

Estimate of Global Solar Radiation Using Artificial Neural Network Based on Meteorological Parameters in Yola

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ABSTRACT: Artificial neural networks have been used widely in many application areas. Artificial Neural Networks (ANNs) are currently accepted as an alternative technology offering a way to tackle complex and ill-defined problems. Despite the great importance of Global Solar Radiation (GSR), the number of radiation stations are very less when compared to the stations that collect regular meteorological data like air temperature and humidity. The main objective of this paper is to study the feasibility of an Artificial Neural Network (ANN) based method to estimate and predict GSR based on meteorological parameters. It is very encouraging to observe a very close agreement between the ANN and the measured values. The Root Mean Square Error values, which are the measure of accuracy of a particular model or correlation use. For the present analysis, it was found to be lowest for ANN model value (4.74). The Mean Bias Error value has the lowest under estimation with a value of -1.029, which fall within the expected and acceptable range. A low value of MPE is expected, ANN model was observed to have a Mean Percentage Error value of (- 2.345). The result of this study proves that ANN can be used to predict global solar radiation potential in Yola, Nigeria using meteorological data.

Keywords: Artificial Neural Networks, Back Propagation, Global Solar Radiation, Meteorological

INTRODUCTION

For the improvement of quality of life of human being as well as economic and social development, energy is an essential factor. Solar energy reaches to the earth for the every year is 160 times the world's proven fossil fuel reserves, it is expected that the recent worldwide research and development on solar energy will help to reduce the energy crisis of the world (Kartini *et al.*, 2015; Medugu *et al.*, 2013). Solar radiation data are a fundamental input for solar energy utilization such as photovoltaic and solar thermal system design. For optimization and performance evaluation of

solar technology for any particular location, the solar radiation data should be easily and readily available (Gana *et al.*, 2014). Solar radiation at the earth's surface is essential for the development and utilization of solar energy. It is needed for designing collectors for solar heaters and other photovoltaic equipment that depend on solar energy. Incoming solar radiation has a significant role in hydrological and crop growth modelling. For instance, it is a key input for estimating potential evapotranspiration which play a major role in the design of water supply storage reservoirs and irrigation systems. In spite of the importance of

global solar radiation data, its measurements are not frequently available especially in developing countries (Allen, 1997).

An accurate knowledge of solar radiation distribution at a particular geographical location is of vital importance for the development of many solar energy devices. Unfortunately, for many developing countries solar radiation measurements are not easily available due to the shortage of measurement equipment's (Okundamiya and Nzeako, 2010). It is therefore important to consider methods of estimating the solar radiation using Artificial neural networks on the readily available meteorological parameters.

Artificial neural networks have applications in various fields of aerospace, defence, automotive, mathematics, engineering, medicine, economics, meteorology, psychology, neurology, and many others. They have also been used in weather and market trends forecasting, in the prediction of mineral exploration sites, in electrical and thermal load prediction, in adaptive and robotic control and many others². Neural networks are used for process control because they can build predictive models of the process from multidimensional data routinely collected from sensors. Several researchers have demonstrated that they can be more reliable at predicting energy consumption in a building than other traditional statistical approach because of their ability to model non-linear patterns (Anstett and Kreider, 1992; Stevenson, 1994).

Artificial neural networks are composed of simple elements operating in parallel. The most popular learning algorithms are the back-propagation and its variants⁵. The Back-Propagation (BP) algorithm is one of the most powerful learning algorithms in neural networks. It tries to improve the performance of the neural network by reducing the total error by changing the

weights along its gradient. The training of all patterns of a training data set is called an epoch. The training set has to be a representative collection of input-output examples.

When building the neural network model the process has to be identified with respect to the input and output variables that characterise the process. The inputs include measurements of the physical dimensions, measurements of the variables specific to the environment and equipment and controlled variables modified by the operator. Three types of networks used most commonly in ANN applications are feed forward networks, competitive networks and recurrent associative memory networks. A practical description of ANN methods with sample applications was presented in Hagan, Demuth and Beale (1997).

Many of the building energy systems are exactly the types of problems and issues for which the artificial neural network (ANN) approach appear to be most applicable. Neural networks have the potential for making better, quicker and more practical predictions than any of the traditional methods. The performance of a building energy system depends on the environmental conditions such as solar radiation and wind speed, the direction, strength and duration of which are highly variable. Many of the building energy systems are exactly the types of problems and issues for which the artificial neural network (ANN) approach appear to be most applicable. In these computational models attempts are made to simulate the powerful cognitive and sensory functions of the human brain and to use this capability to represent and manipulate knowledge in the form of patterns. Based on these patterns neural networks model input- output functional relationships and can make predictions about other combinations of unseen inputs. Neural networks

have the potential for making better, quicker and more practical predictions than any of the traditional methods (Kreider and Wan, 1991).

MATERIALS AND METHOD

Yola, the capital of Adamawa State, comprising of Yola North and Yola South Local Government Areas, is located between Longitudes 12° 12'E, 12° 33'E of the Prime Meridian and between Latitudes 09° 12'N, 09° 19'N of the Equator. It is situated in the Benue Valley area of the state with a mean elevation 186 m.a.s.l. The area falls within the Tropical Wet and Dry/ West African Savanna Climate zone of Nigeria, with pronounced dry season in the low-sun months and wet season in the high-sun months. It is characterized by an average range of sunshine hours of 5.5 hours per day in August to 9.7 hours per day from the months of January through March. On balance, there are 2,954 sunshine hours annually and approximately 8.1 sunlight hours per day. Its Temperature characteristic is high all year round due to high solar radiation effect. However, seasonal changes usually occur such that there is a gradual increase in temperature from January to April when the seasonal maxima is recorded. Then a distinct gradual decline is recorded from the onset of rains in April/May due to cloud effects. This temperature characteristic continuous until October when a slight increase is experienced at the cessation of rains before the arrival of cold dry continental winds (harmattan) conditions (Adebayo, 1999). Thus, the study area is characterized by a mean temperature of 27.9 °C with a mean monthly range of 6.5 °C. The warmest mean maximum/ high temperature of the area is 39 °C in March & April, while the coolest mean minimum/ low temperature is 16 °C in December (Yola Climate Report, 2012).

The Angstrom- Prescott regression equation which has been used to estimate the monthly average daily solar radiation on a horizontal surface in Nigeria or other places is given as:

$$\frac{H_m}{H_o} = \left[a + b \frac{S_o}{S_o} \right] \quad (1)$$

H_m is daily mean values of global radiation ($MJm^{-2}day^{-1}$), S_o the daily average value of day length, and 'a' and 'b' values are known as Angstrom constants and they are empirical. H_o is daily mean values of extraterrestrial radiation ($MJm^{-2}day^{-1}$), calculated using equation (2) as described by Prescott, (1940).

$$H_o = \frac{24 \times 3,600}{\pi} I_{sc} E_o \left[\cos(\varphi) \cos(\delta) \sin(\omega_s) + \frac{\pi \omega_s}{180} \sin(\varphi) \sin(\delta) \right] \quad (2)$$

$$I_{sc} = \frac{1,367 \times 3,600}{1,000,000} MJm^{-2} day^{-1} \quad (3)$$

I_s the solar constant, The units in $kWhm^{-2}day^{-1}$ E_o represents the eccentricity correction, and described using Eq. (3.4) in Eq. 3.2

$$E_o = 1 + 0.033 \cos \frac{360n_d}{365} \quad (4)$$

n_d is the day number of the year /Julian day (1 Jan, $n_d = 1$ and 31st December, $n_d = 365$), φ is the latitude of the site, δ the solar declination and, ω_s , the mean sunset hour angle for the given month. The solar declination (δ) and the mean sunset hour angle (ω_s) can be calculated as suggested by Duffie and Beckman, (1991):

$$\delta = 23.45 \sin 360 \frac{284+n_d}{265} \quad (5)$$

$$\omega_s = \cos^{-1}(-\tan \varphi \tan \delta) \quad (6)$$

For a given day, the maximum possible sunshine duration (monthly values of day length, (S_o)) can be computed by using Cooper's formula (1969):

$$S_o = \frac{2}{15} \cos^{-1}(-\tan \varphi \tan \delta) \quad (7)$$

For a given day, the maximum possible sunshine duration (monthly values of day length, (N)) can be computed by using (Duffie and Beckman, 1991):

$$N = \frac{2}{15} \omega_s \quad (8)$$

Falayi (2011), developed a model containing relative humidity, rainfall, cloud cover and temperature for Sokoto, which is Model 1.

$$\frac{H_m}{H_o} = -4.03308 + 0.0740 (T_{max} - T_{min}) + 0.01075 (RH) - 0.00065 (RF) + 9.008 (CC) \quad (8)$$

He also developed for Maiduguri, considered as Model 2 for this work:

$$\frac{H_m}{H_o} = 0.22093 + 0.02179 (T_{max} - T_{min}) + 0.21792 (RH) - 0.7561 (RF) - 0.0008 (CC) \quad (9)$$

Bristow and Campbell Model

Bristow and Campbell (1984) developed a simple model for daily global solar radiation with a different structure in which H is an exponential function of ΔT in 1984:

$$\frac{H_m}{H_o} = a [1 - e^{(-b\Delta T^c)}] \quad (10)$$

Application of Artificial Neural Network

Artificial neural networks have been used widely in many application areas. Most applications use a feed-forward neural network with the back-propagation training algorithm. There are numerous variants of the classical back-propagation algorithm and other training algorithms (Haykin, 1999). All these training algorithms assume a fixed ANN architecture and during training, they change the weights to obtain a satisfactory mapping of the data. The main advantage of the feed-forward neural networks is that they do not require a user-specified problem solving algorithm (as is the case with classic programming) but instead they “learn” from examples, much like human beings. Another advantage is that they possess inherent generalization ability. This means that they can identify and respond to patterns which are similar but not identical to the ones with which they have been trained. On the other hand, the development of a feed-forward ANN-model also poses certain problems, the most important being that there is no

prior guarantee that the model will perform well for the problem at hand (Benghanem *et al.*, 2009).

A feed-forward back-propagation neural network was used in this study. A typical neural network consists of an input, a hidden, and output layer. Other components include a neuron, weight, and connections or transfer function as shown in

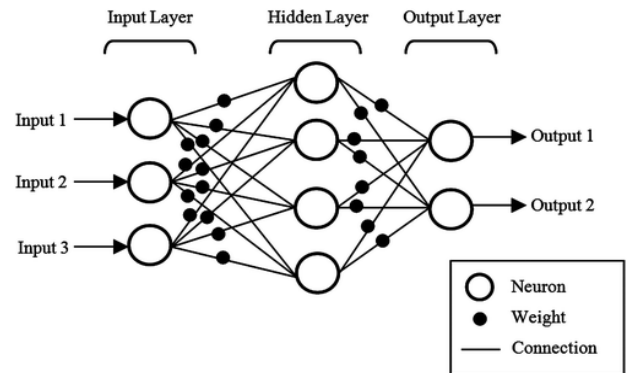


Fig. 1 and Fig. 2.

Fig. 1: A typical neural network for filtration

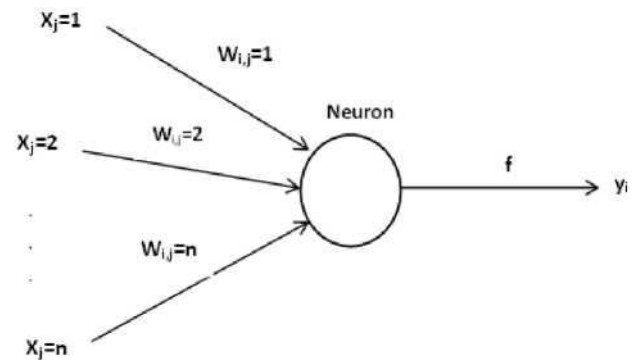


Fig. 2: Feed forward neural network

The values of $X_1; X_2; X_n$ are inputs and W_1, W_2, W_n are weights. Each input is multiplied by the relevant weight. Obtaining products and bias are summarized. By applying activation function to the result of summary, the output of neuron is obtained. There are three steps in solving an ANN problem which are 1) training 2) generalization and 3) learning. Training is a process that network learns to recognize present pattern from input data set together with the desired pattern of activities for the output units. Generalization or testing evaluates network ability in order to extract a feasible solution when the inputs are unknown to network

and are not trained to network. We determine how closely the actual output of the network matches the desired output in new situations. In the learning process the values of interconnection weights are adjusted so that the network produces a better approximation of the desired output. The disadvantage is that its operation can be unpredictable, because the network finds out by itself how to solve the problem.

The most common neural network model is the Multilayer Perceptron (Sharda and Patil, 1990). 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 shows the block diagram of a single hidden layer multiplayer perceptron (MLP). 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. To perform any task, a set of experiments of an input output mapping is needed to train the neural network. These data are one of the most important factors to obtain reliable results from any trained ANN. Thus, the training sample data have to be fairly large to contain all the required information

and must include a wide variety of data from different experimental conditions and process parameters.

In the present study, feed-forward, back-propagation, multilayer perceptron artificial neural network models are developed and trained separately by using Levenberg- Marquardt (LM) training algorithm and Gradient descent back propagation (GD) algorithm on 'Neural Network Toolbox' in MATLAB 9.7 version , to predict the average global solar radiation using meteorological data from 2014 – 2018 for Yola. The aim of this study is to investigate the feasibility of using ANN to model the non-linear relationship between solar radiation and other easily measurable important meteorological parameters. The predicted solar radiation values from the model can be used easily for design and assessment of renewable energy application systems.

Design of the Artificial Neural Network Model

Multi-layer feed-forward back-propagation network with different architecture were designed using the 'Neural Network Toolbox in MATLAB 9.7 version. The network consist of three layers: input layer, hidden layer and output layer. There are two input parameters for the models 1 and 2 and three input parameters for the model 3 and one output parameter average global solar radiation for all the three models. Two different algorithms (LM and GD method) with single and double hidden layer topologies were used and the number of neurons was also varied to enhance the generalization capability of the network. No transfer function was used for input layer, hyperbolic tangent sigmoid transfer function for hidden layer and linear transfer function (purelin) for output layer.

Selecting the number of neurons for the hidden layer is a complicated problem. So far, no mathematically justifiable method is available for

determining the hidden elements. Too many network nodes will increase the training time of the network and weaken the generalization and forecasting ability of the network. The number of the hidden elements is obtained by trial and error. Training is started with a minimum number of elements, the number of these elements is constantly increased and re-training of the ANN is continued until satisfactory training is achieved. The number of the hidden elements used for satisfactory training is considered as the optimal number.

Statistical Analysis

The performance of the models was evaluated on the basis of the following statistical error tests: the mean percentage error (MPE), root mean square error (RMSE) and mean bias error (MBE). These tests are the ones that are applied most commonly in comparing the models of solar radiation estimations. It is recommended that a zero value for MBE is ideal while a low RMSE and low MPE are desirable (Igbal, 1983; Akpabio *et al.*, 2004; Chen, 2011).

Mean percentage error: The Mean percentage error is defined as:

$$MPE (\%) = \frac{1}{n} \sum_{i=1}^n \left(\frac{H_{i,m} - H_{i,c}}{H_{i,m}} \right) \times 100 \quad (11)$$

Where $H_{i,m}$ is the i th measured value, $H_{i,c}$ is the i th calculated value of solar radiation and N is the total number of observations.

$$RMSE = \left[\frac{1}{n} \sum_{i=1}^n (H_{i,m} - H_{i,c})^2 \right]^{\frac{1}{2}} \quad (12)$$

$$MBE = \frac{1}{n} \sum_{i=1}^n (H_{i,m} - H_{i,c}) \quad (13)$$

According to Medugu and Yakubu (2011), regression coefficient a and b from the calculated monthly average global solar radiation has been obtained from the relationship given as:

$$a = -0.110 + 0.235 \cos \varphi + 0.323 \left(\frac{n}{N} \right) \quad (14)$$

$$b = 1.449 - 0.553 \cos \varphi - 0.694 \left(\frac{n}{N} \right) \quad (15)$$

To compute estimated values of the monthly average daily global radiation H_{cal} , the values of computed a and b from equations (14) and (15) were used. where $a = 0.293$ and $b = 0.537$.

RESULTS AND DISCUSSIONS

Table 1 below gives the average computed values for the period of five years.

Table 1: Monthly Daily Average Meteorological data for Yola

Months	RH (%)	RF (mm)	T _{max} (°C)	T _{min} (°C)	$\frac{n}{N}$	H _m
Jan.	33.4	0.00	35.1	19.7	0.79	19.9
Feb.	30.2	0.00	39.6	22.2	0.64	21.3
Mar.	27.7	0.00	42.8	26.3	0.61	22.5
Apri.	49.5	44.9	38.9	29.5	0.65	20.4
May	68.7	98.7	34.6	27.1	0.52	19.7
Jun.	88.3	150.4	32.9	25.9	0.53	18.1
Jul	89.5	160.9	31.6	24.7	0.58	17.6
Aug.	96.2	203.2	32.3	24.3	0.44	15.8
Sept.	94.8	167.8	34.5	24.7	0.54	17.6
Oct.	78.5	87.4	35.8	24.5	0.68	20.3
Nov.	65.2	34.98	38.6	23.9	0.44	22.9
Dec.	53.5	0.00	36.5	21.8	0.53	18.4

Table 2: Monthly average daily global solar radiation for Yola.

Months	$\frac{n}{N}$	H _m	H _o	$\frac{H_m}{H_o}$
Jan.	0.79	19.9	35.8	0.55
Feb.	0.64	21.3	37.7	0.56
Mar.	0.61	22.5	39.8	0.56
Apri.	0.65	20.4	40.9	0.49
May	0.52	19.7	39.3	0.50

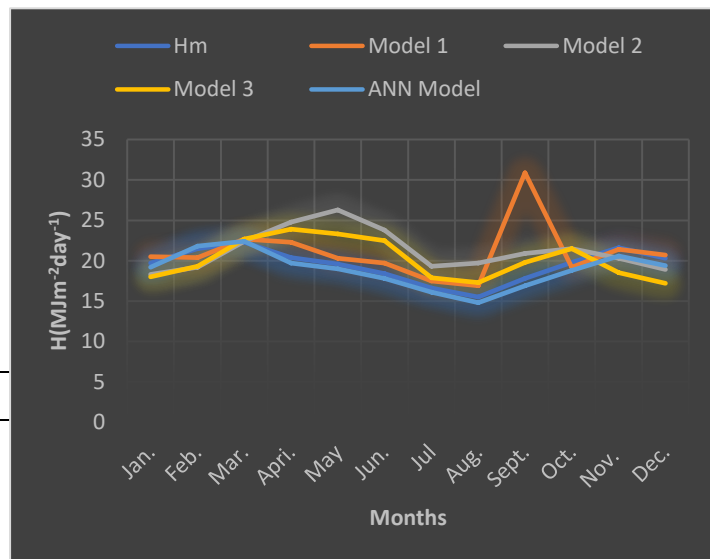
Jun.	0.53	18.1	38.4	0.47
Jul	0.58	17.6	37.5	0.46
Aug.	0.44	15.8	36.3	0.43
Sept.	0.54	17.6	39.5	0.44
Oct.	0.68	20.3	38.2	0.53
Nov.	0.44	22.9	33.7	0.67
Dec.	0.53	18.4	32.5	0.56

Table 3: Monthly average daily global solar radiation for the three models and ANN

Months	H _m	Model 1	Model 2	Model 3
Jan.	19.7	20.5	18.3	18.0
Feb.	21.5	20.4	19.2	19.3
Mar.	22.3	22.7	22.4	22.7
Apri.	20.4	22.3	24.8	23.9
May	19.6	20.3	26.3	23.3
Jun.	18.4	19.7	23.8	22.5
Jul	16.6	17.5	19.3	17.9
Aug.	15.5	16.9	19.7	17.3
Sept.	17.8	30.9	20.9	19.8
Oct.	19.8	19.2	21.5	21.5
Nov.	21.6	21.4	20.3	18.5
Dec.	20.3	20.7	18.9	17.2

All numerical values are in units of $(MJm^{-2}day^{-1})$

Figure 3: Relationship between the clearness index and relative sunshine duration in Yola.



19.7

19.01

17.8

Figure 4: Estimated value of monthly average daily global solar radiation and measured value

14.88

16.9

18

20

19

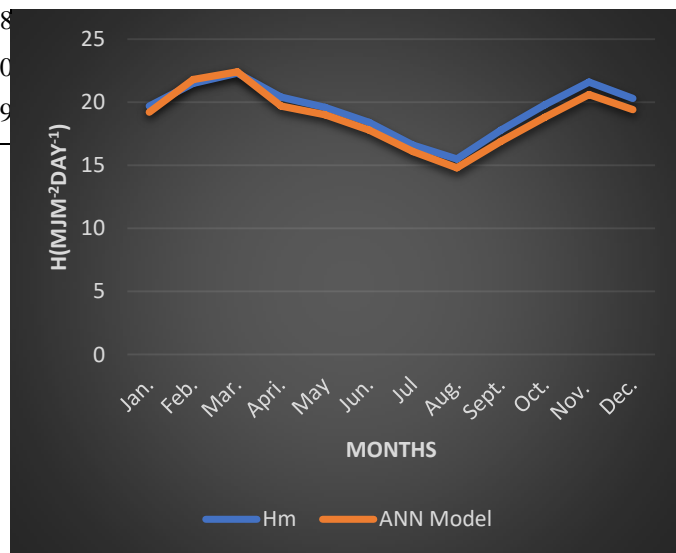


Figure 5: Estimated value of monthly average daily global solar radiation (Model 1) and measured values.

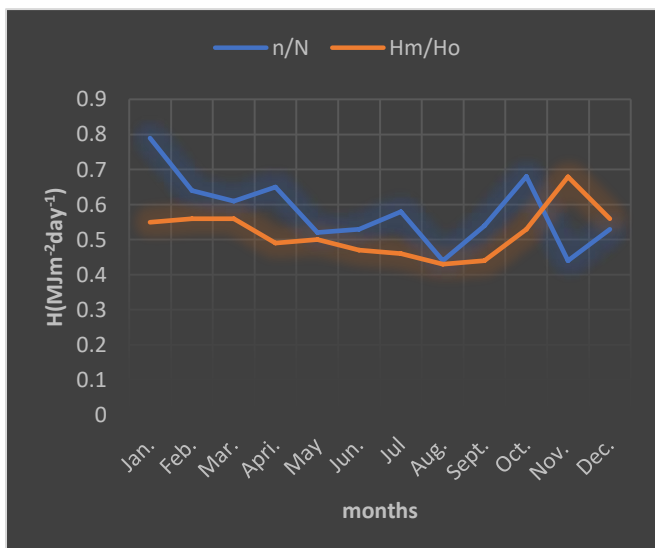


Table 4: RMSE, MBE, and MPE computed in the comparison between measured and estimated monthly average daily solar radiation

Models	Statistical Analysis Methods		
	RMSE	MBE	MPE (%)
Model 1	6.72	0.42	- 1.194
Model 2	10.39	2.39	0.378
Model 3	9.83	1.76	2.256
ANN Model	4.74	-1.029	- 2.345

The best predicted versus measured irradiation values for ANN model was presented in Figure 5 and the values were presented in Table 3. In Table 2 and figure 3, the value of clearness Index, $K_T = 0.519$ correspond to the lowest value of $\frac{n}{N} = 0.44$ and $H_m = 15.8$ ($\text{MJm}^{-2}\text{day}^{-1}$) in the month of August indicate poor sky conditions. These conditions correspond to the wet or rainy season (June – September) observed in Yola during which is much cloud cover. The monthly average daily solar radiation estimated through model 1 and model 4 for Yola are given in Table 3, along with the measured values. It is very encouraging to observe a very fine agreement between the ANN and the measured values. Figure 2 indicates that ANN model is the most suitable for the estimation of monthly average daily global solar radiation for Yola. Shown in table 4 are the statistical test results. The RMSE values, which are is the measure of accuracy of a particular model or correlation use. For the present analysis, it was found to be lowest for ANN model value (4.74) as shown in table 4. The MBE values obtained from the models are positive in some cases and negative in others, which shows that these models vary between under and over estimate of global solar

radiation. However, model has the lowest under estimation with a value of -1.029, which is expected and acceptable. A low value of MPE is expected, ANN model was observed to have an MPE value of (- 2.345).

The global solar radiation can be adequately estimated using different proposed models using daily recorded meteorological variables of maximum and minimum temperature difference, relative humidity, cloud cover and rainfall. In order to obtain some accurate solar radiation estimations, it requires accurate mathematical modelling of all the climatological parameters. From figure 3, there is high proportion of cloudy days, relative to low solar energy with low temperature in the wet season while low cloudy day with high solar energy and high temperature in dry season across the latitudes. It was observed that the ANN models which gives good results when considering statistical indicators, RMSE, MBE, and MPE. It is found that the new model can be used for estimating daily values of global solar radiation with a higher accuracy and has good adaptability to highly variable weather conditions. The estimated value of global solar radiation reveals that solar radiation can be efficiently used to compensate for energy inadequacy.

CONCLUSION

This study has been proposed the model of ANN to predict monthly average daily global solar irradiation in horizontal surface in Yola, Nigeria as area of study. This study proves that ANN can be used predicting of global solar irradiation potential in Yola, Nigeria by using meteorological data. In view of the worldwide concern about the economic importance of global solar radiation as an alternative renewable energy, the monthly global solar radiation using relative humidity, sunshine

hour, cloud cover, rainfall, maxi maximum temperature have been employed in this study to estimate global solar radiation for Yola, Adamawa State, Nigeria. This model will provide useful information for designers and engineers of solar energy and other renewable energy devices in Yola and environs. From the results when considering statistical indicators that are MBE, RMSE and MPE. This study plan can be introduced neural network technique for modeling the global solar irradiation in Yola.

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