Journal of Electrical Engineering and Automation (ISSN: 2582-3051)
www.irojournals.com/iroeea/

Global Solar Radiation Modelling using an Artificial Neural Network for Kazaure, Jigawa State, Nigeria

John Ohabuiro[1], Ugochukwu O. Matthew[2*], Salisu Umar[3], Danladi Agadi Tonga[1], Amaonwu Onyebuchi[2]

[1]Electrical & Electronics Engineering Dept, Hussaini Adamu Federal Polytechnic, Nigeria.
[2]Computer Science Department, Hussaini Adamu Federal Polytechnic, Nigeria.
[3]Department of Mechatronics Engineering, Hussaini Adamu Federal Polytechnic, Nigeria.

E-mail: macdon4ru2003@gmail.com*

Abstract

This research presents an algorithm based on Artificial Neural Networks (ANN), for estimating monthly mean daily and hourly values of solar global radiation. To effectively investigate solar energy consumption and estimate solar renewable energy resources, the Hourly Global Solar Radiation measurements are necessary. In order to predict monthly average daily global sun irradiance on a horizontal area of Kazaure- Nigeria, this study creates a model utilizing ANN to solve the problem of solar energy distribution. Five empirical correlations are developed using the data from 42 months to aid in the prediction of the solar energy distribution pattern. The software is constructed around the Multilayer Perceptron under categorized tabs, with Multilayer perception in neural network Toolbox in MATLAB 9.7 version as a feed forward ANN that maps sets of input data into a set of suitable output. It differs from conventional linear perception by employing three or more layers of neurons (nodes) with nonlinear activation functions. It is also more effective than perceptrons in identifying input that is not linearly separable by a linear hyper-plane. Results obtained utilizing the suggested structure reveals good agreement between the calculated and measured levels of global solar irradiation. The ANN model is shown to be superior when compared to empirical models, due to negligible noise margin.

Keywords: Hourly global solar radiation, solar global radiation, Artificial Neural Networks (ANN), solar energy, multi-layer feed forward networks

1. Introduction

Photovoltaic (PV) cells and concentrated solar power technologies can both be used to create electricity directly from sun radiation (Sharma et al., 2022),(Ogunmodimu &

DOI: https://doi.org/10.36548/jeea.2022.4.008
Received: 09.12.2022, received in revised form: 09.01.2023, accepted: 15.01.2023, published: 21.01.2023

Okoroigwe, 2018). The PV solar cells' efficiency has increased, and they can now achieve up to 34.1% efficiency in multi-junction PV cells when fully energized (Hayat, Ali, Monyake, Alagha, & Ahmed, 2019). Due to their high capacity, efficiency, and energy storage capabilities, concentrated solar technologies for the production of electricity have a bright future. However, depending on the type of PV cell used, PV panels have peak efficiencies that range from 2 to 20% when converting solar radiation to electricity (K. H. Ibrahim, Hassan, AbdElrazek, & Saleh, 2023). Variations on the amount of solar energy that reaches the surface of the earth directly affect the climate since air temperatures are caused by the sun's radiant energy being absorbed (Nollas, Salazar, & Gueymard, 2023). The biggest and cleanest renewable energy source on the planet, solar radiation, can provide electricity with a very small carbon footprint. Knowing the anticipated sun radiation in advance is very helpful from both an economic and social standpoint, particularly for Sun Belt nations like Nigeria. Solar engineers need information on solar radiation on the earth's surface for many applications, to optimize the usage of solar renewable energy (Hai et al., 2023). The world recognizes the value of solar energy as a clean, renewable source of energy, especially in light of growing fuel prices and negative environmental repercussions including ozone layer depletion and climate change. Data on solar radiation show how much of the sun's energy is incident on the surface of the planet at a specific location and time. The most reliable information comes from measured global solar radiation values, which are also required for efficient study into solar energy consumption (Lu et al., 2023).

The total number of global rays that strike the surface of the earth directly and indirectly is known as global radiation (Kumar et al., 2023). Through its impact on air temperature and evaporation, global radiation at the earth's surface is among other things of great significance for the climate system. Solar radiation is constantly being emitted by the sun in all directions through the earth's surface which is either absorbed or reflected (Duffie, Beckman, & Blair, 2020). Nigeria has a lot of solar energy resources available because it is a tropical country (Ho, Lomi, Okoroigwe, & Urrego, 2019). Approximately 5250 $Whm^{-2}day^{-1}$ of solar radiation is received annually by the nation's coastline regions and 7000 $Whm^{-2}day^{-1}$ near its northern border. In order to solve the issue of electrifying remote rural areas in Nigeria that are not covered by the national grid, the usage of autonomous solar energy power systems is beneficial. The most important input parameter for designing a solar energy conversion system is accurate information on the Global Solar Radiation (GSR) at the site of interest (Li, Chen, Li, & Lou, 2019). Based on reliable detailed long-term data of measured GSR at the location, which is best gathered from a network of ground-based measurement sensors as well as from satellites, an exact design of the conversion systems is necessary. However, measuring equipment can be expensive to buy, install, and maintain, and satellite measurements might have issues, such as overestimation because the atmospheric conditions at the time of a satellite overpass are presumed to remain the same throughout the whole day (Zhang & Chen, 2022).

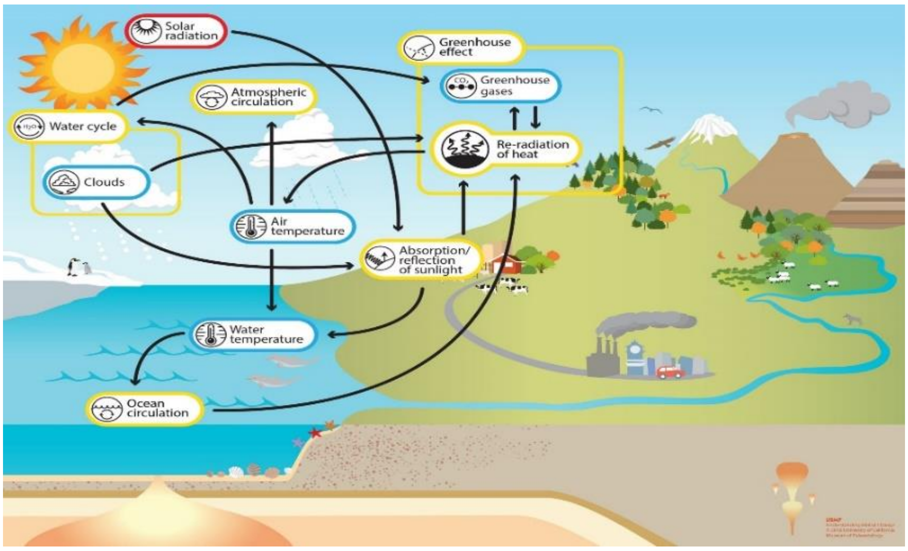

Figure 1. Global Radiation causes at the earth's surface and significance for the climate system (Wu et al., 2022)

As a result, when GSR data is unavailable or absent due to the aforementioned constraints, it must be predicted using models that have been built using scientific principles (Kuhe, Achirgbenda, & Agada, 2021). Despite the fact that estimated data is always less accurate than measured data, it is nonetheless relevant information for applications that are not sensitive to sun radiation intensities. Stochastic, analytical, empirical, and Artificial Neural Network (ANN) models are the most often used models for scientific estimation. Autoregressive models are among the stochastic models; they are fundamentally linear models, straightforward and intuitive but unable to reproduce the nonlinear nature of numerous dynamic processes in the actual world. One of the most effective and reliable methods for forecasting global solar radiation is thought to be analytical models (Das et al., 2018). Empirical models, on the other hand, are thought to be less effective ways and are founded on the linearity principle, therefore developing them is frequently a very tough undertaking. Their drawback is due to the fact that noise can sometimes obscure empirical regularities in a dynamic process.

Artificial neural network studies have outperformed empirical studies because the ANN consistently reflects the non-linear, non-stationary nature of solar radiation (Khosravi, Koury, Machado, & Pabon, 2018). Because of their great degree of interconnectedness, ANNs are particularly tolerant of errors or noise in the input data. North and southern Africa, as well as America and Europe, have all used ANN to forecast sun radiation and have subsequently improved on the solar system fabrications. There has to be more research done in West Africa, particularly Nigeria to replicate the tide. Based on the availability of all information sources, it appears that no ANN global solar radiation model has been created for Jigawa State in Nigeria. In this work, an ANN model is created for the Kazaure site in Jigawa State in order to forecast mean monthly global solar radiation. Weather information (temperature and hours of sunshine) is used as an input parameter for the constructed ANN model. Additionally, empirical models based on four meteorological parameters—maximum and minimum temperatures, relative humidity, sunshine hours, and global solar radiation on a horizontal surface are created for the sake of comparison. The use of temperature change and daylight hours as input factors produce the best-performing empirical model as discovered.

2. Statement Of Problem

In Kazaure, Jigawa state, the actual measurements made with pyranometers are now used to generate Global Solar Radiation (GRS) data. However, in cases where real measured data cannot be obtained because of equipment failure or deleted data records, prediction models based on locally accessible meteorological data are typically used as an alternate data source. Since the models are founded on the linearity principle, they are not very accurate because the empirical regularities in dynamic processes are not always linear and are often obscured by noise and data imputation errors. The non-linear, non-stationary nature of solar radiation is accurately captured by ANN, which are also very tolerant of errors or noise in the input data. In order to create both ANN and empirical models, the study focuses on selecting a subset of weather data as input parameters, and t then examines how well each model could predict the mean monthly GSR at Kazaure in Jigawa State, required for solar energy optimization.

3. Research Objectives

In the current study, the objective of creating empirical models and ANN based on weather information as input parameters for forecasting GSR at the Kazaure site in Jigawa state, Nigeria is pursued as follows.

- The research adopts temperature, relative humidity, and sunshine hours as input parameters to create an empirical model for forecasting mean monthly values of global solar radiation as requirement for optimized solar renewable energy consumption in the study area.

- The work creates an ANN model that uses temperature and sunshine hours as input parameters to forecast mean monthly values of global solar radiation.
- The study compares the results of the ANN and empirical models, makes important observations about the optimum solar renewable energy consumption, and reaches a conclusion.

4. ANN Architecture for Global Solar Radiation

Numerous instances have shown the effectiveness of ANN in modelling complex mappings and implementing system identification (Petelin, Cenikj, & Eftimov, 2023). Several researchers were inspired by those developments to investigate the potential of neural network models in real-world applications such as control systems, data classification, optimization, and modelling of complex process transformations. The ANN were created to simulate how the human brain processes information. An ANN is made up of processing units called neurons and has a parallel-distributed processing topology (Paul, Prasad, & Kumar, 2022). An input layer that gathers data from the environment outside and an output layer that sends information to users or other external devices make up a neural network. Given that they have no direct contact with the outside world, the layers between the input and output levels are referred to as hidden layers (Maduabuchi, Eneh, Alrobaian, & Alkhedher, 2023). Every neuron in a layer is connected to every neuron in the layer above it and below it. The input layer of a model is made up of the variables, and the output layer is made up of the variables. The number of hidden layers and total neurons in each layer are affected by the particular model, convergence rate, generalization potential, underlying physical process, and training data that the network will stimulate. The neuronal connections are weighted unidirectional connections. The strength of the connections between neurons, or synaptic weights, are used to store the knowledge. Fig. 2 depicts how a neural network functions in terms of information processing. Each neuron has a single output, a local memory, and an activation function, in addition to many inputs.

The totality of the dendritic inputs determines whether an action potential will be released by a neuron after it receives a variety of inputs. Linkages allow for the utilization of every input. The inputs are multiplied by the weights attached to the individual links through which they are applied. An activation function is applied to the weighted input summation. After that, the output is sent back into new neurons. One of the ANN topologies with the highest usage rates is the feed forward backpropagation network. Backpropagation training is a technique used to correct gradient descent errors. Generalized delta rule is used in the approach to train the network using exemplary patterns. Utilizing a method, the network weights are modified to reduce the output of the network's sum-squared error. In a typical ANN operation, the connection weights are updated using an appropriate learning technique in an organized manner during the training step (Kardani et al., 2022). The training set patterns that contain the relevant expected outputs and related inputs are presented one at a time in a random order to the network in order to maximize learning. During training, the network picks up the basic rule regulating how inputs and desired outputs are associated. The generalization capabilities of the networks allow it to perform similarly on data that wasn't used in training.

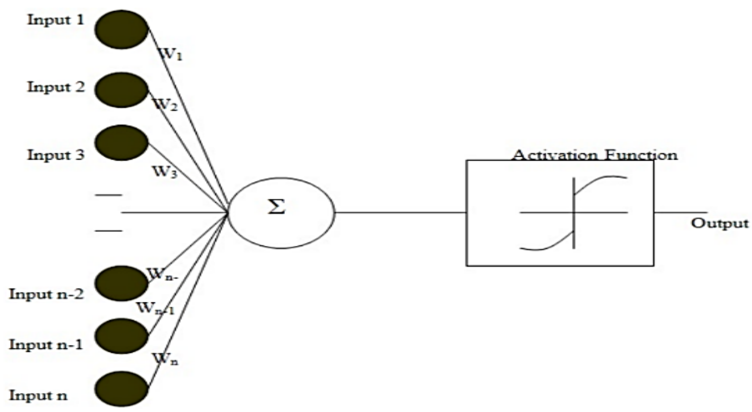

Figure 2. A Neural Network unit processing information (Geronikolou, Zimeras, Tsitomeneas, Cokkinos, & Chrousos, 2023)

The recall phase will start following sufficient training for the network. The network is now subjected to a set of test data that was not utilized during the modelling phase. The effectiveness of the network is then assessed. The architecture, activation function, and learning method are crucial ANN model components. A variety of feed-forward multilayer neural network topologies have been investigated with the aim of identifying which one would offer the best overall performance for estimating the hourly global sun radiation. The chosen ANN architecture is shown in Fig. 2, which includes the hidden layer, three visible levels, and an output layer that make up the structural design. The input layer contains 10 neurons, the hidden levels have nine, eight, and seven, and the output layer contains one neuron. Ten input neurons have been used to represent the training dataset's ten element input vectors, which include latitude, longitude, altitude, month, time, wind speed, humidity, rainfall, air temperature, and ambient air quality. The outcome is a single-element vector that depicts the radiation exposure levels encountered globally. The sigmoid function of neurons is used for activation. The learning algorithm used is standard back propagation with generalized delta rule, and gradient descent is used to lower the sum of the squared discrepancies between the desired and actual network outputs. Long training times are avoided by using an algorithm termination condition.

5. Material and Method

With reference to Fig. 3, Kazaure is situated at 12.65° N and 8.42° E and is 475 meters above the sea level. At present, there are about 250,494 people living in Kazaure as per the 2006 national population census information (Isma'il, Salisu, Yusuf, & Muhammed, 2013). Geographic coordinates for Kazaure are 12.6485 Latitude and 8.41178, Longitude, 12° 38' 55" North, 8° 24' 42" East, 178,000 hectares (1,780.00 km²) (687.26 sq mi) Kazaure Area, Kazaure Altitude 429 m (1,407 ft), and semi-arid climatic condition.

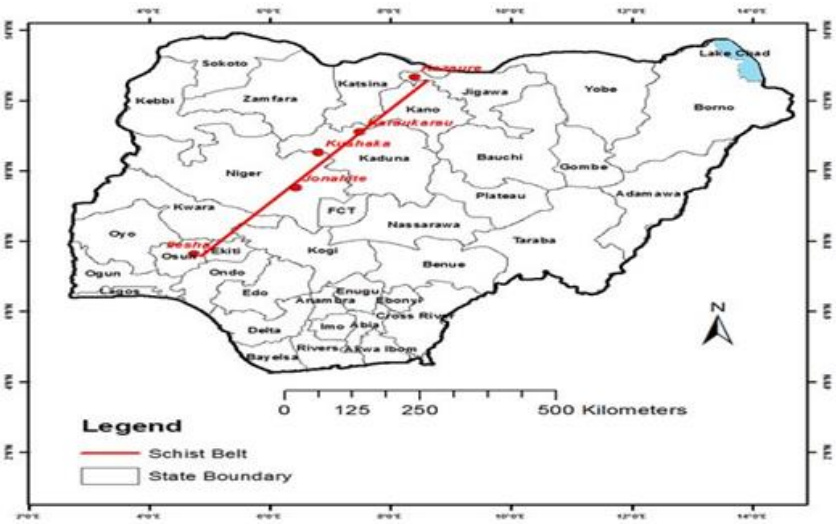

Figure 3. Map of Nigeria showing the location of Kazaure (A. K. Ibrahim & Musa, 2020)

5.1 Method of Data Collection

Data on worldwide solar irradiation are best obtained by distant observations made using specialized equipment at a particular location. However, the collection of solar irradiation data is restricted to a number of meteorological stations worldwide due to the expensive nature of calibration and maintenance of these instruments (Rocha et al., 2019). In the current study, the Nigerian Meteorological Agency statistical information on the world's solar radiation and climate is adopted. The monthly average global solar radiation for Kazaure, Nigeria, can be forecasted by using a variety of meteorological characteristics, including minimum and maximum temperatures, relative humidity, sunshine hours, latitude, longitude, altitude, wind speed, humidity, rainfall quality and GSR.

A number of models and algorithms have been developed to predict worldwide solar irradiation using a few meteorological characteristics measured often, such as maximum, minimum, and mean atmospheric temperature, relative humidity, cloudiness etc. The ANNs, in particular, have been extensively used in recent years to solve real-world problems using computational and artificial intelligence techniques. As a result, the current study entails developing a worldwide solar radiation estimating model that tries to estimate radiation from more easily observed climatic variables gathered at the same time as the intended forecast. Meteorological factors obtained at NIMET Kazaure Jigawa State are used as predictors in this research specifically.

5.2 The ANN Model Pre-Processing Design for Kazaure Location

The Neural Network Toolbox in the MATLAB 9.7 edition is used to create multi-layer feed-forward backpropagation networks with various architectural styles. The input layer, hidden layer, and output layer are the three layers that make up the network. For models 1 and 2, there are two input parameters, for model 3, there are three, and for all three models, the output parameter is the average worldwide solar radiation obtained for Kazaure-Nigeria. To improve the network's ability to generalize, two distinct algorithms: Levenberg-Marquardt (LM) and Gradient Descent (GD) techniques, with single and double hidden layer topologies are applied (Ahmed & Adam, 2013). The LM is conceived to work explicitly with loss functions which take the form of a sum of squared errors while GD as the most straight forward algorithm request information from the gradient vector.

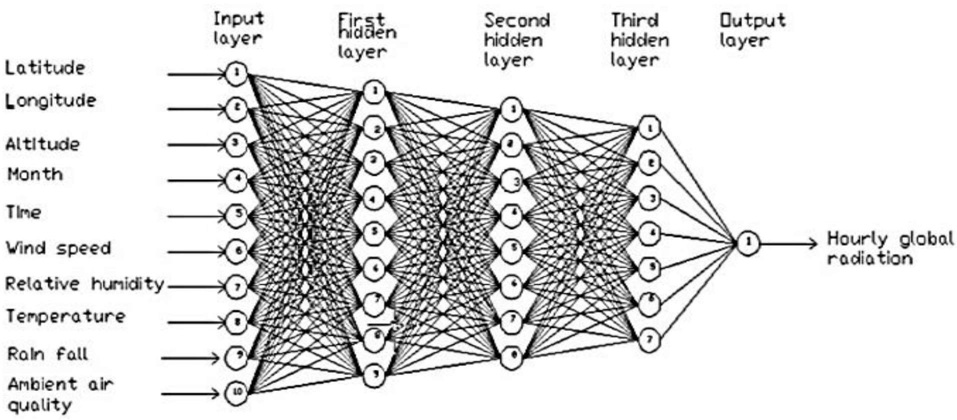

Figure 4. ANN structure for the prediction of global solar radiation (Goliatt & Yaseen, 2023)

The input layer had no transfer function, the hidden layer had a hyperbolic tangent sigmoid transfer function, and the output layer had a linear transfer function (purelin) (Yogitha & Mathivanan, 2018). It is a challenging challenge to choose the number of neurons for the hidden layer. No method that can be justified mathematically exists to date for finding the hidden elements. A network with an excessive number of nodes will take longer to train and be less capable of generalization and forecasting. Trial and error method is used to determine how many hidden elements are present. Starting with a small number of training components, the number of these components is gradually increased, and the ANN is continually retrained until acceptable training is accomplished. The ideal number of hidden elements is thought to be the number required for effective training (Fig.4).

6. Statistical Analysis

The Mean Percentage Error (MPE), Root Mean Square Error (RMSE), and Mean Bias Error (MBE) statistical error tests are used to evaluate the performance of the models. These tests are the ones that are used most frequently when contrasting models for estimating solar radiation. It is advised that a zero value for MBE is preferred and low values for RMSE and MPE are preferable (Maraj, Firat, & Gebremedhin, 2022).

6.1 MBE, RMSE and MABE

The MBE is defined by,

$$MBE = \left(\sum_{i=1}^{N}(y_i - x_i)\right)/N \tag{1}$$

where, i is an index, y_i is the i^{th} estimated value, x_i is the i^{th} measured value and N is the number of observations.

The results of the MBE test reveal how well a particular correlation has held up over time. A positive MBE indicates that the computed or estimated value has been overestimated, whereas a negative MBE indicates that the value has been underestimated. A low MBE is preferred, although it should be recognized that overestimating one data piece will cancel out underestimating another in a different observation.

The RMSE is defined by,

$$RMSE = \sqrt{\left(\sum_{i=1}^{N}(y_i - x_i)^2\right)/N} \tag{2}$$

The RMSE test offers details on how well a correlation performs over a short period of time. It enables a term-by-term comparison of the actual difference between the numbers that are calculated and those that are really measured. The RMSE value is always positive and, in the ideal situation, equals zero. The performance of the model is improved by a decreased RMSE value (the lower the RMSE, the more accurate the estimate). Although low RMSE values are preferred, the indication can be significantly raised by a handful of severe summation errors.

Also, it is possible to have a large RMSE value and at the same time a small MBE, or a relatively small RMSE and a relatively large MBE.

The MABE is defined by,

$$MABE = \left(\sum_{i=1}^{N}(\,|y_i - x_i\,|)\right)/N \tag{3}$$

MABE is the mean of the absolute bias error, and a small value is desirable. However, in this study RMSE, correlation coefficient, regression coefficient and ranking would be employed for evaluating the performance of the empirical models.

7. Results of the Research and Discussions of the Findings

The average computed values for the five-year period are shown in Table 1 below.

Table 1. Monthly Daily Average Meteorological Data of Kazaure

Months	RH(%)	RF(mm)	T_{max} (°C)	T_{min} (°C)	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
Apr.	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 in Kazaure

Months	n/N	H_m	H_o	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

Apr.	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. ANN and the Three Models' Monthly Average Daily Global Solar Radiation

Months	**H_m**	**Model 1**	**Model 2**	**Model 3**	**ANN Model**
Jan.	19.7	20	18.3	18.0	19.2
Feb.	21.5	20.4	19.2	19.3	21.8
Mar.	22.3	22.7	22.4	22.7	22.4
Apr.	20.4	22.3	24.8	23.9	19.7
May.	19.6	20.3	26.3	23.3	19.01
Jun.	18.4	17.5	23.8	22.5	17.8
Jul.	16.6	17.5	19.3	17.9	16.1
Aug.	15.5	16.9	19.7	17.3	14.8
Sept.	17.8	30.9	20.9	19.8	16.9
Oct.	19.8	19.2	21.5	21.5	18.8
Nov.	21.6	21.4	20.3	18.5	20.6
Dec.	20.3	20.7	18.9	17.2	19.4

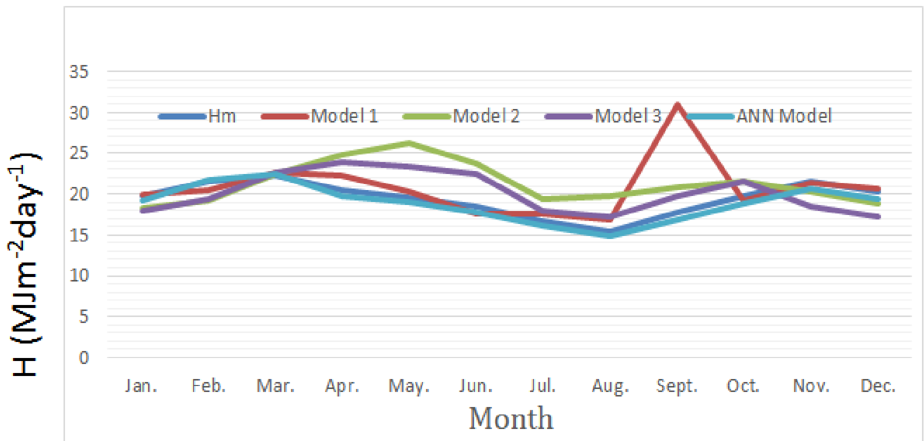

Figure 5. Correlation between the Clearness Index and Relative Sunshine Duration in Kazaure

ISSN: 2582-3051

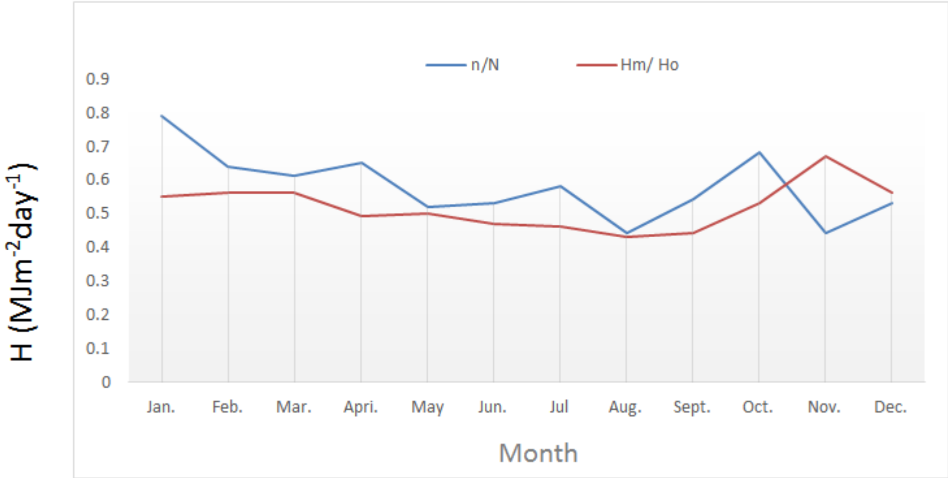

Figure 6. Observed Measurement and Estimated Value of Monthly Average Daily Global Solar Radiation

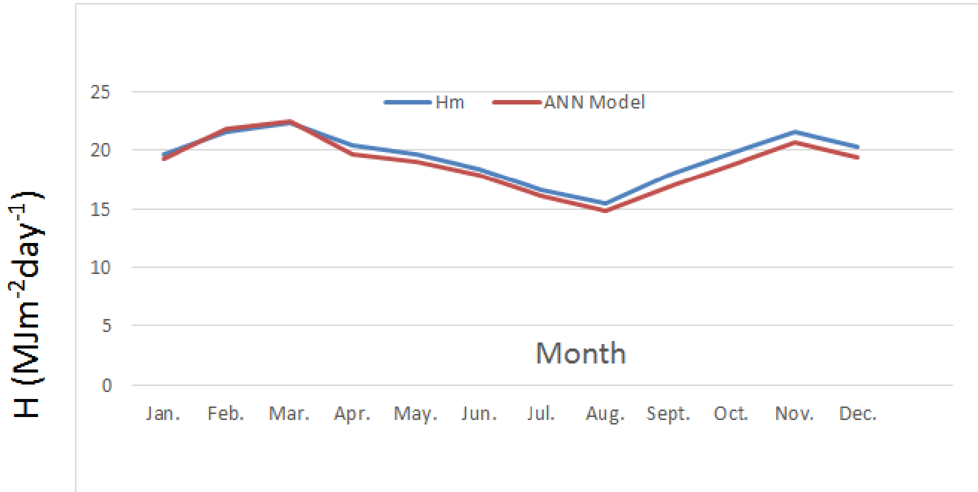

Figure 7. Estimated (Model 1) and Observed Values for the Monthly Average Daily Global Solar Radiation

Table 4. Comparison of Measured and Predicted Monthly Average Daily Solar Radiation (Computation of RMSE, MBE, and MPE)

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 irradiation values compared to measured irradiation values for the ANN model are shown in Fig.7, and the data are shown in Table 3. The clearness index value of 0.519 in Table 2 and Fig.5 corresponds to the lowest value of 0.44 and the H_m value of

15.8 in the month of August, both of which indicate poor sky conditions. These circumstances fit with Kazaure rainy or wet season, which lasts from June to September and is marked by a lot of cloud cover. In Table 3, along with the measured values, the monthly average daily solar radiation for Kazaure predicted using models 1 and 4 is found. A very good agreement between the measured values and the ANN is quite gratifying. According to Fig.2, the ANN model is best for estimating the average daily global solar radiation for Kazaure on a monthly basis. The outcomes of the statistical test are displayed in Table 4. The correctness of a specific model or correlation is measured by the RMSE values. The ANN model value for the current analysis is found to be the lowest (4.74), as shown in Table 4. The MBE values derived from the models are positive in some cases and negative in others, demonstrating that these models can differ in their estimation of the amount of solar radiation received on a worldwide scale. The model, with a value of -1.029, has the least under estimate, which is expected and acceptable.

The MPE is projected to have a low value; the ANN model is found to have an MPE value of - 2.345. Using several proposed models and daily recorded climatic variables such as maximum and lowest temperature differences, relative humidity, cloud cover, and rainfall, the worldwide solar radiation may be accurately estimated. It takes thorough mathematical modelling of all the climatological parameters in order to achieve some reliable estimates of solar radiation. Figure 3 shows that across the latitudes, there is a large proportion of cloudy days with low solar energy and low temperatures during the wet season, and low overcast days with high solar energy and high temperatures during the dry season. When statistical metrics like RMSE, MBE, and MPE are taken into account, ANN models have been found to perform well. The new model is shown to have better flexibility to extremely fluctuating weather circumstances and may be used to estimate daily levels of global solar radiation with a higher degree of accuracy. According to the estimates of solar radiation, solar energy can effectively make up for inadequate energy supplies.

8. Conclusion

In this study, an ANN model has been presented to forecast monthly average daily global sun irradiation on horizontal surfaces in the study area of Kazaure, Nigeria. This study establishes that utilizing meteorological information, ANN may be utilized to predict the potential for global sun irradiation in Kazaure, Nigeria. The monthly global solar radiation using relative humidity, sunshine hour, cloud cover, rainfall, and maximum temperature have been used in this study to estimate global solar radiation for Kazaure, Jigawa State, Nigeria.

This is due to the widespread concern regarding the economic importance of global solar radiation as a substitute renewable energy source.

9. Acknowledgement/Conflict of Interest

The authors wish to state categorically that this research was sponsored by Tertiary Education Trust Fund (TETFUND-Nigeria). However, there is no conflict of interest between the funder and the research team.

References

[1] Ahmed, E. A., & Adam, M. E.-N. (2013). Estimate of global solar radiation by using artificial neural network in Qena, Upper Egypt. Journal of Clean energy technologies, 1(2), 148-150.

[2] Das, U. K., Tey, K. S., Seyedmahmoudian, M., Mekhilef, S., Idris, M. Y. I., Van Deventer, W., . . . Stojcevski, A. (2018). Forecasting of photovoltaic power generation and model optimization: A review. Renewable and Sustainable Energy Reviews, 81, 912-928.

[3] Duffie, J. A., Beckman, W. A., & Blair, N. (2020). Solar engineering of thermal processes, photovoltaics and wind: John Wiley & Sons.

[4] Geronikolou, S., Zimeras, S., Tsitomeneas, S., Cokkinos, D., & Chrousos, G. P. (2023). Total Solar Irradiance and Stroke Mortality by Neural Networks Modelling. Atmosphere, 14(1), 114.

[5] Goliatt, L., & Yaseen, Z. M. (2023). Development of a hybrid computational intelligent model for daily global solar radiation prediction. Expert Systems with Applications, 212, 118295.

[6] Hai, T., Aziz, K. H. H., Zhou, J., Dhahad, H. A., Sharma, K., Almojil, S. F., . . . Mehrez, S. (2023). -Neural network-based optimization of hydrogen fuel production energy system with proton exchange electrolyzer supported nanomaterial. Fuel, 332, 125827.

[7] Hayat, M. B., Ali, D., Monyake, K. C., Alagha, L., & Ahmed, N. (2019). Solar energy—A look into power generation, challenges, and a solar- powered future. International Journal of Energy Research, 43(3), 1049-1067.

[8] Ho, S. M., Lomi, A., Okoroigwe, E. C., & Urrego, L. R. (2019). Investigation of solar energy: The case study in Malaysia, Indonesia, Colombia and Nigeria. International Journal of Renewable Energy Research, 9(1).

[9] Ibrahim, A. K., & Musa, A. I. (2020). Mapping geology and structural features of Kazaure SE, NW Nigeria: Justifying groundwater potential model. Zbornik radova Departmana za geografiju, turizam i hotelijerstvo(49-1), 1-21.

[10] Ibrahim, K. H., Hassan, A. Y., AbdElrazek, A. S., & Saleh, S. M. (2023). Economic analysis of stand-alone PV-battery system based on new power assessment configuration in Siwa Oasis–Egypt. Alexandria Engineering Journal, 62, 181-191.

[11] Isma'il, M., Salisu, A., Yusuf, S., & Muhammed, Z. D. (2013). Spatial analysis of urban growth in Kazaure local government area of Jigawa state, Nigeria. International Journal of Geomatics and Geosciences, 4(1), 47-60.

[12] Kardani, N., Bardhan, A., Gupta, S., Samui, P., Nazem, M., Zhang, Y., & Zhou, A. (2022). Predicting permeability of tight carbonates using a hybrid machine learning approach of modified equilibrium optimizer and extreme learning machine. Acta Geotechnica, 17(4), 1239-1255.

[13] Khosravi, A., Koury, R., Machado, L., & Pabon, J. (2018). Prediction of wind speed and wind direction using artificial neural network, support vector regression and adaptive neuro-fuzzy inference system. Sustainable Energy Technologies and Assessments, 25, 146-160.

[14] Kuhe, A., Achirgbenda, V. T., & Agada, M. (2021). Global solar radiation prediction for Makurdi, Nigeria, using neural networks ensemble. Energy Sources, Part A: Recovery, Utilization, and Environmental Effects, 43(11), 1373-1385.

[15] Kumar, C. M. S., Singh, S., Gupta, M. K., Nimdeo, Y. M., Raushan, R., Deorankar, A. V., . . . Pakhale, V. D. (2023). Solar energy: A promising renewable source for meeting energy demand in Indian agriculture applications. Sustainable Energy Technologies and Assessments, 55, 102905.

[16] Li, D. H., Chen, W., Li, S., & Lou, S. (2019). Estimation of hourly global solar radiation using Multivariate Adaptive Regression Spline (MARS)–A case study of Hong Kong. Energy, 186, 115857.

[17] Lu, Y., Wang, L., Zhu, C., Zou, L., Zhang, M., Feng, L., & Cao, Q. (2023). Predicting surface solar radiation using a hybrid radiative Transfer–Machine learning model. Renewable and Sustainable Energy Reviews, 173, 113105.

[18] Maduabuchi, C., Eneh, C., Alrobaian, A. A., & Alkhedher, M. (2023). Deep neural networks for quick and precise geometry optimization of segmented thermoelectric generators. Energy, 263, 125889.

[19] Maraj, A., Firat, C., & Gebremedhin, A. (2022). Modelling and the experimental validation of the long-term averaged solar radiation on a tilted solar collector facing the

south-east direction. International Journal of Renewable Energy Research (IJRER), 12(3), 1404-1413.

[20] Nollas, F. M., Salazar, G. A., & Gueymard, C. A. (2023). Quality control procedure for 1-minute pyranometric measurements of global and shadowband-based diffuse solar irradiance. Renewable Energy, 202, 40-55.

[21] Ogunmodimu, O., & Okoroigwe, E. C. (2018). Concentrating solar power technologies for solar thermal grid electricity in Nigeria: A review. Renewable and Sustainable Energy Reviews, 90, 104-119.

[22] Paul, A., Prasad, A., & Kumar, A. (2022). Review on artificial neural network and its application in the field of engineering. Journal of Mechanical Engineering: PRAKASH, 1, 53-61.

[23] Petelin, G., Cenikj, G., & Eftimov, T. (2023). Towards understanding the importance of time-series features in automated algorithm performance prediction. Expert Systems with Applications, 213, 119023.

[24] Rocha, P., Fernandes, J., Modolo, A., Lima, R., da Silva, M., & Bezerra, C. (2019). Estimation of daily, weekly and monthly global solar radiation using ANNs and a long data set: a case study of Fortaleza, in Brazilian Northeast region. International Journal of Energy and Environmental Engineering, 10(3), 319-334.

[25] Sharma, V. K., Singh, R., Gehlot, A., Buddhi, D., Braccio, S., Priyadarshi, N., & Khan, B. (2022). Imperative Role of Photovoltaic and Concentrating Solar Power Technologies towards Renewable Energy Generation. International Journal of Photoenergy, 2022.

[26] Wu, Z., Li, T., Heavens, N. G., Newman, C. E., Richardson, M. I., Yang, C., . . . Cui, J. (2022). Earth-like thermal and dynamical coupling processes in the Martian climate system. Earth-Science Reviews, 229, 104023.

[27] Yogitha, R., & Mathivanan, G. (2018). Performance analysis of transfer functions in an artificial neural network. Paper presented at the 2018 International Conference on Communication and Signal Processing (ICCSP).

[28] Zhang, Y., & Chen, L. (2022). Estimation of Daily Average Shortwave Solar Radiation under Clear-Sky Conditions by the Spatial Downscaling and Temporal Extrapolation of Satellite Products in Mountainous Areas. Remote Sensing, 14(11), 2710.