCE INDICATOR			
MODELS	***RMSE***	***MBE***	***MPE (%)***
Angstrom-Prescott Model	0.4322	-0.1063	-0.6536
Hargreaves-Samani Model	0.3619	0.0638	0.4328
Artificial Neural Network Model	0.0744	-0.0020	-0.0043

Figure 4 shows the comparison of the computed mean solar radiation with measured data. The month with the highest solar radiation is April with solar radiation of (18.53$MJm^{-2}day^{-1}$), this can be attributed to lowering of the turbidity of the atmosphere due to the removal of aerosol particles by showers of rain in this month. As such, there is less attenuation of the incoming solar radiation and increase in the amount of direct solar radiation reaching the Earth’s surface. The month with the least solar radiation is August with solar radiation of (11.98$MJm^{-2}day^{-1}$), this is due to the raining season being at its peak and it can also be attributed to the high amount of cloudiness, increase in relative humidity, precipitable water molecules in the atmosphere and frequent thunderstorm activities.

Here the root means square error, though still lower than the other two models, shows a slight over estimation of 0.035 but surprisingly a reduced under estimation by mean percentage error.

The result of the estimates of solar radiation in Abuja, when the same number of meteorological parameters are employed, using modified Hargreaves and Samani Model and the Artificial Neural Network model is displayed in Figure 5 below, while the error indicators are depicted in Table 4.

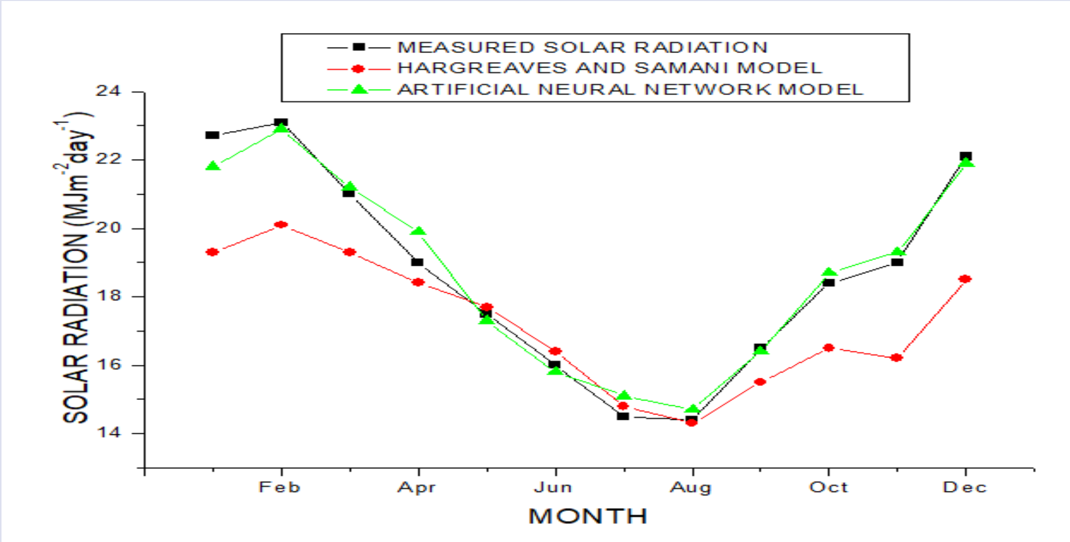

Figure 5: Comparison of the computed mean solar radiation with measured data

Table 4: Error analysis of the result of the Prediction of solar radiation in Ibadan, when different numbers of meteorological parameters are employed.

MODEL PERFORMANCE INDICATOR			
MODELS	*RMSE*	*MBE*	*MPE (%)*
Angstrom-Prescott Model	0.5876	0.1181	0.5577
Hargreaves-Samani Model	0.1301	0.0053	0.0441
Artificial Neural Network Model	0.5876	0.1181	0.5577

Figure 5 shows the comparison of the computed mean solar radiation with measured data. The month with the highest solar radiation is February with solar radiation of (23.12 $MJm^{-2}day^{-1}$), which is due to the dry season being at its peak. The month with the least solar radiation is August with solar radiation of (14.43 $MJm^{-2}day^{-1}$), this is due to the raining season being at its peak and the rain bearing clouds pervade. Also, this indicates that the month of August is characterized by overcast and cloudy condition. The variations showed by the predictive models followed the same trend but with various degrees of over and under predictions by the different models.

The computed results compared favorably with that of [9] that showed good agreement between the ANN estimated and actual values of global solar radiation. A correlation coefficient of 0.974 was obtained with MBE of 0.059 $MJm^{-2}day^{-1}$ and RMSE of 0.385 $MJm^{-2}day^{-1}$. These results confirmed the superiority of the ANN prediction model. The model used several parameters, and the data used in its development was run only for three years. Also, the results are better compared to[10], where the ANN model performed well with all inputs used, but with the MBE and RMSE values obtained were 0.12% and 5.67%, respectively which were higher than obtained in this study. This might not be unconnected with in improved capacity of ANN over time.

CONCLUSION

The result of the estimation of solar radiation in Ibadan showed that the artificial neural network model performed slightly better than the existing models when both the same and different numbers of metrological parameters were employed in the prediction. In the estimation of solar radiation in Abuja, the artificial neural network model performed slightly better than the Hargreaves-Samani model when the same numbers of metrological parameters were employed in the prediction. The performance of the ANN model is in agreement with a work done by [9], in which they used ANN to estimate monthly average daily global solar irradiation on a horizontal surface in Uganda. The data used in their research covered a period of three years in their result; a correlation coefficient of 0.974 was obtained with MBE of 0.059 $MJm^{-2}day^{-1}$ and RMSE of 0.385 $MJm^{-2}day^{-1}$. Hence, the models are versatile for predicting global solar radiation in locations in the same climatic zones as location studied in this research, where there are no direct measurements of solar radiation but there is availability of common meteorological parameters such as sunshine duration, minimum temperature, maximum temperature and relative humidity.

The computing power of Artificial Neural Networks should further be explored, since the field is very diverse, with a view to accessing more of its potentialities in solving data acquisition and analysis in mitigating climate change and bringing green energy to the populace at a relatively cheap costs. Other machine learning techniques should also be explored for estimation of global solar radiation in developing countries and the results be compared with that obtained in this study.

More importantly, government, non-governmental organizations and individuals should step up their effort in harnessing this renewable energy, among which is the solar energy, in order to boost the economy and standard of living in their countries.

Conflicts of interest

There are no conflicts of interest in this work.

Acknowledgments

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