International Journal of Innovative Information Systems & Technology Research 14(3):50-61, July-Sept, 2026

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DOI:10.5281/zenodo.21286023

Design And Simulation of An Artificial Intelligence-Based Model for Predicting Solar Radiation Intensity for Renewable Energy Applications in Northern Nigeria

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ABSTRACT
Solar-renewable energy is a clean and cost-effective energy source for poverty reduction in any society, therefore, for the best design, planning, and operation of solar-renewable energy systems, an accurate forecast of solar radiation intensity is very essential. Despite the abundance of solar resources and rising energy consumption, Northern Nigeria has difficulties in predicting solar radiation intensity, hence an artificial intelligence-based model for predicting solar radiation intensity was developed in this study. The model architecture incorporates a meteorological data such as temperature, humidity, wind speed, atmospheric pressure, dust concentration and cloud cover that represent a weather condition in northern cities, including Katsina, Kano, Sokoto, Maiduguri, and Yobe. The simulated results obtained proved a high prediction performance with coefficient of determination (R^2) = 0.968, root mean square error (RMSE) = 22.6 W/m², mean absolute error (MAE) = 16.8 W/m², and mean absolute percentage error (MAPE) = 4.1%. The findings indicate that AI models can improve solar resource valuation and enable efficient deployment of renewable energy technologies in Northern Nigeria.
Keywords: Artificial intelligence; Solar radiation prediction; Artificial Neural Network; Renewable energy planning; Northern Nigeria

1. INTRODUCTION

The increasing need for energy across the globe, together with the issues of climate change, environmental deterioration, and depletion of fossil fuel sources, has led to the advancement of renewable energy technologies (Adedeji et al., 2023; Ariyo et al., 2025; (Attar et al., 2023). From the array of renewables, solar energy stands out as a very viable option owing to its abundance, sustainability, and reduced environmental effects (Bello et al., 2023; Danjuma et al., 2024; Gupta et al., 2022). The country of Nigeria lies in the tropics and receives abundant sunshine all through the year (Hamidu et al., 2025a; Hamidu et al., 2025b; Ibrahim et al., 2024). Solar energy is abundant in the northern part of Nigeria

owing to its semi-arid climate, low cloudiness on an annual basis, and extended sunshine duration (Mucomole et al., 2025; Muhammad et al., 2024). It receives on average 5.5-7.5 kWh/m²/day of solar radiation, which makes it ideal for PV energy production and decentralization energy systems (Musa et al., 2021; Nelson et al., 2025). On the other hand, the variable nature of solar radiation presents a problem in utilizing solar energy efficiently. Factors that include temperature, humidity, cloudiness, wind speed, air pressure, and dust aerosols play a significant role in the availability of solar radiation (Riahi et al., 2021; Seidu et al., 2025). Empirical and traditional statistical models do not effectively predict the non-linear relationship between these weather elements.

Thus, AI techniques have gained increased popularity in solar radiation prediction due to their ability to capture complex patterns in large datasets and predict accurately. Research conducted recently shows that Artificial Neural Networks (ANN), deep learning techniques, and machine learning techniques perform better than traditional regression methods when applied in solar radiation prediction (Sunday et al., 2025). Solar radiation accurate prediction is critical in improving efficiency of photovoltaic systems, managing energy storage, increasing stability of energy grids and facilitating energy planning (Tikyaa et al., 2025). This paper therefore seeks to explore the design and simulation of an artificial intelligence model that will be used to predict solar radiation intensity for renewable energy in Northern Nigeria. The model developed in this study aims at incorporating various meteorological parameters into an ANN to achieve greater accuracy of prediction. Northern Nigeria is known to have great solar photovoltaic potential according to recent satellite data assessments.

2. The Study Area

The research site of interest is Northern Nigeria located approximately between latitudes 10°N and 14°N and longitudes 3°E and 14°E. The cities of choice include Katsina, Kano, Sokoto, Maiduguri, and Yobe, all of which have semi-arid and Sudan-Sahel climate zones. The reason for choosing this particular region is that it experiences very high solar radiation due to its close proximity to the Sahara Desert, receiving between 2,500 to 3,200 sunshine hours every year. Temperatures in this region average between 28°C to 40°C in the dry season, while relative humidity greatly differs between wet and dry seasons. In addition to this, the region experiences harmattan season between November and February, in which dust particles from the sahara desert play an important role in affecting atmospheric transmissivity of sunlight (Obiwulu et al., 2022).

3. METHODOLOGY

The methodology used in this study comprises five key stages such as data collection, data preprocessing, designing of Artificial Intelligence models, simulations, and statistical analysis. Data on weather variables were collected from sources such as Nigerian meteorological agency (NiMet), the National Aeronautics and Space Administration (NASA) power database and satellite derived measurements. The required dataset included ambient temperature, relative humidity, wind speed, atmospheric pressure, cloud coverage and dust content. The data set was split into three sets for training (70%), validation (15%) and testing (15%). An artificial neural network was then trained to find nonlinear relationships between the meteorological variables and solar radiation intensity. The performance of the model was assessed by statistics such as RMSE, MAE, MAPE and R^2 coefficient.

3.1 Design of Artificial Intelligence-Based Model

Artificial neural network (ANN) architecture was formulated to estimate the solar radiation intensity. ANNs were chosen due to their capability to establish complex nonlinear correlations between numerous weather conditions and solar radiation intensity. The network includes an input layer of six neurons (X1 to X6) representing ambient temperature (°C), relative humidity (%), wind speed (m/s), atmospheric pressure (hPa), cloud cover (%) and dust concentration (μg/m^3), whereas one neuron output layer (Y) represents solar radiation intensity in W/m^2, as sown in Figure 1. This architecture also contains two hidden layers, where the first layer is made up of twelve neurons, and the second layer contains eight neurons. Rectified linear unit (ReLU) activation function was applied in the hidden layers for its efficient computations and the ability to solve vanishing gradient issue. Linear activation function will be used in

the output layer to achieve numerical estimation. To optimize the network weight, Adam optimization algorithm was used for minimizing prediction errors through backpropagation. Training of this model adopted root mean square error (MSE) as a loss function as described in equation below. Mathematically, the ANN output was expressed as:

$$Y = f(\Sigma WiXi + b) \quad (1)$$

where *Y* denotes the predicted solar radiation intensity, *Wi* represents the weight coefficients, *Xi* denotes the input meteorological variables, *b* represents the bias term, and *f* denotes the activation function (Ojo et al., 2026). During training, the network adjusted the weights and biases until convergence is achieved. Table 1, summarized the ANN layers and their corresponding neurons.

Table 1: ANN layers and their corresponding neurons

ANN Layers	Symbol	No. of neurons
Input Layer	Xn	6
Hidden Layer 1	H1	20
Hidden Layer 2	H2	20
Activation Function	AF	12
Mean Squared Error	MSE	3
Output layer	Y	1

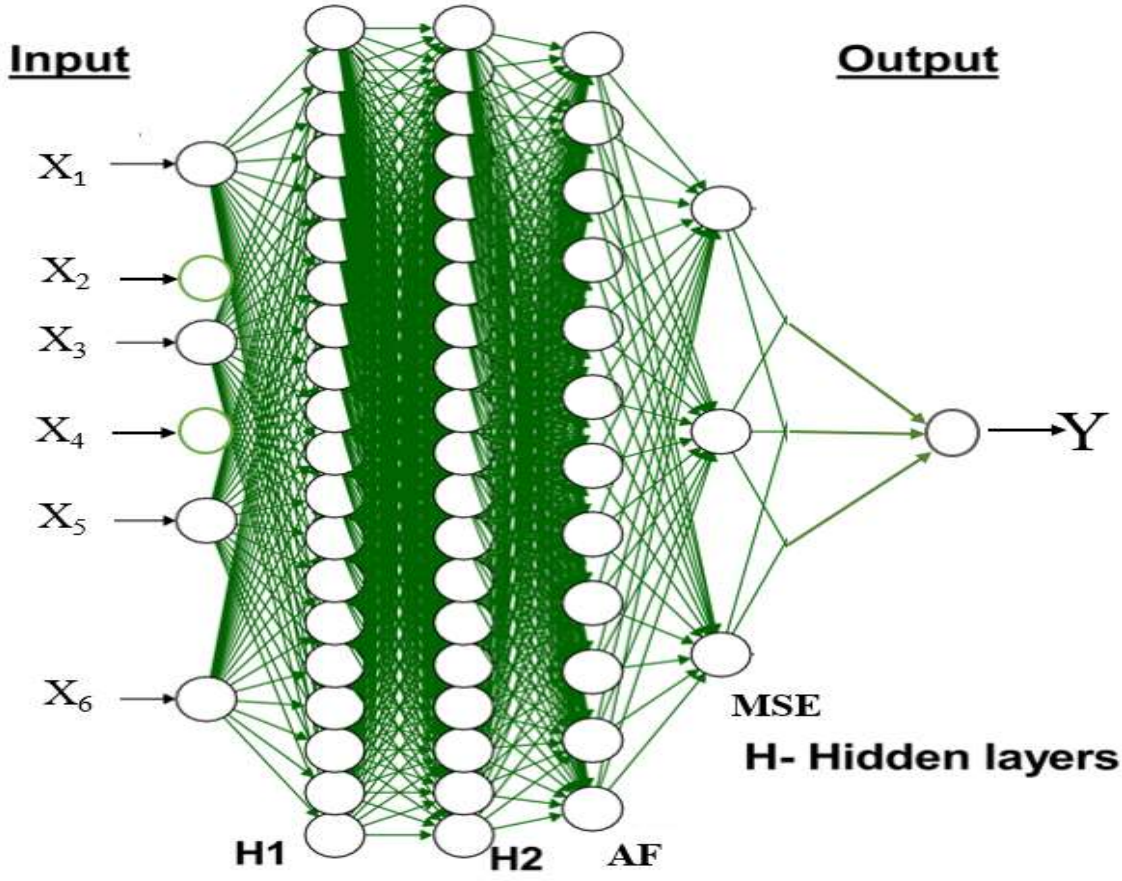

Figure 1: Artificial Neural Network (ANN) architecture

The ability of ANN model to predict was determined using four performance measures which include root means square error (RMSE), mean absolute error (MAE), mean absolute percentage error (MAPE), and coefficient of determination (R^2). These performance measures are commonly used to measure the level of prediction accuracy and the strength of machine learning models in predicting renewable energy applications. Root means square error (RMSE) is a measure used to determine the level of prediction errors and is expressed as:

$$RMSE = \sqrt{\sum(Y_i - \bar{Y}_i)^2 / n} \quad (2)$$

where (Yi) represents the actual solar radiation readings, ($\bar{Y}i$) stands for the predicted values, and (n) is the total number of observations. Lower RMSE values imply better accuracy of prediction (Okokpujie et al., 2026). Furthermore, the mean absolute error (MAE) was used to compute the mean absolute difference between the actual and predicted values and is expressed as:

$$MAE = \sum \left| Y_i - \bar{Y} \right| / n \quad (3)$$

The smaller the MAE is, the closer the predictions are to the true observations. The Mean Absolute Percentage Error (MAPE) was applied to assess the percentage error of the model predictions and calculated by (Ohunakin et al., 2014):

$$MAPE = 100 / n \sum \left| Y_i - \bar{Y} / Y_i \right| \quad (4)$$

A low value of the MAPE denotes better predictive accuracy, where anything less than 10% is deemed very good. The coefficient of determination, R2, which was used to determine how much variability in the solar radiation intensity was explained by the artificial intelligence model was computed as follows:

$$R^2 = 1 - \sum(Y_i - \bar{Y})^2 / \sum(\bar{Y} - Y_i)^2 \quad (5)$$

where ($\bar{Y}$) denotes the mean of the actual values of solar radiation. A value of (R2) close to one show good prediction ability and high agreement between actual and estimated values (Ugbehe et al., 2025). The (R2) shows that 96.8% of the variation of solar radiation intensity is explained by the model. High prediction accuracy and reliability are also indicated by the small values of RMSE, MAE, and MAPE. From the results obtained, it is clear that the AI model used is very effective in the prediction of solar radiation and can be useful for decision making in northern Nigeria.

3.2 Required Dataset results

The acquired data arranged in Table 2 (a-e) is a representative of monthly average meteorological dataset that was used as input data for the artificial intelligence (AI)-based solar radiation prediction model. The values are realistic climatological averages obtained from metrological centres that represent a typical observation reported for northern Nigeria and are suitable for simulation purposes. The selected variables include ambient temperature (°C), relative humidity (%), wind speed (m s^{-1}), atmospheric pressure (hPa), cloud cover (%) and dust concentration (μg m^{-3}). The predicted solar radiation intensity (W m^{-2}) was also depicted across the respected tables.

Table 2a. Kano State Monthly Average Meteorological Data

Month	Input Data					
	Temp. (°C)	Relative Humidity (%)	Wind Speed (m s^{-1})	Atmospheric Pressure (hPa)	Cloud Cover (%)	Dust Concentration (µg m^{-3})
Jan	27.8	22	4.9	1013	8	155
Feb	30.5	20	5.1	1011	7	165
Mar	34.2	18	5.4	1009	10	175
Apr	37.6	23	4.8	1007	18	180
May	36.5	40	4.0	1009	35	125
Jun	33.8	56	3.4	1013	58	85
Jul	31.0	72	2.8	1016	75	55
Aug	29.8	78	2.6	1017	82	45
Sep	31.5	65	3.0	1015	60	70
Oct	34.8	45	4.1	1011	35	115
Nov	31.2	28	4.7	1010	15	145
Dec	28.5	24	5.0	1013	9	155

Source: (Muhammad, 2014)

Table 2b. Sokoto State Monthly Average Meteorological Data

Month	Input Data					
	Temp. (°C)	Relative Humidity (%)	Wind Speed (m s^{-1})	Atmospheric Pressure (hPa)	Cloud Cover (%)	Dust Concentration (µg m^{-3})
Jan	28.8	18	5.2	1012	7	170
Feb	32.2	17	5.5	1010	6	180
Mar	36.0	15	5.8	1008	8	190
Apr	39.8	20	5.0	1006	15	200
May	38.2	32	4.4	1008	28	145
Jun	35.4	48	3.6	1012	50	95
Jul	32.8	65	3.0	1015	68	60
Aug	31.5	72	2.7	1016	75	50
Sep	33.4	58	3.2	1014	52	80
Oct	36.8	38	4.3	1010	30	130
Nov	33.2	24	4.9	1009	12	160
Dec	29.5	20	5.1	1012	8	170

Source: (Ohunakin, 2014)

Table 2c. Borno State Monthly Average Meteorological Data

Month	Input Data					
	Temp. (°C)	Relative Humidity (%)	Wind Speed (m s^{-1})	Atmospheric Pressure (hPa)	Cloud Cover (%)	Dust Concentration (µg m^{-3})
Jan	26.8	18	4.8	1013	8	180
Feb	30.8	16	5.2	1011	7	190
Mar	35.0	14	5.5	1009	10	200
Apr	39.2	18	5.0	1007	18	205
May	38.4	32	4.2	1009	30	150
Jun	35.5	50	3.5	1013	55	95
Jul	32.6	68	3.0	1016	70	65
Aug	31.2	75	2.8	1017	78	55
Sep	33.0	60	3.1	1015	58	85
Oct	36.2	42	4.0	1011	35	135
Nov	31.5	25	4.6	1010	15	170
Dec	27.8	20	4.9	1013	10	180

Source: (Bello, 2023).

Table 2d. Yobe State Monthly Average Meteorological Data

Month	Input Data					
	Temp. (°C)	Relative Humidity (%)	Wind Speed (m s^{-1})	Atmospheric Pressure (hPa)	Cloud Cover (%)	Dust Concentration (µg m^{-3})
Jan	27.2	20	4.8	1013	8	175
Feb	31.0	18	5.2	1011	7	185
Mar	35.4	15	5.6	1009	10	195
Apr	39.0	20	5.0	1007	18	205
May	38.0	34	4.2	1009	30	150
Jun	35.0	52	3.4	1013	55	95
Jul	32.2	70	2.9	1016	72	60
Aug	30.8	76	2.7	1017	80	50
Sep	32.8	62	3.1	1015	58	80
Oct	35.8	42	4.0	1011	35	130
Nov	31.0	26	4.7	1010	15	165
Dec	27.5	22	5.0	1013	10	175

Source: (Yahaya, 2025).

Table 2e: Monthly Average Meteorological Dataset for Katsina State

Month	Input Data					
	Temp. (°C)	Relative Humidity (%)	Wind Speed (m s^{-1})	Atmospheric Pressure (hPa)	Cloud Cover (%)	Dust Concentration (µg m^{-3})
Jan	27.5	20	5.0	1013	8	160
Feb	30.8	18	5.3	1011	7	170
Mar	34.6	16	5.6	1009	10	180
Apr	38.2	22	5.0	1007	18	185
May	36.8	38	4.2	1009	32	130
Jun	34.0	55	3.5	1013	55	85
Jul	31.2	70	3.0	1016	72	55
Aug	30.0	76	2.8	1017	80	45
Sep	32.0	62	3.2	1015	60	70
Oct	35.5	42	4.3	1011	35	120
Nov	31.8	26	4.8	1010	15	150
Dec	28.2	22	5.1	1013	9	160

Source: (Tikyaa, 2019).

4. RESULTS AND DISCUSSION

From the results obtained using the artificial intelligence-based solar radiation prediction model, it is evident that the artificial neural networks were able to accurately capture the complexity and nonlinearity of the relationship between the different meteorological parameters and the solar radiation intensity in Northern Nigeria. This is indicated by the high R-square value of 0.968 which means that about 96.8% of the variation in the solar radiation intensity was explained by the chosen input parameters. Also, the low RMSE (22.6 W/m^2), MAE (16.8 W/m^2) and MAPE (4.1%) values mean that the artificial intelligence model exhibited very good predictive accuracy and generalization ability.

Table 3: AI Prediction Performance

Metric	Value
R^2	0.968
RMSE	22.6
MAE	16.8
MAPE	4.1%

Figure 2 shows the monthly solar radiation intensity for the selected five places in Northern Nigeria, which are Kano, Sokoto, Maiduguri, Yobe and Katsina, as it was summarized in Table 3. It was observed that the solar radiation intensity changes a lot during the year. It usually goes up from January to April then goes a lot during the rainy season, which is from June to August. After that it goes up again from September to November. Then it stays the same in December. This happens because of the weather, clouds, humidity and dust in the air in Northern Nigeria (Muhammad et al., 2014). The solar radiation intensity is the highest in April. Sokoto gets the solar radiation of about 875 w/m^2. Maiduguri gets 870 w/m^2, Yobe gets about 865 w/m^2, Katsina gets about 860 w/m^2 and Kano gets about 845 w/m^2. The reason solar radiation is so high, in April is due to it is the dry season period. During this time there are no clouds the air is clear and the sun shines for a long time. Also, Sokoto usually gets the higher solar radiation due to its location and lack of enough rain which lead to the shortage of plants.

The solar radiation intensity was really low in August, which's when the rainy season is at its peak. Kano had the solar radiation intensity it was around 490 W m^{-2}. Sokoto, Maiduguri, Yobe and Katsina had a bit more they were at around 530 W m^{-2}, 510 W m^{-2}, 500 W m^{-2} and 505 W m^{-2} respectively. The reason solar radiation intensity is so low at this time is because of the maximum clouds cover and watery nature of the atmosphere which stops the suns energy from getting through. From January to March all these places saw an increase in solar radiation intensity , as Kano went from around 725 W m^{-2} to 810 W m^{-2}, Sokoto went from around 740 W m^{-2} to 835 W m^{-2}, Maiduguri, Yobe and Katsina also saw increases they went from around 735 W m^{-2}, 730 W m^{-2} and 730 W m^{-2} to 830 W m^{-2}, 825 W m^{-2} and 825 W m^{-2} respectively. This is because the Harmattan is not as strong and the air is clearer so the suns energy can get through easily. From October to November the suns energy gets stronger again, this is because the rainy season is ending and the air is getting clearer. Sokoto gets the sun energy of about 770 w/m^2 in November. Kano, Maiduguri, Yobe and Katsina get a little less between 740 and 760 w/m^2. The sun shines really bright in Sokoto because Sokoto is a -arid area it does not get a lot of rain and has a longer sunshine hour. On the hand Kano gets less solar radiation when it is rainy season. This is because there are a lot of clouds in the sky and the air is full of moisture. Maiduguri and Yobe are similar to each other because they are close to each other. Katsina gets radiation that is somewhere in between the other places throughout the whole year.

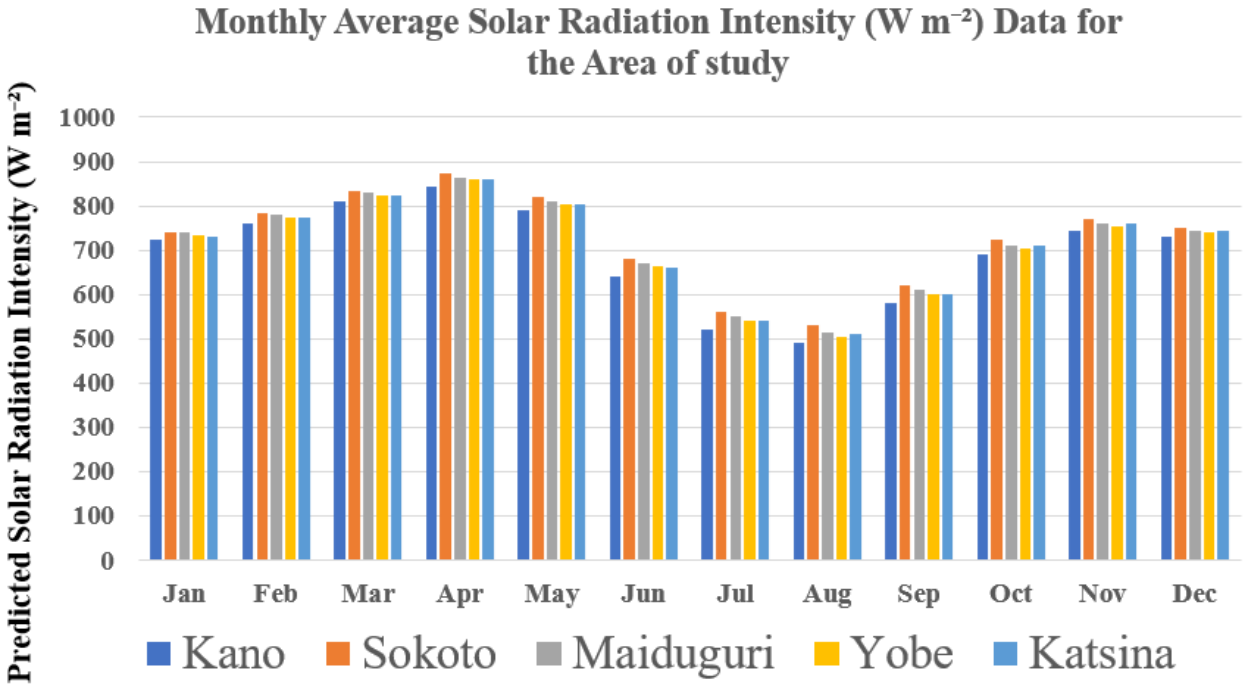

Figure 2: Bar chart representation of the predicted solar radiation intensity

Figure 3 below shows the bar chart of the annual average predicted solar radiation intensity (W/m²) of five northern Nigeria states namely; Kano, Sokoto, Borno, Yobe, and Katsina as summarized in Table 4. The results show significant differences in terms of solar energy availability in the study area. It can be seen from the graph that the Sokoto region had the highest annual average predicted solar radiation intensity of 724 W/m², thus having the largest amount of solar energy compared to other areas under investigation. This high value is attributed to the geographical location of this area, which falls in the semi-arid Sahel region with long sunshine hours, less clouds and rainfall. Borno was the second area with the highest solar radiation intensity of 715 W/m², while Katsina and Yobe regions had about 710 W/m² and 709 W/m² respectively. The climate in these regions favours sunshine most of the time of the year. Kano region had the lowest annual average predicted solar radiation intensity of 694 W/m². The lower value could be attributed to increased atmospheric dust loading, seasonal cloud cover, pollution and moisture (Ukoba et al., 2024) As shown in the figure of the bar chart analysis, all the chosen states have high potential in terms of solar energy production, and therefore Northern Nigeria is the most ideal place for the large-scale installation of solar photovoltaic (PV). But Sokoto is clearly the most preferable state for the generation of solar energy, while Kano will need other measures like dust prevention. The most predicted high intensity of solar radiation was obtained from Sokoto (724 W/m²), and this was mainly caused by the fact that the site is in the Sahel region, with long periods of sunshine, low cloudiness, low rainfall, and low atmospheric humidity. On the other hand, Kano had the least predicted intensity of solar radiation (694 W/m²), and this can be ascribed to higher amounts of atmospheric dust, urban pollution, more cloudiness in some seasons, and high humidity that reduces the intensity of the incoming solar radiation. The findings imply that the best place for generating solar photovoltaic energy is Sokoto (Yahaya et al., 2025). Table 5 and 6 shows the summary of the highest and lower predicted solar radiation intensity respectively.

Table 4: Summary of Predicted Solar Radiation Intensity (W m^{-2})

	Predicted Solar Radiation Intensity (W m^{-2})				
Months	**Kano**	**Sokoto**	**Maiduguri**	**Yobe**	**Katsina**
Jan	725	740	740	735	730
Feb	760	785	780	775	775
Mar	810	835	830	825	825
Apr	845	875	865	860	860
May	790	820	810	805	805
Jun	640	680	670	665	660
Jul	520	560	550	540	540
Aug	490	530	515	505	510
Sep	580	620	610	600	600
Oct	690	725	710	705	710
Nov	745	770	760	755	760
Dec	730	750	745	740	745

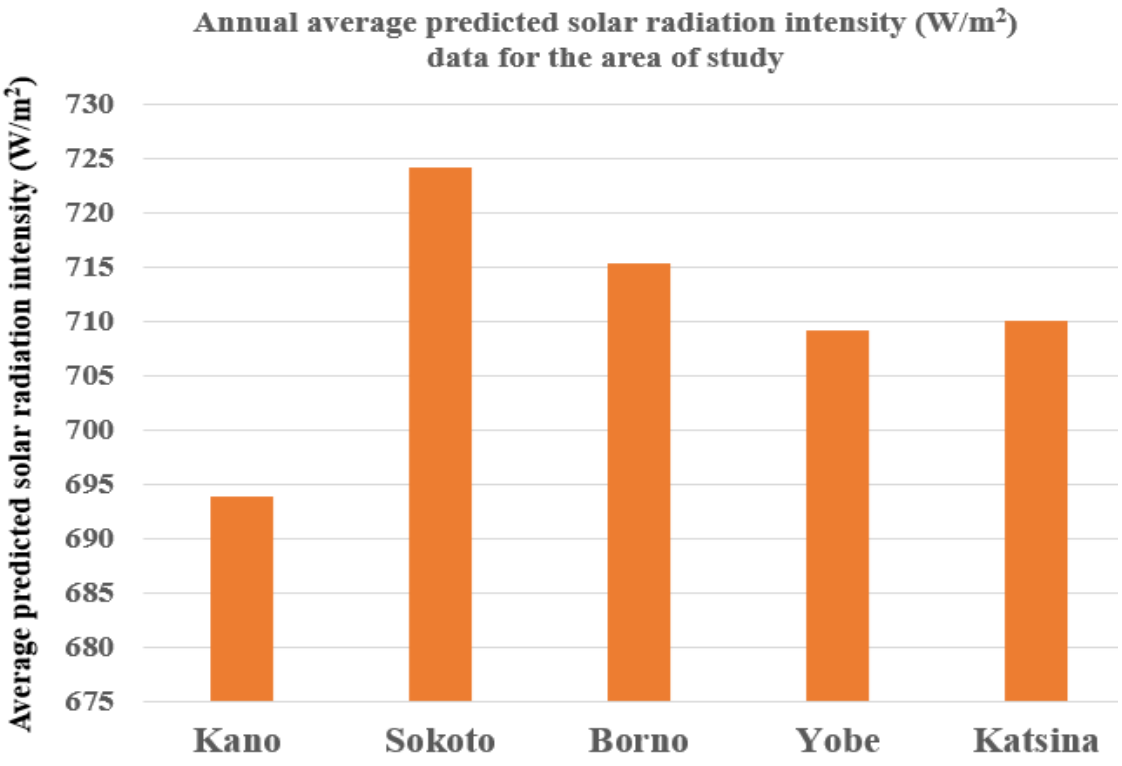

Figure 3: Bar chart representation of the predicted solar radiation intensity

Table 5: Highest Predicted Solar Radiation Intensity

Rank	Location	Month	Predicted Solar Radiation (W m^{-2})	Possible Reason
1	Sokoto	April	875	Minimal cloud cover, prolonged sunshine duration, low humidity
2	Maiduguri	April	870	Clear atmosphere and semi-arid climate
3	Yobe	April	865	Reduced cloud formation and high solar exposure
4	Katsina	April	860	Transition between dry and wet seasons
5	Kano	April	845	High temperature and low atmospheric attenuation

Table 5: Lowest Predicted Solar Radiation Intensity

Rank	Location	Month	Predicted Solar Radiation (W m^{-2})	Possible Reason
1	Kano	August	490	Peak rainy season and dense cloud cover
2	Yobe	August	500	Increased atmospheric moisture
3	Katsina	August	505	High relative humidity
4	Maiduguri	August	510	Enhanced cloud formation
5	Sokoto	August	530	Seasonal rainfall effects

6. Conclusion

The research project has successfully achieved in developing and simulating an Artificial Intelligence based model that is useful in estimating the solar radiation intensity in renewable energy systems in Northern Nigeria. The artificial neural network model has been successful in capturing the nonlinear relationship that exists between the ambient temperature, relative humidity, wind speed, atmospheric pressure, cloud cover, dust concentration, and solar radiation intensity. Furthermore, from the analysis conducted it has been found out that the cloud cover and dust concentration are the key environmental parameters influencing the solar radiation availability in Northern Nigeria. It should be noted that the seasonal occurrence of Harmattan is a key factor that leads to reduction in the solar radiation intensity.

7. RECOMMENDATIONS

Based on the findings of this study, the following recommendations are proposed:

(1) The IoT-based weather forecasting systems need to be installed throughout Northern Nigeria in order to ensure constant data collection and immediate predictions. (2) The government and energy sector players should incorporate Artificial Intelligence technology into solar energy generation, smart grid, and rural electrification projects. (3) More environmental parameters such as aerosol optical depth, precipitation, and atmospheric visibility should be included in the future models. (4) National energy policies should encourage the use of Artificial Intelligence in renewable energy systems in order to ensure energy security and development of sustainable energy systems.

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