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# Model Development for Predicting Solar Radiation on Horizontal Plane for Heipang Community using Artificial Neural Network

**[1]*Maren, I.B., [2] Adisa, A.B., [3] Dandakouta, H., and [3] Ejilah, R.I.,**

[1] *Department of Mechanical Engineering, University of Jos, Plateau State, Nigeria*
mareni@unijos.edu.ng

[2]*Department of Mechanical/Production Engineering, Abubakar Tafawa Balewa University, Bauchi State, Nigeria*
aabello2@atbu.edu.ng
,
[3]*Department of Automobile Engineering Abubakar Tafawa Balewa University, Bauchi State, Nigeria*
hdandakuta@gmail.com, rejilah@gmail.com

**Corresponding Author: Maren, I.B.; mareni@unijos.edu.ng* **(07065845493)**

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**Abstract:** *The optimum design of solar energy systems requires accurate knowledge of the resource profile at a given location. Due to a lack of measuring instruments, and crude techniques used to acquire data, there is non-availability and/or inaccurate measured solar radiation data for most locations. These challenges can be overcome using the Artificial neural network (ANN) technique to model and map solar radiation for any location. This study is aimed at developing a model for predicting hourly global solar radiation data for the Heipang community in Barkin Ladi Local Government Area of Plateau State using hourly ambient temperature, clearness index, and relative humidity data set obtained from the NASA website. A combination of two activation functions (hyperbolic tangent Sigmoid (TanSig) and logistic Sigmoid (LogSig)) with four training algorithms (Levenberg-Marquardt (LM), gradient descent (GD), resilient backpropagation (RP) and scaled conjugate gradient (SCG)) to give TanSig-LM, LogSig-LM, TanSig-GD, LogSig-GD, TanSig-RP, LogSig-RP, TanSig-SCG, and LogSig-SCG as the ANN architectures for training, validating and testing the data using MATLAB programming software. The coefficient of correlation (R2) and root mean square error (RMSE) were used to evaluate the performance of the model. Results show that R2 and RMSE for the different ANNs range from 0.965 to 0.968 and 0.155 to 0.276 respectively. TanSig-GD ANN exhibited the worst result in terms of R2, and RMSE metrics followed by LogSig-GD, while LogSig-LM gives the best result with R2=0.96 and RMSE=0.155, thus, stands as the best prediction model for global solar radiation in Heipang community.*

**Keywords:** *Artificial neural network (ANN), Hourly global solar radiation, Training algorithm, Activation function, Prediction model*

## INTRODUCTION

Renewable energy resources such as solar and wind energy are promising in terms of power generation and are being considered alternatives to fossil fuels due to their availability and topological advantages in local power generation and environmental friendliness (Energy Information Administration, 2022). The application of renewable energy resources requires accurate knowledge of the resource profile at a given location for optimum design and study (Chegaar and Guechi 2009, Prasetyo *et al.,* 2022). However, the inability to buy measuring instruments, especially for solar radiation in most developing countries; crude techniques used to acquire data in some weather data stations and irregular collection of solar radiation data because it is not possible for measuring instruments to be installed at every location of interest due to high cost, results to non-availability of measured solar radiation data for most locations. Also, there are cases of missing records in the data set due to a lack of accurate measuring instruments. These limitations can be tackled nowadays using artificial intelligence (AI) techniques such as Artificial neural network (ANN) to model and map solar radiation in many countries that are developing (Kalogirou and Sencan 2010). ANN is a method in artificial intelligence that involves computations and mathematical techniques that simulate the human–brain processes which have the ability to learn, recall, and generalize from the given data by suitable assignment and adjustment of weights. (Surya, 2021). An artificial neural network model is an intelligent system for solving problems that are complicated in many applications such as prediction purposes as in wind speed and solar radiation prediction, optimization, simulation, modeling, clustering, pattern recognition, classification, process modeling, data mining and others (Islama *et al.,* 2013; Mohammed, 2019; Rachmatullah *et al.,* 2021).

The idea behind ANN was taken from biological neural systems. They can learn, store, and recall information based on a given training dataset. The neural network is trained by presenting input and target data to it and the network continuously adjusts its adaptable weights while evaluating the errors between its output values and the target data until it is minimal enough that it can predict the target data using the input data or recognize a pattern. The internal architecture of ANN that performs this approximation is the Multi-Layer Perceptron (MLP). MLP consists of three layers: the input, hidden, and output layers. Other elements consist of neurons, activation functions, and weights. The direction of the information flow throughout the layers is from the input to the output layer. In each layer, each neuron multiplies the input vector $x_j$ given by the previous layer by the weights vector $w_{ij}$ to give the scalar product $x_j \times w_{ij}$. An activation function f, is then performed to obtain the neuron output as shown in Fig. 1 (Boussaada *et al,* 2018):

$$y_i = f\left(\sum_{j=1}^{n} x_j \,.\, w_{ij}\right) \tag{1}$$

Where $i$ is the index of the neuron in the layer. $j$ represents the input index in the ANN.

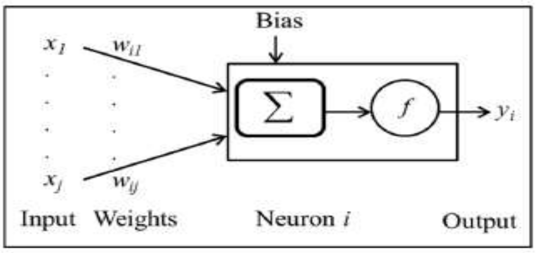


Fig. 1 Details of a neuron inputs and output

ANN has the advantage of being able to provide solutions for complex problems that cannot be solved using conventional technologies, problems without algorithm solutions, or for the algorithm solution to be too complex to be defined (Tamer and Wilfried, 2016). Anwar and Deshmukh (2018) used meteorological (mean sunshine duration, mean temperature, mean wind speed, mean relative humidity, and mean precipitation) and Geographical (latitude, longitude, and altitude) data from 28 locations in Telangana state and Andhra Pradesh for a period of 22 years from the NASA geo-satellite database as input parameters to model a monthly mean global solar radiation using ANN. The results show that the correlation coefficients between the actual mean monthly global solar radiation intensities and ANN predictions for testing and training datasets were higher than 95%. An artificial neural network technique for determining the hourly solar radiation of six chosen provinces in Turkey was initiated by Solmaz and Ozgoren (2012). The results from the developed ANN model show that the model has the capacity to predict the hourly solar radiation in the selected cities of study. Similarly, the ANN model that can determine the solar energy potential in Turkey was developed by Sözen *et al* (2004). The training and testing data results confirm the ability of the neural network model to predict the solar energy potential better as compared to the regression models. An ANN model was developed by Jiang (2009) to predict the mean daily global solar radiation in China. Results show that the ANN model has higher accuracy as compared to other regression models. Kumar and Chandel (2014) reviewed different neural network models for solar energy prediction. While most authors used a single neural network for modelling, Li *et al.* (2011) used a hybrid network architecture. ANN model was developed by Fadare (2009) to predict the potential of solar energy in Nigeria. Results show that the correlation coefficient between the measured data and the ANN prediction is more than 90%, thus presenting a model for the assessment of solar radiation for locations in Nigeria. Kuhe *et al.* (2019) developed a model for predicting solar radiation in Makurdi City, Nigeria, using ANN. The data for training and testing of the ANN were obtained from the Nigeria Metrological Station (NIMET) Makurdi. The model gave a good performance of correlation value $R^2 = 0.998$ and mean square error of MSE = 0.0142. Heng *et al.* (2022) carried out a comprehensive study on the type of backpropagation algorithm (Levenberg–Marquardt (L-M), Scaled Conjugate Gradient (SCG), and Bayesian Regularization (BR)) that gives the best solar radiation predicting model using ANN. Ambient temperature, relative humidity, and wind speed are the data used and were obtained from Kuala Terrenganu meteorological station, Malaysia. Results showed that BR algorithm-trained ANN models outperform other algorithm-trained models with the maximum correlation coefficient $R^2 = 0.8113$ and minimum RMSE = 0.2581.

Usman, (2015) developed a first-order Angstrom-Prescott empirical model of global solar radiation in Jos which was used to estimate the global solar radiation for 34 selected stations in Plateau State and interpolated for the entire state. The results show that Plateau State has an estimated $518.88\times10^6$ MJ/day of solar energy falling on its 26,899km$^2$ land areas with the highest and lowest values in the months of March and August respectively. These developed empirical models are location-specific and hence are limited in scope and application. To address these limitations, artificial intelligence techniques are being used for modeling and mapping solar radiation in many countries (Islam *et al*, 2013). Many researchers have done a lot of work on solar radiation prediction models using empirical and artificial intelligence techniques but to the best of the authors' knowledge, no work is done on the development of the model for solar radiation prediction for the Heipang community using ANN. ANN models are adjudged to be more efficient and consume less time in complex modeling systems compared to other mathematical models, such as regression (Kuhe *et al*., 2019), and give a solution that is better for developing a generalized model for solar radiation prediction using meteorological and climatic parameters (Tymvios *et al*., 2005). This study is aimed at developing a model for predicting solar radiation on a horizontal plane using artificial neural network techniques.

# MATERIALS AND METHODS

## 2.1 Description of Study Area

Heipang community (Tapo, Tatu, and Kpang), which is located between longitudes $8^{o}$ 50' E and $8^{o}$ 59' E and between latitudes $9^{o}$ 34' N and $9^{o}$ 42' N, in Barkin-Ladi L.G.A of Plateau State, Nigeria (Land Survey and Town Planning, 2018).

## 2.2 Materials

The data used for developing the model to predict global solar radiation on a horizontal plane are the 2012 and 2021 typical year hourly weather data obtained from the NASA website (https://power.larc.nasa.gov/data-access-viewer/) (see Fig. 2 and 3). The tools used for the analysis are MATLAB and Excel software.

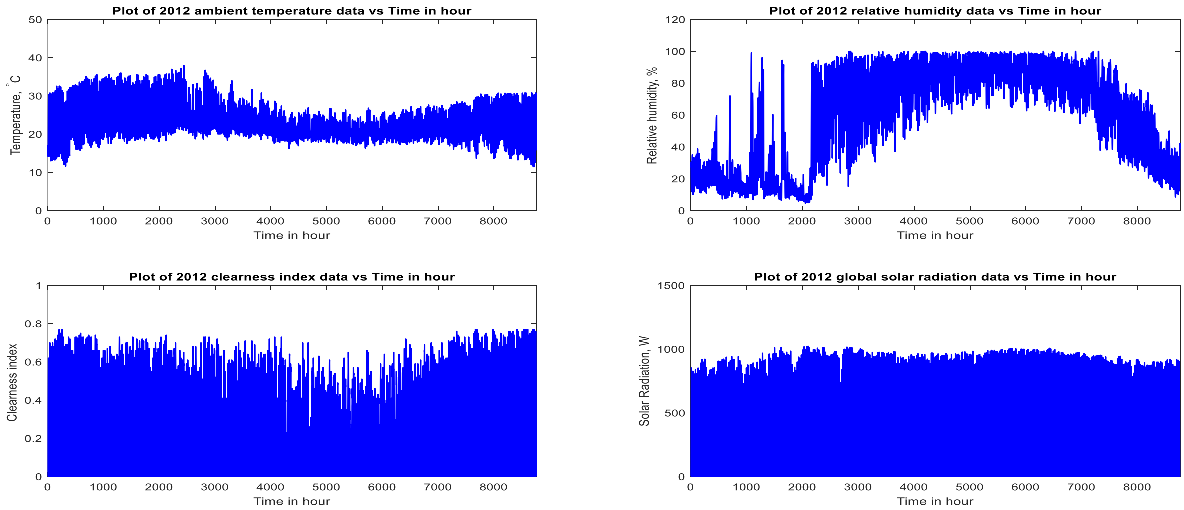


Fig. 2 A plot of 2012 Haipang community weather data against time

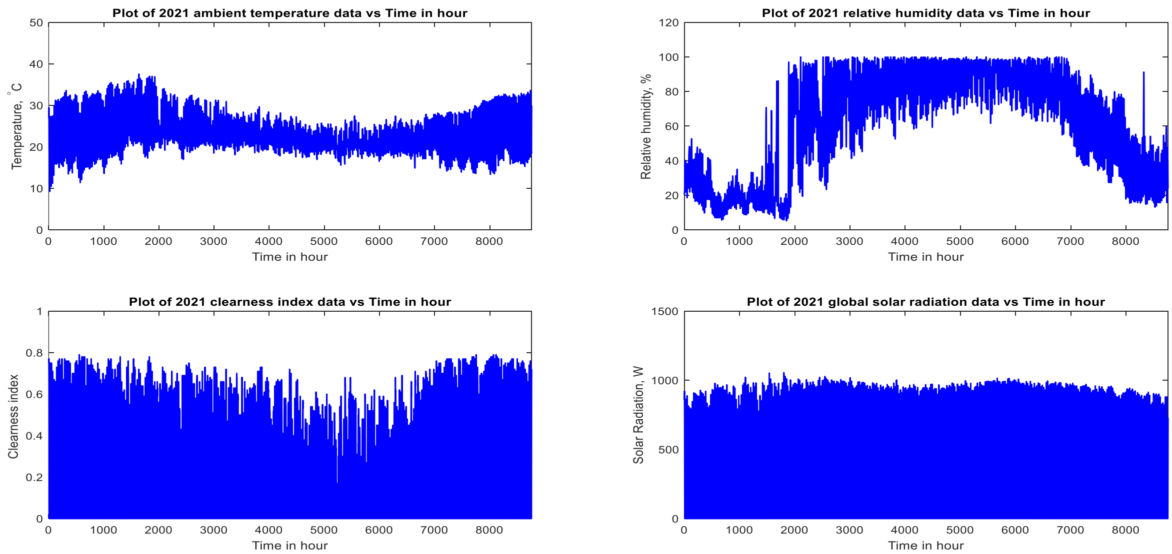


Fig. 3 A plot of 2021 Haipang community weather data against time

### 2.3 Method

#### 2.3.1 Artificial Neural Network Design

The neural network is implemented through the following steps: data collection, data-preprocessing, building the ANN architecture, developing the ANN program codes in MATLAB, and evaluating the performance of the ANN model using root mean square (RMSE) as the evaluation metric. The ANN architecture design procedure flowchart is shown in Fig. 4.

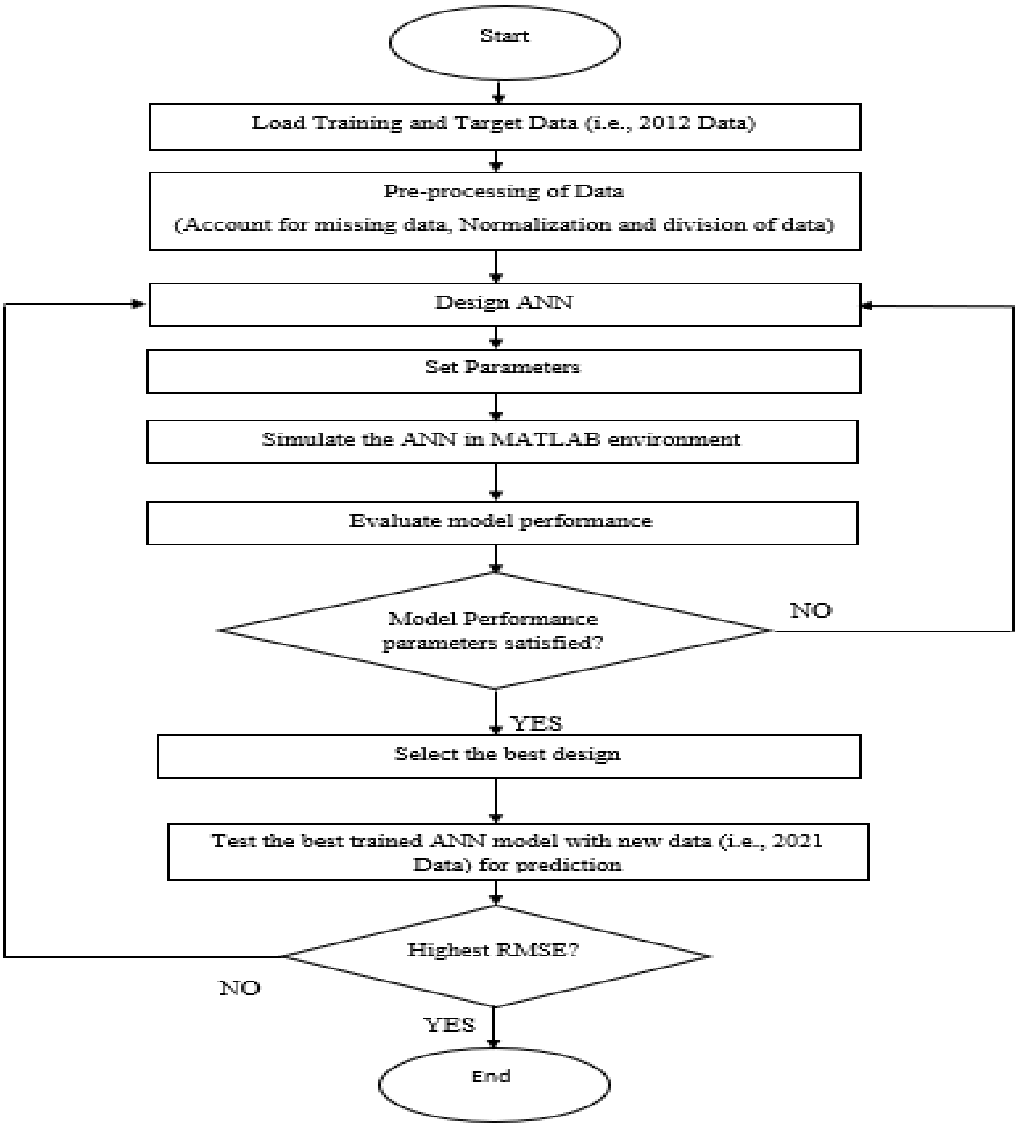


Fig. 4 Flowchart of Artificial Neural Network Model

In this work, two activation functions (Hyperbolic Tangent Sigmoid (TanSig) and Logistic Sigmoid (LogSig)) are used in the hidden and output layer and four training algorithm (Levenberg-Marquardt (LM) backpropagation, gradient descent (GD), resilient backpropagation (RP) and scaled conjugate gradient (SCG)), are combined to give eight ANN architecture (TanSig-LM, LogSig-LM, TanSig-GD, LogSig-GD, TanSig-RP, LogSig-RP, TanSig-SCG, and LogSig-SCG). Three input parameters namely, hourly ambient temperature (T), clearness index (CI), and the relative humidity (RH) in the dataset are used as inputs and hourly global solar radiation (GR) was predicted as an output as shown in Fig. 4.



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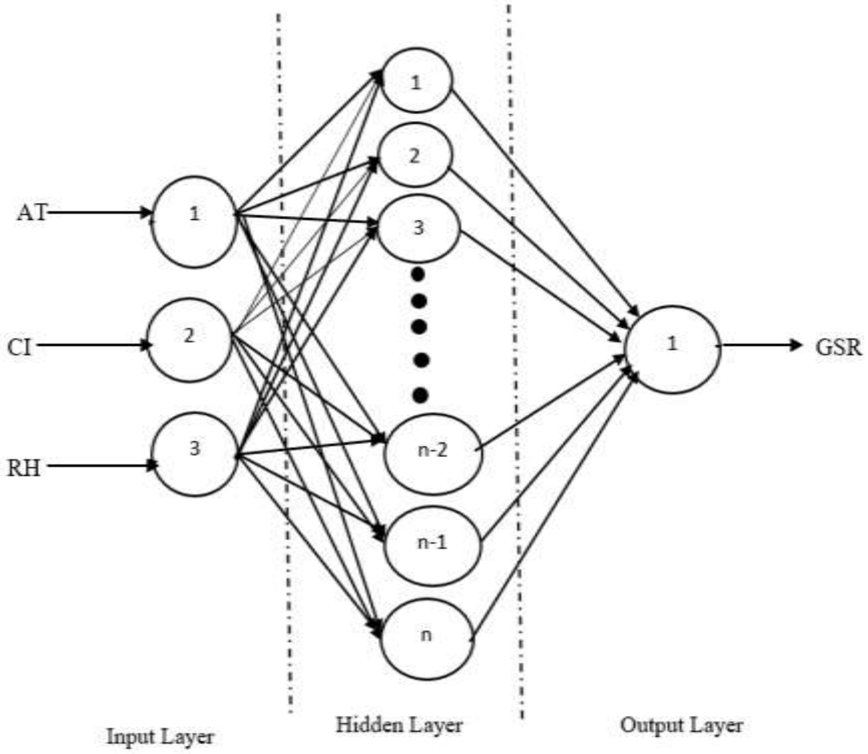


Fig. 5 The ANN architecture of the present study

### 2.2.3 Prediction Model Performance Measure Metric

The model performance measure metric for this study is the Root Mean Square Error (RMSE), which is the square root of the Mean Square Error (MSE). MSE gives a real number to compare against other model results and helps in selecting the best regression model. How much predicted results deviate from the actual number is determined using MSE which is expressed as an absolute number. However, RMSE is used more commonly than MSE because firstly sometimes MSE value can be too big to compare easily. Secondly, MSE is calculated by the square of error, and thus square root brings it back to the same level of prediction error and makes it easier for interpretation. RMSE is computed as:

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2} \quad (2)$$

Where $N$ is the number of observations in the dataset. $y_i$ is the true value and $\hat{y}_i$ is the predicted value.

## RESULTS AND DISCUSSION

Fig. 6 shows the plot of the RMSE generated from ANN for the different training algorithms, ((Levenberg–Marquardt (LM), gradient descent (GD), scaled conjugate gradient (SCG), and resilient backpropagation (RP), activation function (Tang sigmoid (TanSig), Logistic Sigmoid (LogSig)) against the number of neurons.

Only one hidden layer was selected for the ANN (because it gives better performance) with the number of neurons varied from 10 to 50. The graph shows that the RMSE of the ANN architects TanSig-LM and LogSig-LM decrease steadily from 0.1723 and 0.1717 to 0.1641 and 0.1548 respectively as the number of neurons in the hidden layer increase. However, for TanSigGD and LogSigGD architects, the RMSE increases speedily from 0.2004 and 0.2035 to 0.2758 and 0.2599 respectively as the number of neurons increases. For TanSig-SC, LogSig-SC, TanSig-RP, and LogSig-RP the RMSEs are relatively steady as the number of neurons in the hidden layer increase. Based on these results, the ANN models are ranked according to their RMSE values, and the best model has the lowest value (Hassan *et al*, 2016a, Hassan *et al*, 2016b) based on the RMSE values obtained from Figure 3, it indicates that LogSig-LM ANN model which has the lowest value of RMSE (0.1548) among the different proposed ANN models, is the best to predict the hourly global solar radiation on the horizontal as stated in Ridwan *et al.*, (2022). This substantiates the work of Neelamegam and Amirthamba (2016) which states that the Levenberg–Marquardt (LM) ANN training algorithm has good performance in predicting solar radiation. Thus, based on the performance metric of the different ANN architectures selected in this research, the LogSig-LM model performs better than the other models and it is therefore selected as the best model for the prediction of global solar radiation on the horizontal plane for the Heipang community.

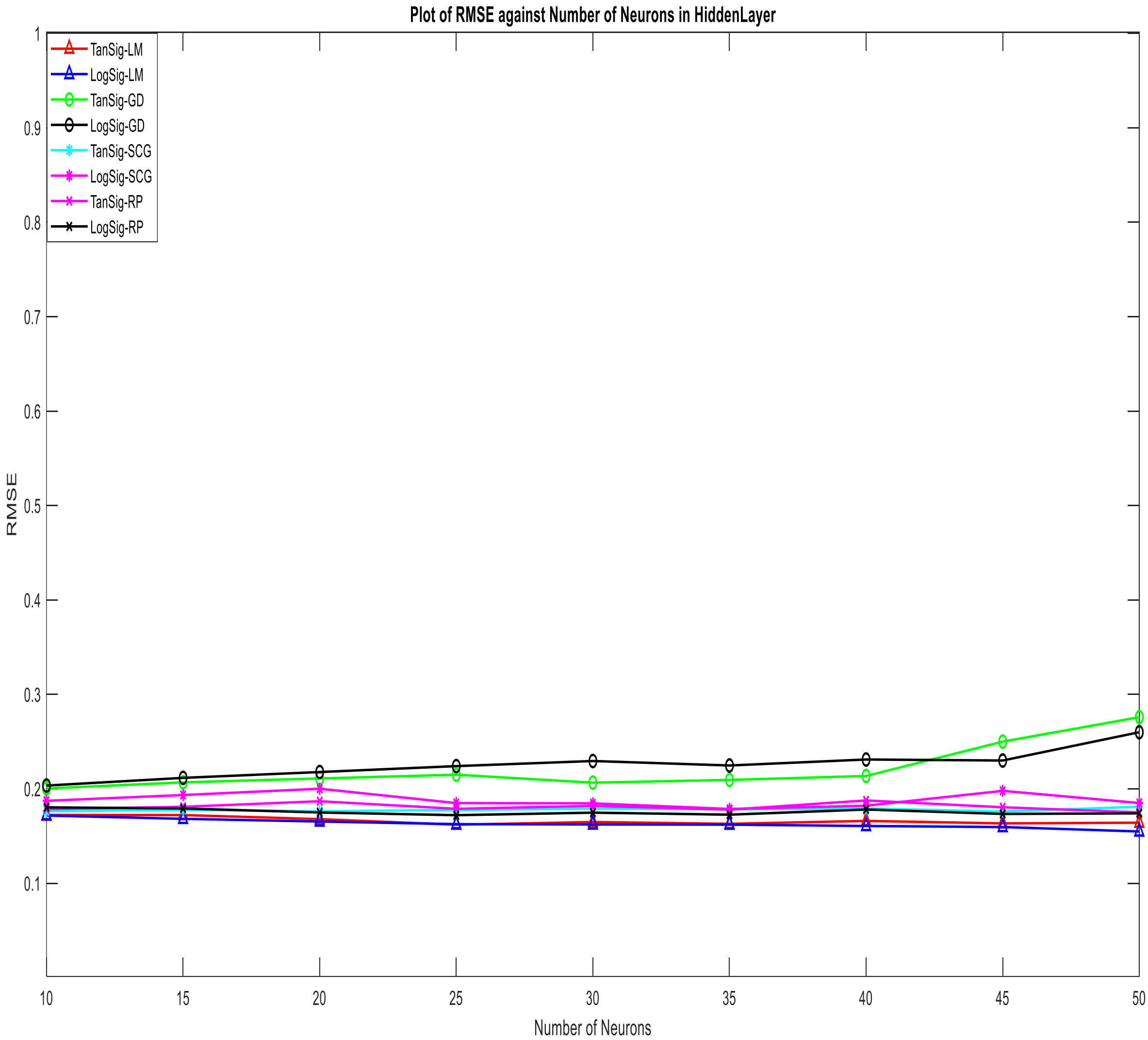


Fig. 6 Plot of RMSE against number of neurons in hidden layer

Fig. 7 is the regression plot for training, validation and testing of ANN using LogSig-LM training algorithm. The training, validation, testing, and all the datasets have of correlation coefficient of 0.96450, 0.96841, 0.96801, and 0.96553 respectively, showing a good correlation between the output and the target data.

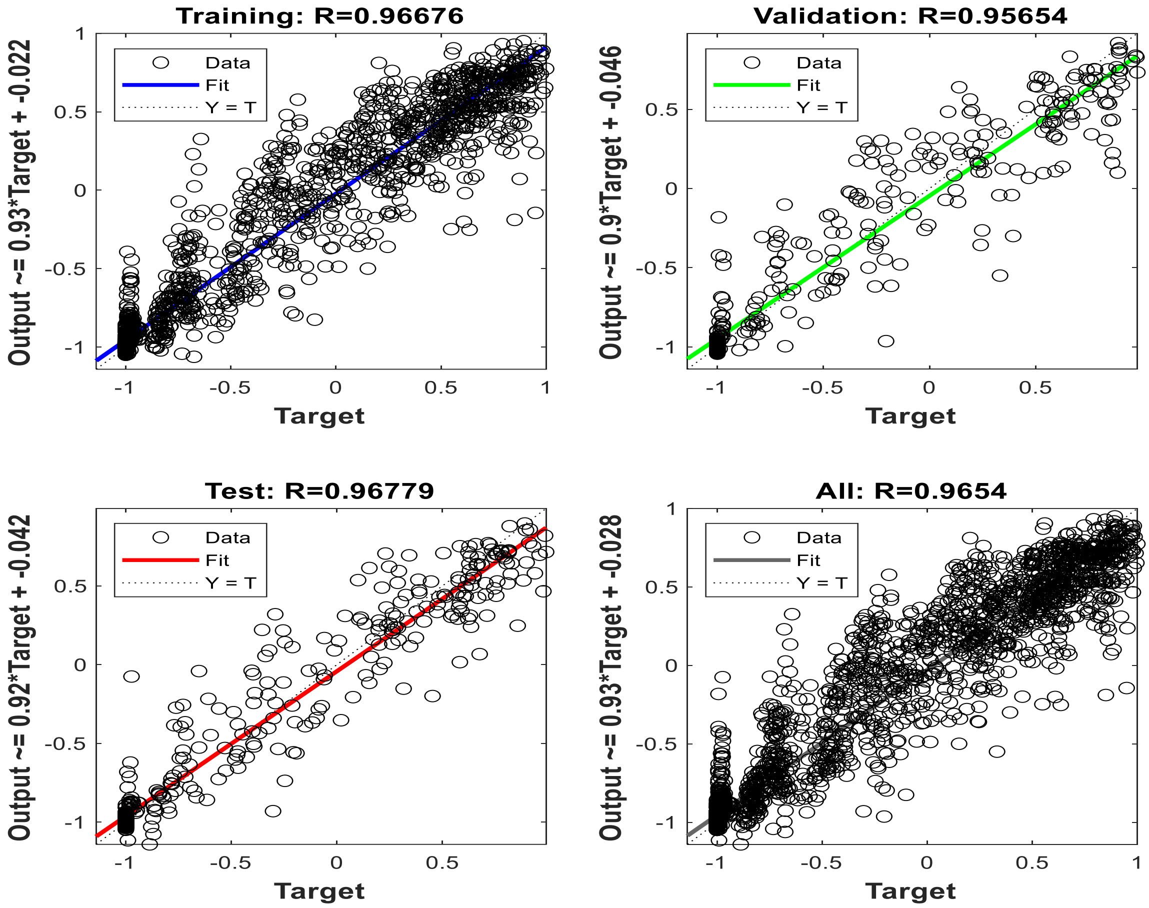


Fig. 7 Regression plot for training, validation and testing of ANN using LM training algorithm and LogSig activation function.

The plot of the predicted value (using the model generated from the LogSig-LM ANN) and the measured solar radiation against time for the year 2021 is shown in Figure 8 with a coefficient of correlation of 0.90. The prediction is based on the independent dataset of the year 2021 that was not subjected to training, validation, or testing. The prediction model follows the data trend of the measured data, with slight errors at some data points. It can be observed that there is a good agreement between the actual and predicted operational data points over the entire range. Between the 10-130th hour data point, the predicted data are almost exactly as the measured data. Similarly, between the 2200-2320th hour data point, there is a close fit between the measured and the predicted data. For data points between 6640-6760th and 8630-8750th points, there is also a relatively good fit between the measured and the predicted data. The plot shows a very strong correlation between the predicted and the measured data as statistically accepted that datasets with a coefficient of correlation between 0.8-1 have a very strong correlation (Bhandari, 2023; Glen, 2023).

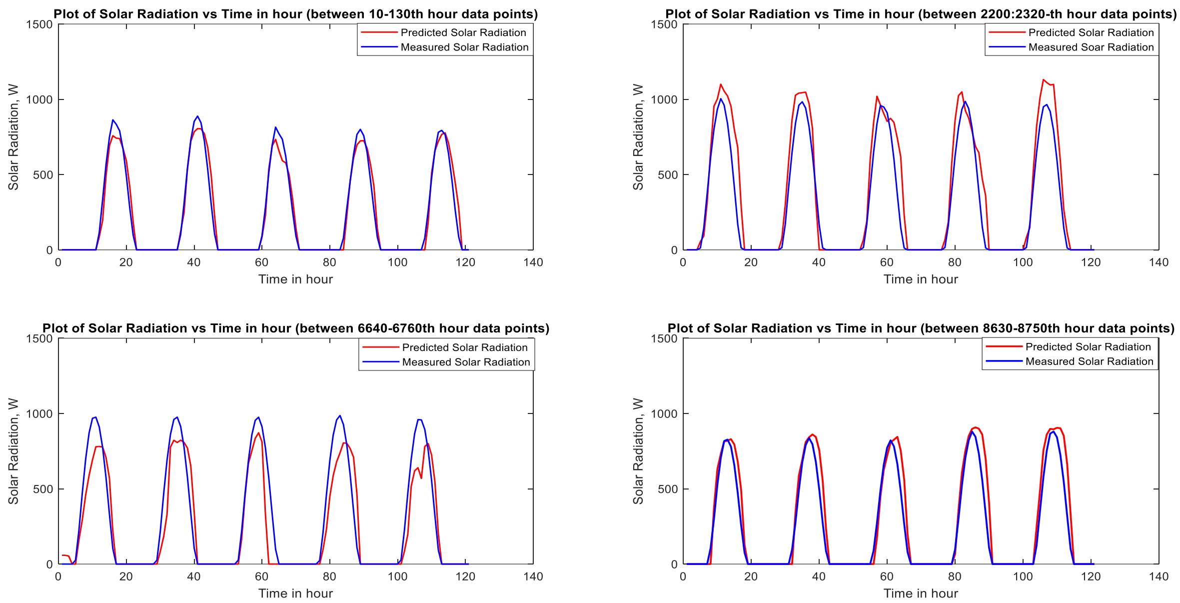


Fig. 8 Plot of predicted and measured solar radiation against time for Heipang community

## CONTRIBUTION TO KNOWLEDGE

Solar radiation data for the Heipang community is difficult to get compared to other weather data. The only source of such data is from the NIMET office in Abuja, Nigeria. Abuja is far from the Heipang community and also hard for researchers, especially students to have access to the data due to the high cost of the data. The model developed will help students generate the global solar radiation data on the horizontal plane for any relevant applications.

## CONCLUSION

In this research paper, the ANN model was developed to predict the global solar radiation of the Haipang community, and the LogSig-LM model is selected for the prediction of global solar radiation on the horizontal plane in the Heipang community due to its relatively better evaluation metric. The model developed can be used to predict the global solar radiation of Heipang of any year when the input parameters of the prediction model are available, thereby solving the problem of the unavailability of solar radiation data for engineering, agriculture, and aviation purposes.

## CONFLICT OF INTEREST

The authors declare no conflict of interest for this research work.

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