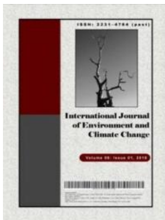

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Assessment of Global Solar Radiation at Selected Points in Nigeria Using Artificial Neural Network Model (ANNM)

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Authors' contributions

This work was carried out in collaboration among all authors. Author IGF designed the study, wrote the first draft of the manuscript and manage the literatures, author BCU managed the supervision of the study, authors TI and TA wrote the protocol and proofreading of the study, while author OJN managed the modeling. All authors read and approved the final manuscript.

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ABSTRACT

In this study, spatial distribution, temporal variations, annual distribution, estimation and prediction of solar radiation in Nigeria was carried out using ANNs. Levenberg-Marquardt backpropagation algorithms was used for the training of the network using solar radiation data along the years (1979-2014). The data records were divided into three portions (training, testing and validation). The network processed the available data by dividing it into three portions randomly: 70% for the training, 15% for validation and the remaining 15% for testing. Input parameters were chosen as latitude, longitude, day of the year, year while observed solar radiation was chosen as targeted data (from a processed file). The output parameter was the estimated solar radiation. The network designs were tested with root mean square error and then the most successful network (taken to be best network) which is network with less error was used to carry out the study. The hyperbolic tangent sigmoid transfer function was also used between the input and the hidden layers as

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activation function, while the linear transfer function was used from hidden layers to the output layer as the activation function. The performance of ANNs was validated by; estimating the difference between the annual measured and estimated values were determined using coefficient of determination (R^2). Results revealed that the R^2 result was 0.82 (82%). The result of spatial variations indicated that both wet and dry seasons have their highest concentration in North-East of Nigeria. It is pertinent to also note that the lowest concentration occurred in North-West during wet season, while the lowest occurred at the South-South and South-West of Nigeria in dry season. In addition, the lowest in dry season is about 25W/m^2, while that of wet season is about 15W/m^2. The agreement between the temporal and annual variation of observed and estimated solar radiation reveals that the model exhibits good performance in studying solar radiation. The model was further used to predict two years ahead of the years of study.

Keywords: Solar radiation; spatial variation; temporal variation; neural networks.

1. INTRODUCTION

Solar radiation travels to Earth through space as discrete packets of energy. Only half of that amount, however, reaches Earth's surface [1]. The atmosphere and clouds absorb or scatter the other half of the incoming sunlight. The amount of light that reaches any particular point on the ground depends on the time of the day, the day of the year, the amount of cloud cover, and the latitude at that point [1]. Knowledge of the solar radiation is essential for many applications, including architectural design, meteorological forecasting, solar energy systems, crop growth models, conversion for electricity, sciences and technology, etc. The amount of solar radiation reaching the Earth that is used to study its distributions for essential applications can best be obtained by installing pyranometer at any site, and day to day readings from the instrument give us the data. The unavailability of the instruments in many sites result to the use of atmospheric parameters at a particular location to predict the global solar radiation in that location with help of different models such as artificial neural network (ANN) model. . In Nigeria, paucity of data records has been exacerbated as a result of the difficult terrain and few number of observation stations across the country. Many researchers in several areas had used artificial neural network to study the solar radiation by looking at its distributions and predictions using atmospheric parameters. The use of ANN in MATLAB to study solar radiation variations has been done in America, Europe, North and Southern Africa, but is almost nonexistent in Nigeria. This work intends, therefore, to utilize ANN algorithm in MATLAB to model and study solar radiation across Nigeria by determining its partial variation, temporal distribution, estimation and predicting two years ahead of the years of the study.

1.1 Review of ANN Models on Solar Radiation

Tymvios [2] used back-propagation method with tangent sigmoid as the transfer function to train seven ANN models using daily values of measured sunshine duration, maximum temperature, and the month number as input parameters. Normalization method was use during training. They based their study on six years data. The model deployed two hidden layers with neurons varying between 23 and 46. The best performing ANN model was one with all inputs except the month number.

Alawi and Hinai [3] used ANN to predict solar radiation. The model used location parameters, month, temperature, vapor pressure, relative humidity, wind speed, average of pressure and sunshine duration as inputs. The model reveals excellent performance in prediction of solar radiation with ANN.

Mohandes [4] used data from 41 stations to study solar radiation. Data from 31 stations was used in training the neural network; the data from the other stations was used for testing of the model. The model used the following input parameters: latitude, longitude, altitude and sunshine duration for the training.

Mihalakakou [5] used ANN to simulate total solar radiation time series in Athens, Greece. Twelve years data measured from a location in Athens, situated at latitude 37.97°N, longitude 23.72°E and altitude 107 m was split into two datasets. The portion measured from 1984 to 1992 was used in training and the other dataset between 1993 and 1995 was used for testing. A multilayer feed-forward neural network (FFNN) based on back-propagation algorithm was designed to predict time series of global solar radiation. The selected ANN architecture consisted of one hidden layer with 16 log-sigmoid neurons and an output layer of one linear neuron. Results showed that the differences between the predicted and actual values of total solar radiation were less than 0.2%.

Reddy and Ranjan [6] looked at solar radiation estimation using ANN and comparison with other correlation models. They created ANN models for estimation of monthly mean daily and hourly values of global solar radiation. Solar radiation data from 13 stations spread over India were used for training and testing the ANN. The solar radiation data from eleven stations (six from South India and five North India) were used for training the neural networks, and data from the remaining two locations (one each from South India and North India) were used for testing the estimated values. The solar radiation estimations by ANN were in good agreement with the actual values. The results showed that the ANN model is capable of generating global solar radiation values at places where monitoring stations were not established.

The estimation of solar radiation in Turkey using artificial neural networks was carried out by Sozen [7]. They used Scaled conjugate gradient (SCG), Pola-Ribiere conjugate gradient (CGP) and Levenberg-Marquardt (LM) learning algorithms. Logistic sigmoid transfer function was used. In order to train the neural network, meteorological data for three years from 17 stations; 11 for training and 6 for testing were used. The maximum mean absolute percentage error was found to be less than 6.7% for the testing stations. The result revealed that ANN model seemed promising for evaluating solar resource values at the places where there are no monitoring stations in Turkey.

Mubiru and Banda [8] used ANN to estimate monthly average daily global solar irradiation on a horizontal surface at four locations in Uganda based on weather station data (sunshine duration, maximum temperature, and cloud cover) and location parameters of (latitude, longitude, and altitude). Results showed good agreement between the estimated and actual values of global solar radiation. A correlation coefficient of 0.974 was obtained with MBE of 0.059 MJ/m2 and RMSE of 0.385 MJ/m^2. These results confirmed high performance of ANN model in predicting global solar radiation.

2. MATERIALS AND METHODS

2.1 The study Area

The study areas used in this work are thirty six (36) data points covering the spatial extent of Nigeria as shown in Fig. 1(gridded map of selected stations in Nigeria), while Table 1 shows the coordinates of the selected stations over Nigeria.

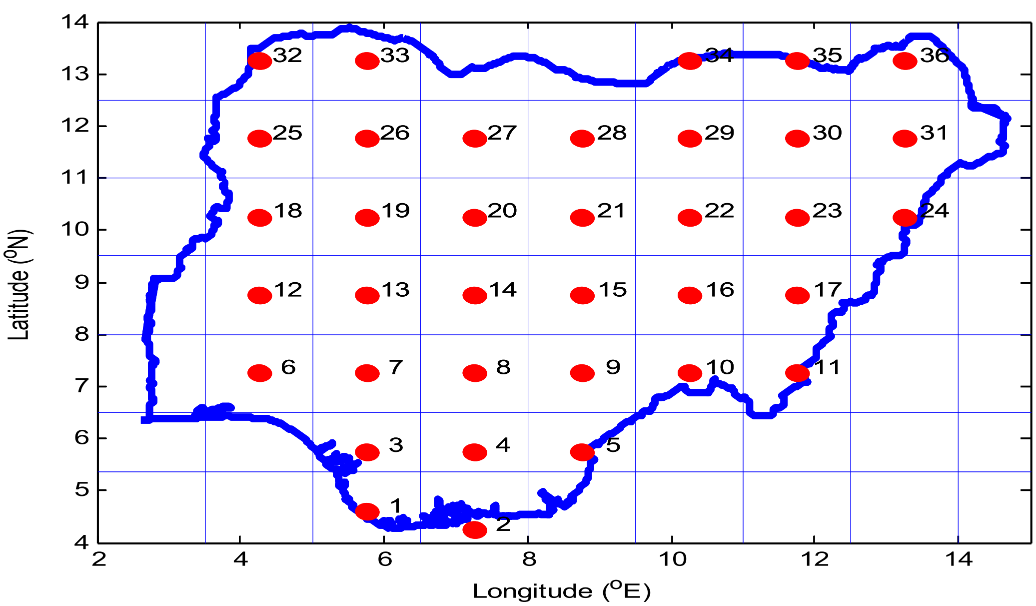

Fig. 1. Gridded map of nigeria showing data points of the selected stations in Nigeria

2.2 Designing of Artificial Neural Network (ANN) Using Multilayer Perceptron (MLP)

FFNN with MLP was used in this study. Designing, building and use of ANN multilayer perceptron (MLP) network for simulation requires that one must follow a number of systemic procedures. The six basics steps followed in this study include:

1. Data collection;
2. Pre-processing of data;
3. Building the network;
4. Training the network;
5. Testing the performance of the network; and
6. Using of the network (best network).

2.2.1 Data collection

The solar radiations for the period 1979-2014 at the selected points were obtained from National Centers for Environmental Prediction and Climate Forecast System Reanalysis (NCEP-CSFR) under Earth System Research Laboratory, Boulder.

2.2.2 Pre-processing data (Data extraction, sorting and file merging)

The solar radiation data which was in NetCDF format were extracted and converted to binary format using panoply software, while data file merging and sorting were carried out using ferret software. The merged file contains the processed data in seven (7) columns, which compresses of year, month, day, day of the year (DOY), latitude, longitude and observed data. The interval between one point and another in the study area (Fig. 1) is 1.5º, where 1º represents about 111 km. The data collected were daily data, but were processed to monthly and yearly data with Microsoft excel package. The MATLAB codes was used to write the script that was used to build the neural network.

2.2.3 Building and training the network

In building the neural network of this study, the parameters used to build a suitable network were, network type, algorithm, network name, numbers of neurons in each layers, transfer function, weight bias, learning function, data division function and performance function. The network name used in this work was “net”, representing neural network. Feed-forward multilayer perceptron and back propagation neural network was used (from toolbox in MATHLAB version 6.5 program) because it had a better training performance and regression analysis. Fig. 2 shows the schematic setup (topology) of the developed network. There are other types of networks such as nonlinear autoregressive network (NARX), autoregressive integrated moving average (ARIMA) network etc. The architecture used to build the multilayer feed-forward network comprises of three main layers; an input layer, a hidden layer and an output layer, each layer contains one or more neurons. Feed-forward networks are those in which the signal flows from the input to the output neurons, in a forward direction. The neurons on one layer are connected to those on the next layer using connections (also called weights). The neurons in the input layer act as buffers for distributing the input signals to the neurons in the hidden layer. Training and learning processes occur in the hidden layer. The training process involves optimization of weights in order to minimize input-output errors. The hidden layer has a hyperbolic tangent sigmoid transfer function which acts on the input to produce the hidden weight matrix output. The output layer has a linear transfer function which act on the hidden weight matrix output to produce output matrix. Levenberg-Marquardt backpropagation algorithms were used in this study to build the network because of its high speed and efficiency in learning. This is in line with [9,10] assertions. Buhari and Adamu [11] also observed that Levenberg-Marquardt optimization techniques has better learning rate compared to the other available functions.

The neural network architecture built for the training were 4-20-1, which means that we have 4 neurons in the input layer, 20 neurons in the hidden layer and 1 neuron in the output layer. The input data through the input neurons were; year, DOY representing the time, latitude and longitude represent the coordinates. These are input from the processed filed out of the seven columns as the input data, with the help of the MATLAB code. The observed data were also inputted but as a targeted data. The network processes the available data during learning and training by dividing it into three portions at random: 70% for the training, 15% for validation and the remaining 15% for testing. During the training process, the weights were adjusted systematically until the simulated output was close to the observed (targeted) data of the network.

Table 1. Coordinates of the selected stations and their data points over Nigeria

Points	Y latitude (°N)	X longitude (°E)	Stations	Local government area	State
1	4.59	5.84	Apoi Creek	Southern Ijaw	Bayelsa
2	4.25	7.25	Offshore	Atlantic Ocean	Atlantic Ocean
3	5.75	5.75	Ukpe Sobo	Okpe	Delta
4	5.75	7.25	Obiohoro Osu	Unuimo	Imo
5	5.75	8.75	Nsarum	Etung	Cross River
6	7.25	4.25	Mowo	Isokan	Osun State
7	7.25	5.75	Idosale	Ose	Ondo State
8	7.25	7.25	Allomo	Ofu	Kogi
9	7.25	8.75	Ahile	Gboko	Benue
10	7.25	10.25	Danjuma	Ussa	Taraba
11	7.25	11.75	Filinga Sekenoma	Gashaka	Taraba
12	8.75	4.25	Alajere	Moro	Kwara
13	8.75	5.75	Pategi	Pategi	Kwara
14	8.75	7.25	Kabi	Kuje	Abuja
15	8.75	8.75	Arugwadu	Lafia	Nassarawa
16	8.75	10.25	Ibi	Ibi	Taraba
17	8.75	11.75	Tainho	Yorro	Taraba
18	10.25	4.25	Luma	Borgu	Niger
19	10.25	5.75	Beri	Mariga	Niger
20	10.25	7.25	Gwagwada	Chikun	Kaduna
21	10.25	8.75	Bauda	Lere	Kaduna
22	10.25	10.25	Dindima	Bauchi	Bauchi
23	10.25	11.75	Pelakombo	Bayo	Borno
24	10.25	13.25	Mubi	Hong	Adamawa
25	11.75	4.25	Giro	Suru	Kebbi
26	11.75	5.75	Bukkuyum	Bukkuyum	Zamfara
27	11.75	7.25	Lugel	Faskari	Katsina
28	11.75	8.75	River Armatai	Dawakin Kudu	Kano
29	11.75	10.25	Galadao	Katagum	Bauchi
30	11.75	11.75	Damaturu	Fune	Yobe
31	11.75	13.25	Dalori	Jere	Borno
32	13.25	4.25	Gudu	Gudu	Sokoto
33	13.25	5.75	Kadagiwa	Wurno	Sokoto
34	13.25	10.25	Gunshi	Yusufari	Yobe
35	13.25	11.75	Daratoshia	Yunusari	Yobe
36	13.25	13.25	Abadam	Abadam	Borno

2.2.4 Training the network

A total of 20 neural networks were trained through simulation; the difference between them is in the number of hidden layer neurons we applied (we varied the number of hidden layer neurons from 1 to 20). This is to decide an optimal number of hidden-layer neuron which is regarded as the best network. The performance of the simulation was tested using root mean square error (RMSE). There are no specific or perfect rules for deciding the most appropriate number of neurons in a hidden layer. Using an excessive number of hidden-layer neurons causes over-fitting, while a lesser number leads to under-fitting. Either scenario greatly degrades the generalization capability of the network with significant deviance in estimation and forecasting accuracy of the models [12]. Hence, according to Sheela and Deepa [12] over-fitting or under-fitting is capable of leading to inaccurate estimation or forecasting if it continues. There is, therefore, a need to strike a balance such that the networks are neither under-trained nor over-trained by choosing a considering apt number of hidden neurons that gave optimal values of the best or acceptable root mean square error (RMSE).

Modeling using Artificial Neural Networks: The neural network model used in this study uses principle of optimizing weights and biases during training. The network uses optimization method during training from input to output with the input weight matrix, bias vector(s), hidden weight matrix and layer weight matrix respectively. Fig. 2 is the topology of the learning and training network structure which includes input layer neurons, hidden layer neurons and output layer neurons. The input vector elements to the desired output in Fig. 2 were computed in line with [13].

The training sample are $\{I, O\} = \{I_i, O_i\}$ (i = 1, 2, . . ., h). The input vector (I) = $[I_{i1}, I_{i2} \cdots I_{ih}]$ and desired output $(O) = [O_{j1}, O_{j2} \cdots o_{jh}]$. The input matrix (I_m) and the output matrix (O_m) were expressed as follows:

$$I_m = \begin{bmatrix} I_{m\,1,1} & I_{m\,1,2} & \vdots & I_{m\,1,4} \\ I_{m\,2,1} & I_{m\,2,2} & \vdots & I_{m\,2,4} \\ \vdots & \vdots & \ddots & \vdots \\ I_{m\,4,1} & I_{m\,4,2} & \cdots & I_{m\,4,4} \end{bmatrix} \qquad (1)$$

$$O_m = [o_{m_{1,1}} \quad o_{m_{1,2}} \quad o_{m_{1,3}} \cdots \quad o_{1,h}] \qquad (2)$$

The input vector elements enter the network through the weight matrix, that is, each element of the input vector is connected to the weight matrix (Fig.2). Then the learning machine randomly sets the weights between the input layer and the hidden layer in the network as shown in equation 3 and Fig. (2). Again, learning machine randomly sets weights between hidden layers to output layer in the network in form of layer weight matrix as shown in equation 4 and Fig. 2.

$$I_{wm} = \begin{bmatrix} I_{wm\,1,1} & I_{wm\,1,2} & \vdots & I_{wm\,1,4} \\ I_{wm\,2,1} & I_{wm\,2,2} & \vdots & I_{wm\,2,4} \\ \vdots & \vdots & \ddots & \vdots \\ I_{wm\,h,1} & I_{wm\,h,2} & \cdots & I_{wm\,h,4} \end{bmatrix} \qquad (3)$$

$$L_{wm} = [L_{wm_{1,1}} \quad L_{wm_{1,2}} \quad L_{wm_{1,3}} \cdots \quad L_{wm_{1,h}} \qquad (4)$$

where h is the number of hidden layer neurons that is the dimension of hidden layer matrix . The feed-forward neural network equations from input layer to hidden layer give the net input (n_1) in equation at the hidden layer and the net out (n_2) from the hidden layer to the output layer are shown in equations 5 and 6.

$$n_1 = I_{wm1} * I_{m1} + I_{wm\,2} * I_{m2} + \ldots + I_{wmh} * I_{m4} + b_1 \qquad (5)$$

$$n_2 = L_{wm_1} * H_{vm} + L_{wm_2} * H_{vm} + \ldots + L_{wm_{h,1}} * H_{vm} + b_2 \qquad (6)$$

The express of equation 5 and 6 are written with MATLAB codes as equation 7 and 10 [14]. Hyperbolic tangent sigmoid transfer function (f_1) equation 8 is applied to equation 7 to have hidden layer matrix (H_{vm}) equation 9. Equation 7 is the sum of the input weight matrix multiplied with input matrix plus the bias vector one.

$$\sum(I_{wm} * I_m + b_1) = n_1 \qquad (7)$$

$$f_1\,(n_1) = \text{tansig}(n_1) = \frac{e^{n_1} - e^{-n_1}}{e^{n_1} + e^{-n_1}} = H_{vm} \qquad (8)$$

$$H_{vm} = f_1\,(I_{wm} * I_m + b_1) \qquad (9)$$

The sum of the layer weight matrix multiplied with hidden variable matrix plus the bias vector two gives net out (n_2) as shown in equation 10. Linear function is applied to equation 10 as shown in equation 11 to predict the targeted output called the output matrix as expressed in equation 12 in the network model. The combination of equations 7 to 11 gives the straight line equation 12 for the model that is used for the study.

$$\sum(L_{wm} * H_{vm} + b_2) = n_2 \qquad (10)$$

$$f_2(n_2) = \text{purelin}(n_2) = \text{purelin}(L_{wm} * H_{vm} + b_2) = O_m \qquad (11)$$

$$O_m = \text{purelin}\,(L_{wm} * (\text{tansig}(I_{wm} * I_m + b_1)) + b_2) \qquad (12)$$

where O_m depicts the output matrix which contains the predicted data with the network model, while I_m depict the input matrix (year, day of the year (DOY), latitude, longitude), I_{wm} represent inputs weight matrix, b_1 is bias vector one, H_{vm} is the hidden variable matrix, L_{wm} is layer weight matrix, b_2 is bias vector two, tansig (f_1) is hyperbolic tangent sigmoid transfer function used between the input and the hidden layers as activation function, while purelin (f_2) is the linear transfer function used from hidden layers to the output layer as the activation function. The values of I_{wm}, L_{wm}, b_1 and b_2 of this study we be made available on request. The application of Neural Network architecture used for building the network and training from input to output is shown in Fig. 2, while Fig.3 is the drop down window showing the neural network training (nntraintool) process at network 20.

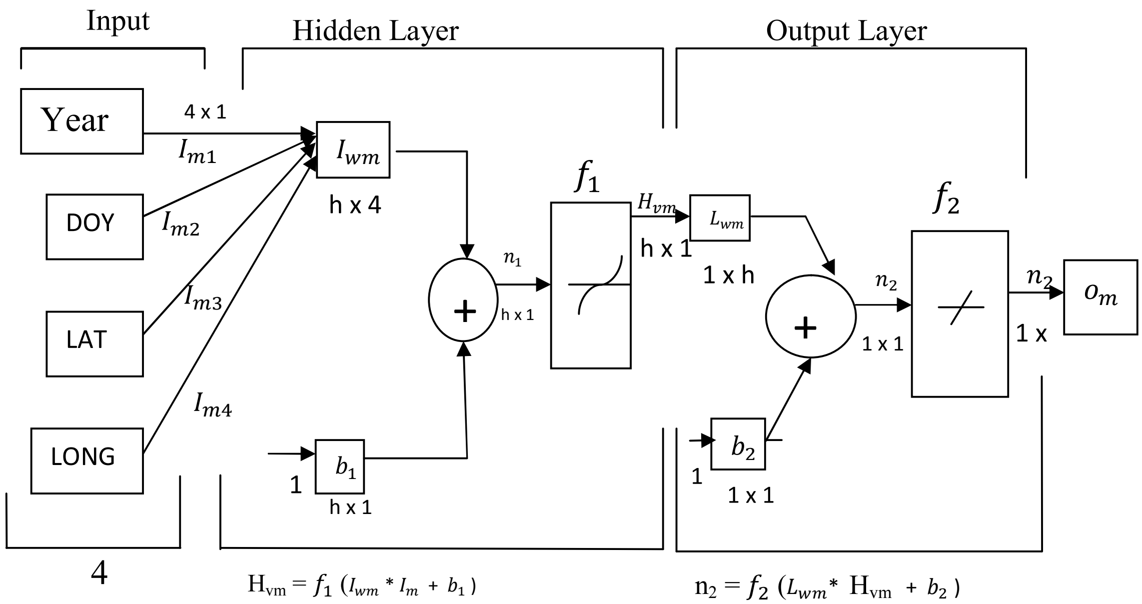

Fig. 2. Feed-Forward Neural Network (FFNN) Three layers Model Training Setup Structure

Fig. 2 showed that the size of I_{wm} is h-by-4 because there are 4 inputs layer neurons. The size of L_{wm} is 1-by-h because there is one output layer neuron. The sizes of b_1, n_1, H_{vm}, b_2 and n_2 are h x 1, h x 1, h x 1, 1 x 1 and 1 x 1 respectively, where h is the number of hidden layer neurons

2.2.5 Testing the performances

The performance function used to test the network of the data set after training before choosing the best network (net) were the mean square error (MSE) and root-mean-square-errors (RMSE) functions as given in equation 14 .

$$\text{RMSE} = \sqrt{\frac{(p-obs)^2}{N}} \tag{14}$$

where p and obs depict estimated and observed data, while N represent the total number of sample respectively.

2.2.6 Using the network

In this work, the best network obtained using the RMSE values at the end of the training was observed to network (net) 16. This best network model was used to determine the spatial distributions of solar radiation, estimate the daily values of solar radiation (temporal) and the annual average variations of the estimated and observed solar radiation. It was also used to forecast two-year (2018 and 2019) step ahead of daily solar radiation. It is pertinent to note that the model (net 16) has the ability of studying the distributions of solar radiation for each day from January to December across the years of study, but the month of January (1st) has taken to represents dry season, while the month of July (1st) was used to represent wet season for this study. This was done in order to also determine the seasonal variations of solar radiation in Nigeria.

3. RESULTS AND DISCUSSION

Fig. 5 is the graph showing the relationship between RMSE and number of hidden layer neurons (1 to 20). The result reveals net 16 (indicated by a downward arrow) as the best network from the training of solar radiation data.

Data from thirty-six points over thirty-five years (1979-2014) were used to train, validate and test the networks. The data from thirty-six points during learning and training were divided into three portions randomly: 70% for the training, 15% for validation and the remaining 15% for testing. Geographical parameters for these cities are given in Table 1, while location of the cities on map is shown in Fig.1. The input parameters were year, day of the year, latitude and longitude, while output parameter is the solar radiation. The observed data were also inputted as the targeted data. Artificial neural network topology used for the estimation of solar radiation is shown in Fig. 3, while the network diagram of the training is shown in Fig. 4. The drop down window at the end of the network training is shown in Fig. 5. It was found that the most successful network (best network) was at layer network with 16 neurons in hidden layer.

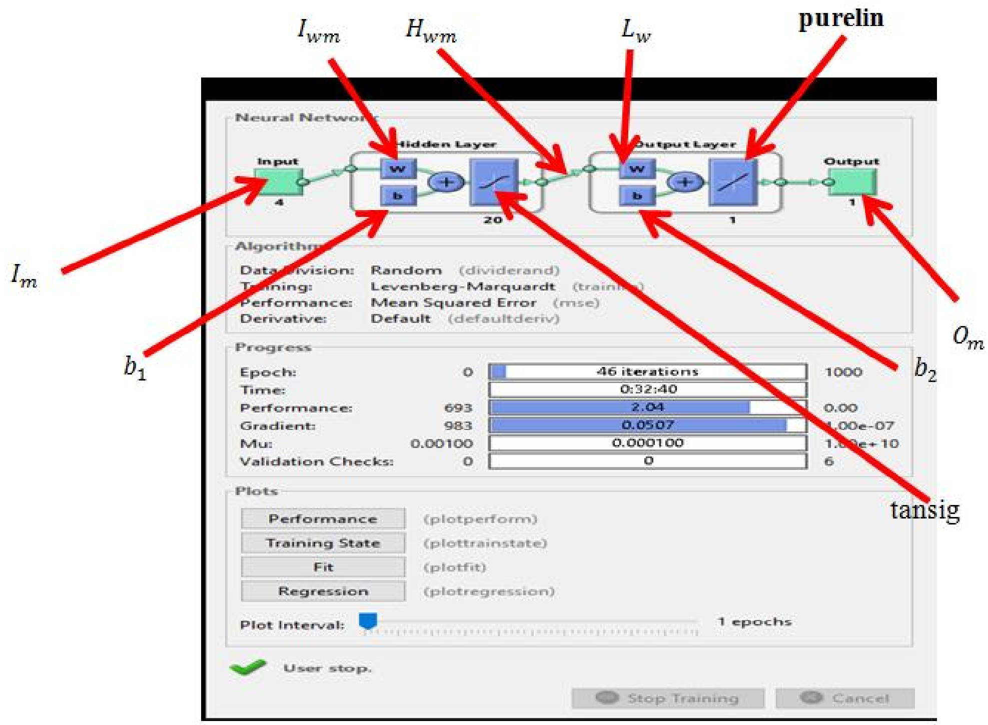

Fig. 3. Schematic diagram of neural network training window

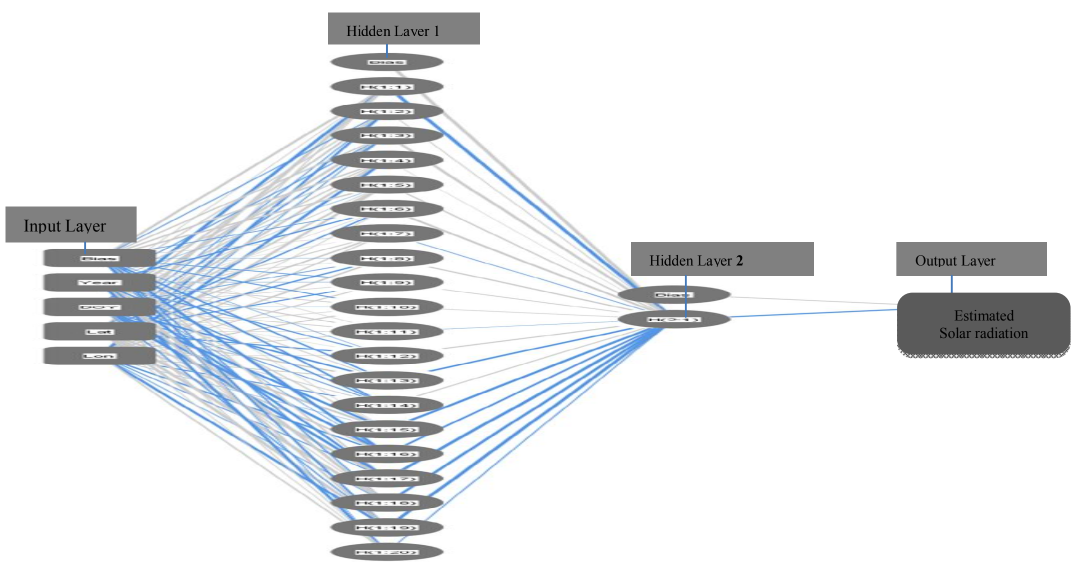

Fig. 4. Network diagram of the model

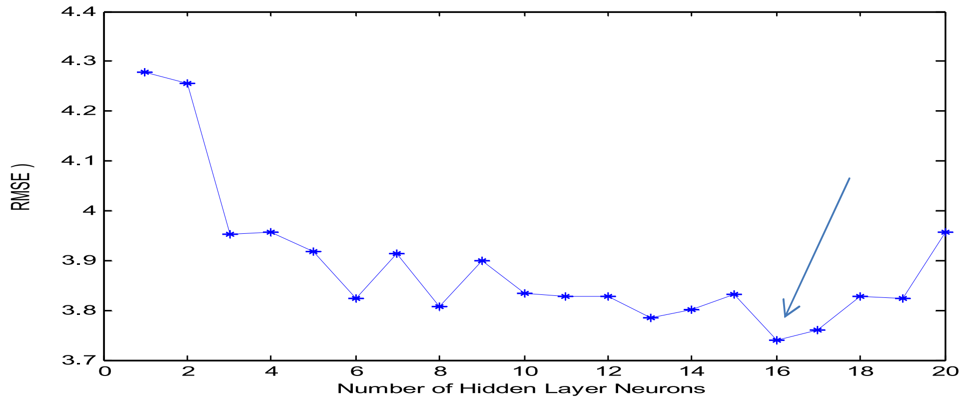

Fig. 5. Variations of the root means square errors (rmse) of solar radiation with no of hidden layer neuron

Fig. 6 (a – e) shows that the average radiation intensit obtained in Nigeria between 1979 and 2014 is in the range about 20 to 50 W/m^2. The highest solar radiation of about 40 – 50 W/m^2 were obtained in the East and North-Eastern parts of Nigeria and the lowest of about 20-30 W/m^2 were obtained in the South-West and Southern parts of the country. From Fig. 6 (a–e), it is observed that in dry season, between1979 and 2014, the increase trends flow from

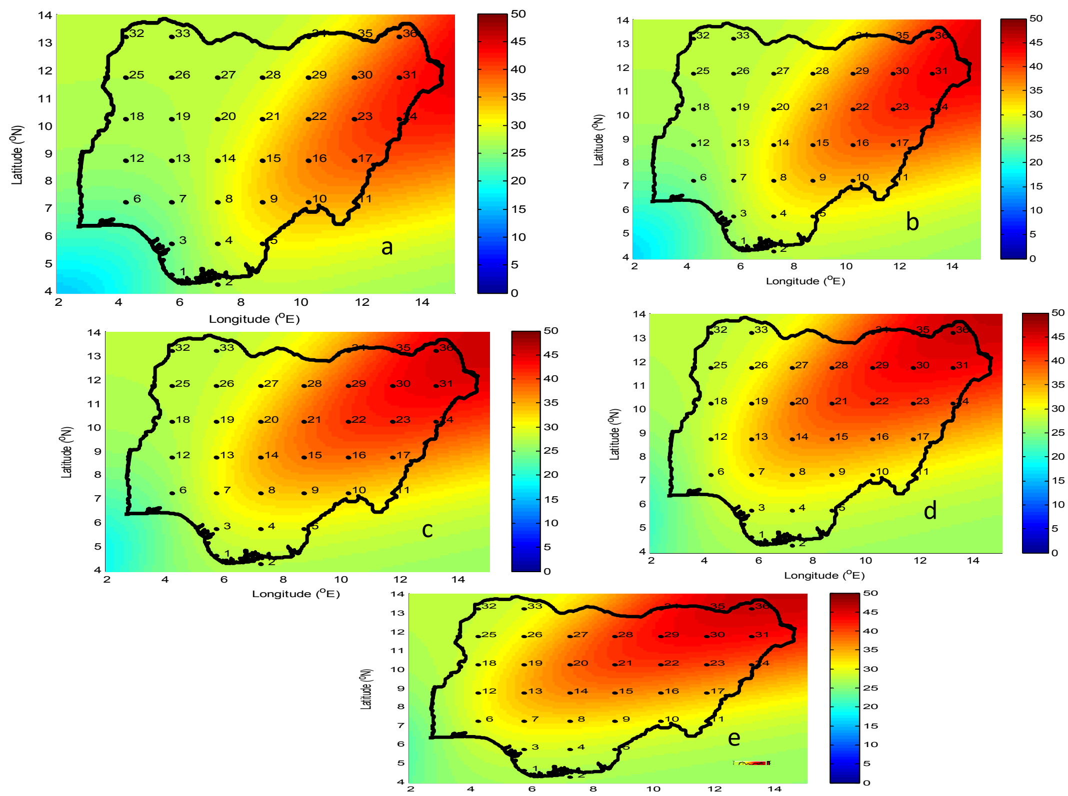

Fig. 6. The spatial variations in solar radiation (w/m^2) in dry season over Nigeria for the periods: (a) 1979 (b) 1989 (c) 1999 (d) 2009 and (e) 2014

North-East to North-West. This could be due to high intensity of solar irradiance in the Northern part of Nigeria particularly from Maiduguri (Borno State) as confirmed by [15,16]. This could also be due to increase in the greenhouse gases as well as the gaseous pollutants due to high desert encroachment and human activities in the recent times over the region.

In Fig. 7 (a – e), the result reveals that the spatial variations of solar radiation in wet season has the highest intensity of solar radiation at the North-Eastern part of the country from 1979 to 2014. The locations with lowest amount of solar radiation 5 – 15W/m^2 increased drastically, while the locations with high amount (30 – 50 W/m^2) reduced, especially in the North –Eastern part of Nigeria. It could be observed that within the periods under study, there was an increase in the number of points that received high intensities of solar radiation with more increase in the dry season than the wet season.

The comparison of solar radiation spatial variations during wet and dry seasons in Figs .6 and 7 reveals that both of the seasons have their highest concentration in the North-East of Nigeria. It is pertinent to note that the lowest concentration occurred at North-West during wet season, while the lowest occurred at the South-South and South-West of Nigeria in dry season. In addition, the lowest in dry season is about 25 W/m^2, while that of wet season is about 15 W/m^2. Figs. 8 and 9 reveal that the signature of both the estimated and observed variations of solar radiation exhibit similar trends across the years of study. Hence the model exhibits good performance in estimating temporal solar radiation.

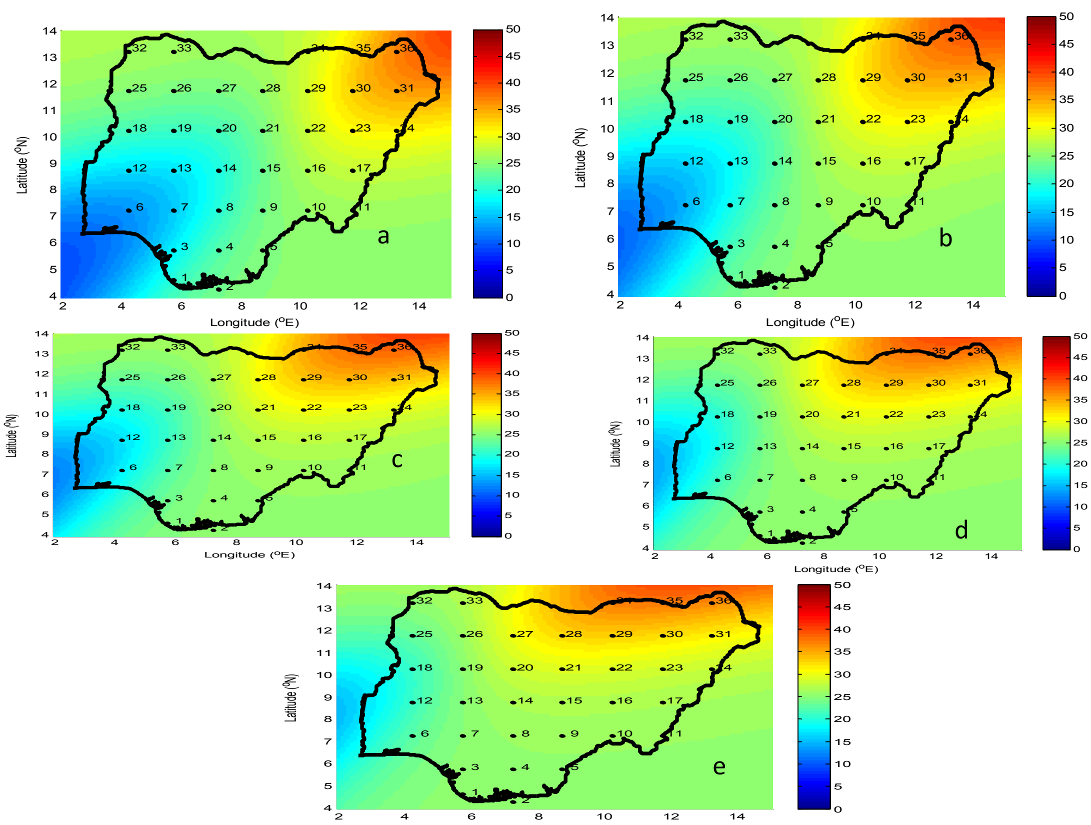

Fig. 7. The spatial variations in solar radiation (w/m^2) in wet season over Nigeria for the periods: (a) 1979 (b) 1989 (c) 1999 (d) 2009 and (e) 2014

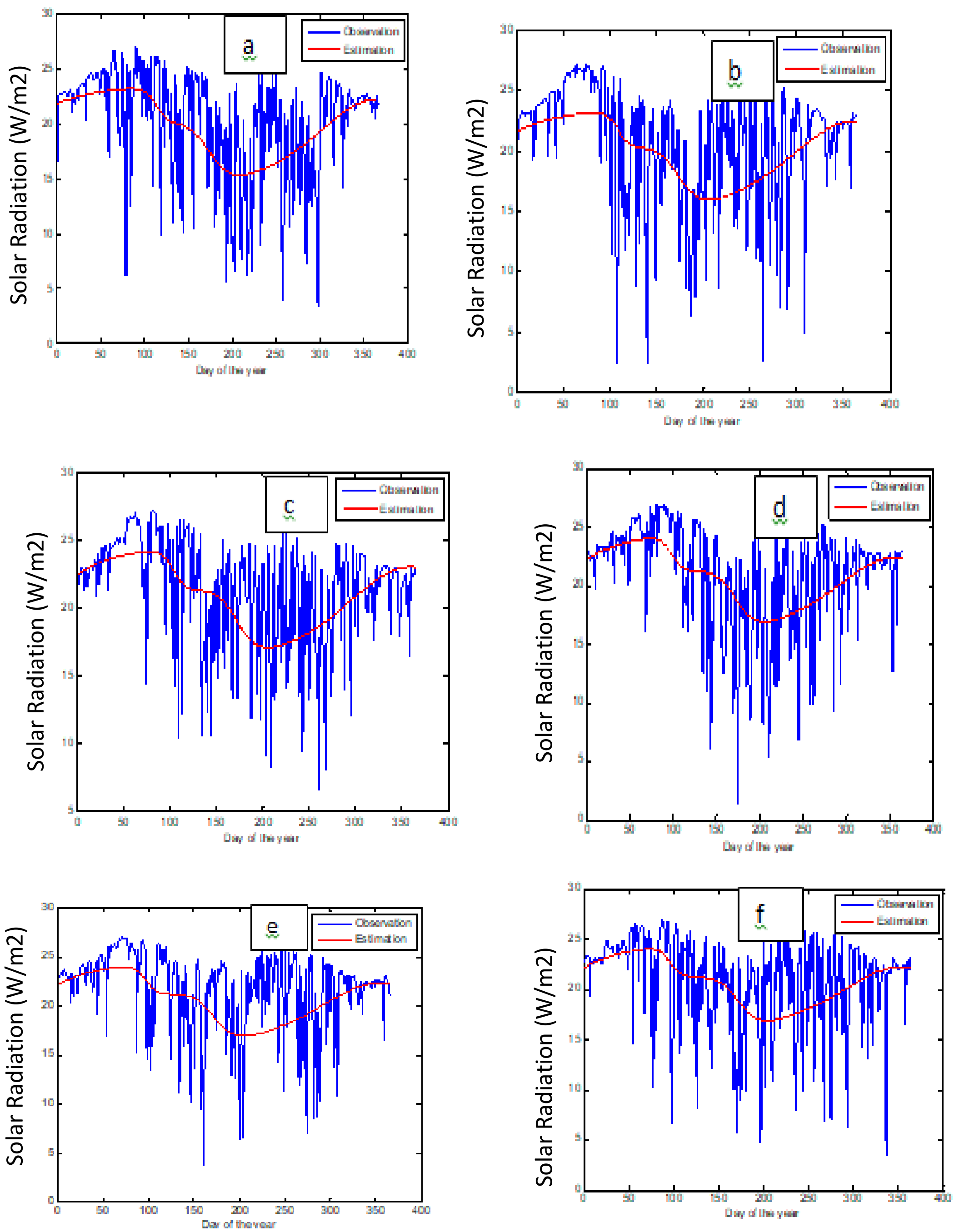

Fig. 8. The diurnal variations of observed and estimated solar radiation at Mowo, Osun State (4.25°N: 7.25°E) for the periods: (a) 1980 (b) 1990 (c) 2000 (d) 2010 (e) 2012 and (f) 2013

The coefficient of determination between the average yearly estimated and the observed solar radiation is 0.82, this imply 82% accuracies between the average yearly observed and estimated values. Fig. 10 was further used to check the performance of the model. The graph indicates the annual patterns of flow of the global radiation for the period of 1979-2014; for both the real data and the simulated using neural network model. The graphs show how well the simulated data mimic the real data. The results show an excellent agreement between averages annually observed and estimated data. This observation indicates strong relation between the observed and estimated. It confirms high performance of the neural network model used for the estimation. This is in line with [17], which state that impressive performance of the neural networks model supports the application of neural network in modeling climatic parameters. Isikwue and Ibeh [18] also observed that neural network model performance were excellent and efficient in determination of spatial distribution of atmospheric parameters.

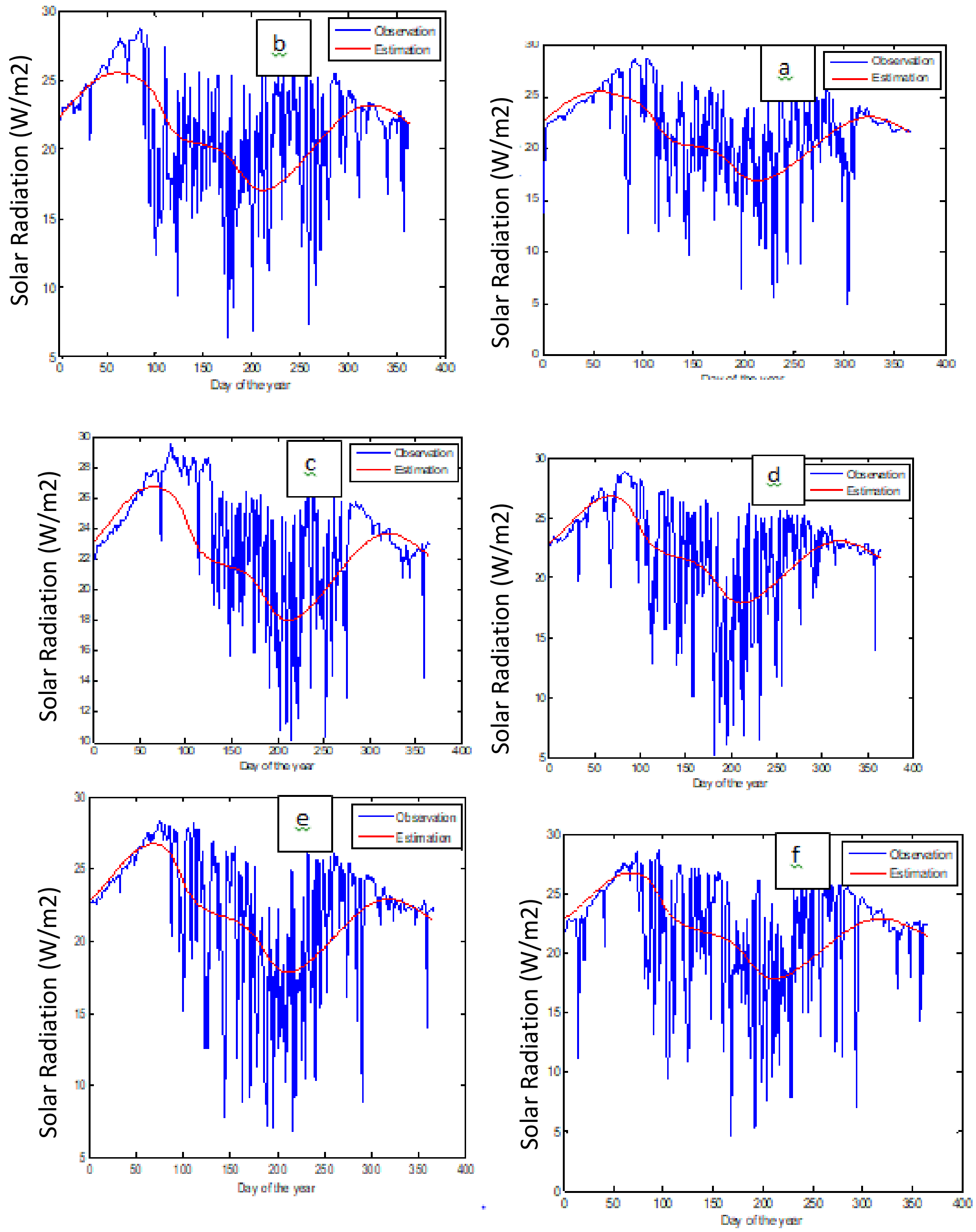

Fig. 9. The temporal variations of solar radiation at Dindima, Bauchi State (10.25 ^{o}N: 10.25 ^{o}E) for the periods: (a) 1980 (b) 1990 (c) 2000 (d) 2010 (e) 2012 and (f) 2013

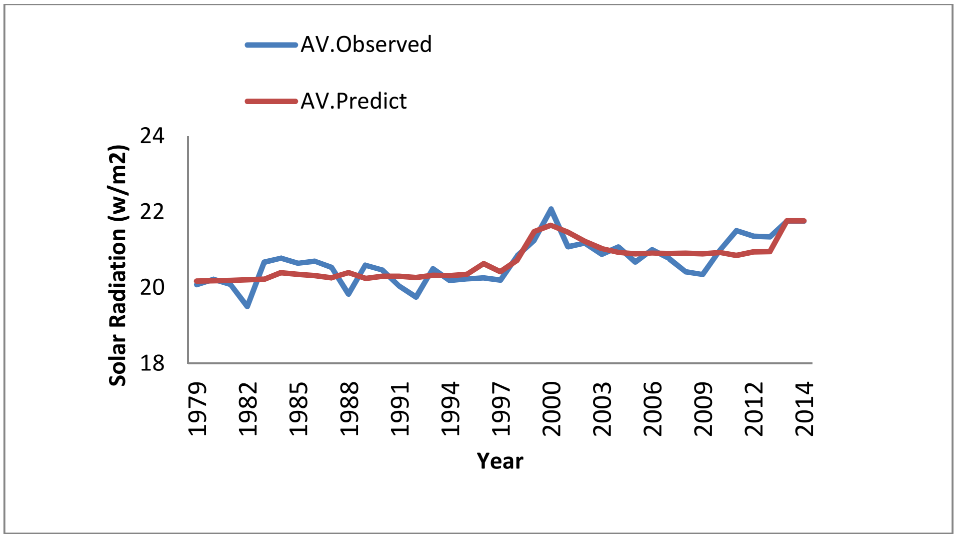

Fig. 10. The Annual average variations of estimated and observed values of solar radiation (1979-2014)

The model was used to predict daily data for two years steps (2018 and 2019) ahead the period of the study for two locations. One from the North, while the second from the South. In Fig. 11 (a); solar radiation concentrations will be about 15.5-22.5 W/m^2. The highest value of about 21- 22.5 W/m^2 is predicted to be prevailing between January-March and October - December, while the small value of about 15.5 W/m^2 will be in June and July. This could be as a result of high dryness content in January-March and October – December, and high moisture content in June and July respectively. Observation shows that solar radiation decreases from day 60 – 180 (February-June), remain constant with about 15.5 W/m^2 between day 180 to 190 (July) before increasing again gradually to about 22.5 W/m^2 in day 365 (December). It is important to note that

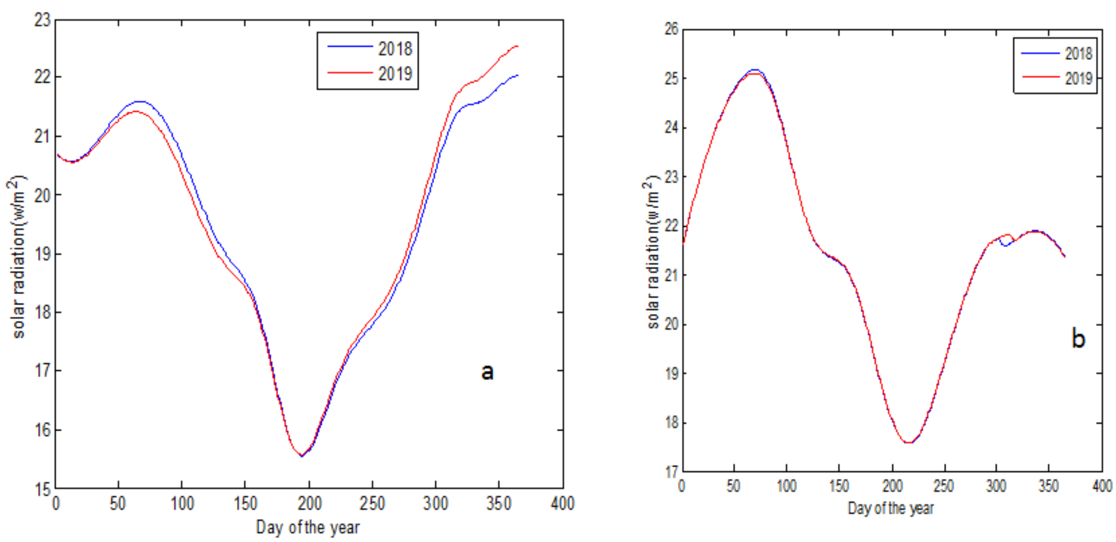

Fig. 11. (a) Variations of forecast of 2018 and 2019 at Apoi Creek, Bayelsa State (4.59°N: 5.84°E) for solar radiation and (b) Variations of forecasts of 2018 and 2019 at Danjuma, Taraba State (7.25°N: 10.25°E) for solar radiation

the result of the study reveals that solar radiation concentration will be lower in 2019 compared to 2018 between March to May, but will be higher in 2019 compared to 2018 between August and December. On the other hand, Fig. 11b reveals the prediction of temporal distributions for two years steps ahead (2018 and 2019) for Danjuma, Taraba State, Northern part of Nigeria of solar radiation. The corresponding concentrations were between 15.5-25.5 W/m^2 respectively. It is important to note that the variation of the solar radiation in the South will be in variance with that of the North. Solar radiation concentration will be higher in the North. This could be as a result of Northern wind trade, proximity to Sahara desert and burning of fossil fuel in the region.

4. CONCLUSION

Spatial distribution, temporal variations, annual distribution, estimation and prediction of solar radiations was carried out in this study using ANNs. Solar radiation data along the years (1979-2014) belonging to the thirty-six points in Nigeria were divided into three portions (training, testing and validation) during the applications of neural network model. The results of the validation and comparative study of the estimated and observed indicate that the ANN based estimation technique for solar radiation can be used to predict solar radiation as alternative to areas were in situ measurement cannot be possible in Nigeria. This study confirms the ability of the ANN models to predict solar radiation values precisely. The comparison results indicate that the ANN model is promising for evaluating the global solar radiation resource potential at the places where there are no monitoring stations in Nigeria.

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COMPETING INTERESTS

Authors have declared that no competing interests exist.

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