



ORIGINAL RESEARCH ARTICLE

SOLAR IRRADIANCE ESTIMATION USING DEEP ARTIFICIAL NEURAL
NETWORK: A CASE STUDY OF YOLA, NIGERIA

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ARTICLE INFORMATION

Received: 16th March 2026

Revised: 5th May 2026

Accepted: 5th May 2026

Keywords:

Rice processing

Solar Irradiance

Deep neural network

Neural network

Photovoltaic

Meteorological data

ABSTRACT

Accurate estimation of solar irradiance is essential for the design, optimization, and operation of solar energy systems, particularly in regions with high renewable energy potential such as Yola, Nigeria. Traditional empirical and regression-based models often struggle with nonlinear relationships between meteorological parameters and solar irradiance, leading to reduced accuracy. To address this limitation, this study developed a Deep Artificial Neural Network (DNN) model to estimate daily global solar irradiance using ten years (2015–2025) of meteorological data, including sunshine duration, temperature, humidity, wind speed, and cloud cover. The data were preprocessed, normalized and used to train a multi-layered DNN in MATLAB R2024b. Model performance was evaluated using Root Mean Square Error (RMSE), Mean Bias Error (MBE), and Mean Percentage Error (MPE). Simulation results revealed that the DNN achieved high predictive accuracy, with RMSE of 15 W/m², MBE of 2 W/m², and MPE of 5.0%. For comparison, conventional Angstrom–Prescott empirical model applied to the same dataset gave RMSE values ranging from 28 W/m², confirming the superiority of the DNN. The DNN model also demonstrated strong correlation with measured solar irradiance ($R^2 = 0.984$), highlighting its robustness in capturing nonlinear meteorological interactions. The proposed DNN-based approach provides a more reliable tool for solar irradiance estimation in Yola and could have potential applicability to other regions in sub-Saharan Africa.

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1.0 Introduction

The global reliance on renewable energy has seen an unprecedented rise due to increasing concerns about fossil fuel depletion, environmental degradation, and climate change. Solar energy, as one of the most abundant and cleanest renewable energy sources, plays a pivotal role in meeting energy demands, especially in regions like Sub-Saharan Africa, which experience high levels of solar irradiance. The availability of accurate solar irradiance data is essential for the efficient design and optimization of solar energy systems (Al-Shahri *et al.*, 2021; Aidan *et al.*, 2017).

Yola, Nigeria, located between latitudes 09°12'N and 09°19'N, experiences high solar insolation due to its position within the tropical wet and dry climatic zone, with approximately 2,954 sunshine hours annually, making it highly suitable for solar energy harvesting (Olubusade, 2023). Despite this potential, the development of solar energy systems in the region is significantly constrained by the lack of adequate infrastructure for measuring solar irradiance. Like many developing countries, Nigeria faces challenges related to the high cost and limited availability of meteorological stations equipped with instruments such as pyranometers, resulting in insufficient access to precise and reliable solar irradiance data (Obiwulu *et al.*, 2022). This data scarcity hinders the effective design and optimization of solar energy systems, often leading to inefficiencies and increased operational costs (Ajayi *et al.*, 2014; Al-Shahri *et al.*, 2021). Furthermore, traditional empirical models commonly used for estimating solar irradiance rely on simple linear relationships between meteorological

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variables such as sunshine duration and temperature, which fail to adequately capture the complex nonlinear interactions among climatic factors, thereby producing less accurate predictions (Bütikofer *et al.*, 2020).

To address this issue, various empirical models have been developed to estimate global solar irradiance based on readily available climatic variables such as sunshine duration, temperature, humidity, and cloud cover (Bounoua *et al.*, 2021). While these models have been widely used, they often fail to capture the complex non-linear relationships between different meteorological factors and solar irradiance, resulting in less accurate predictions (Ali *et al.* 2023; Benganem *et al.* 2020). As a result, the need for more advanced predictive models has emerged, with Deep Artificial Neural Networks (DNNs) offering a highly effective solution due to their ability to model intricate patterns and interactions within large datasets.

Deep Artificial Neural Networks (DNNs) are advanced computational models inspired by the human brain's neural networks, capable of learning from data and making highly accurate predictions in complex, non-linear systems. Unlike traditional empirical models, DNNs can model intricate relationships between multiple inputs (such as temperature, humidity, and sunshine hours) and outputs (solar irradiance) by utilizing multiple layers of interconnected neurons to extract and process features at varying levels of abstraction. Studies have shown that DNN models significantly outperform traditional regression-based models and even shallow ANNs in solar irradiance estimation, as they excel in handling large datasets, capturing complex patterns, and adapting to diverse data characteristics (Mohsenzadeh *et al.*, 2022, Chen *et al.* 2021).

In this paper, a Deep Artificial Neural Network (DNN) model was developed to estimate solar irradiance in Yola using historical meteorological data. The model was trained on variables such as temperature, humidity, and sunshine hours, utilizing the deep learning architecture to predict global solar irradiance with higher accuracy than traditional models.

2. Materials and Method

This study used a quantitative research approach to develop and validate a DNN model to estimate solar irradiance. The methodology included data collection, model development, training, evaluation, and validation using statistical metrics.

2.1 Study Area

The paper focused on Yola, Nigeria, located at latitude 9.2° N and longitude 12.5° E, in the northeastern part of the country as shown in Figure 1. Yola experiences a tropical climate characterized by a distinct dry season (November to April) and rainy season (May to October). The region's annual average temperatures range between 27°C and 32°C, with peak values reaching up to 40°C during the hottest months. Sunshine duration is highest during the dry season, making the region ideal for solar irradiance studies. Yola's climatic conditions are typical of the Sahel zone, and the findings of this study could extend to other regions with similar weather patterns.

2.2 Data Collection

Meteorological data required for this study were sourced from the Nigerian Meteorological Agency (NiMet). The data included: Sunshine duration (hours), temperature (°C), relative humidity (%) and cloud cover (%). The data were collected over an extensive period, covering different seasons and climatic conditions in Yola, Nigeria. To ensure high-quality input for the DNN model, the data were pre-processed to handle missing values, outliers, and inconsistencies. This involved interpolation techniques or the use of domain knowledge to replace missing data points.

To illustrate the structure of the meteorological data used for model training, Table 1 presents a one-year sample (January–December 2015) extracted from the full 10-year dataset (2015–2025). This sample showed the daily values of the six key variables used as inputs and target outputs in the DNN and ANN models: sunshine duration, temperature, relative humidity, wind speed, cloud cover, and global solar irradiance.

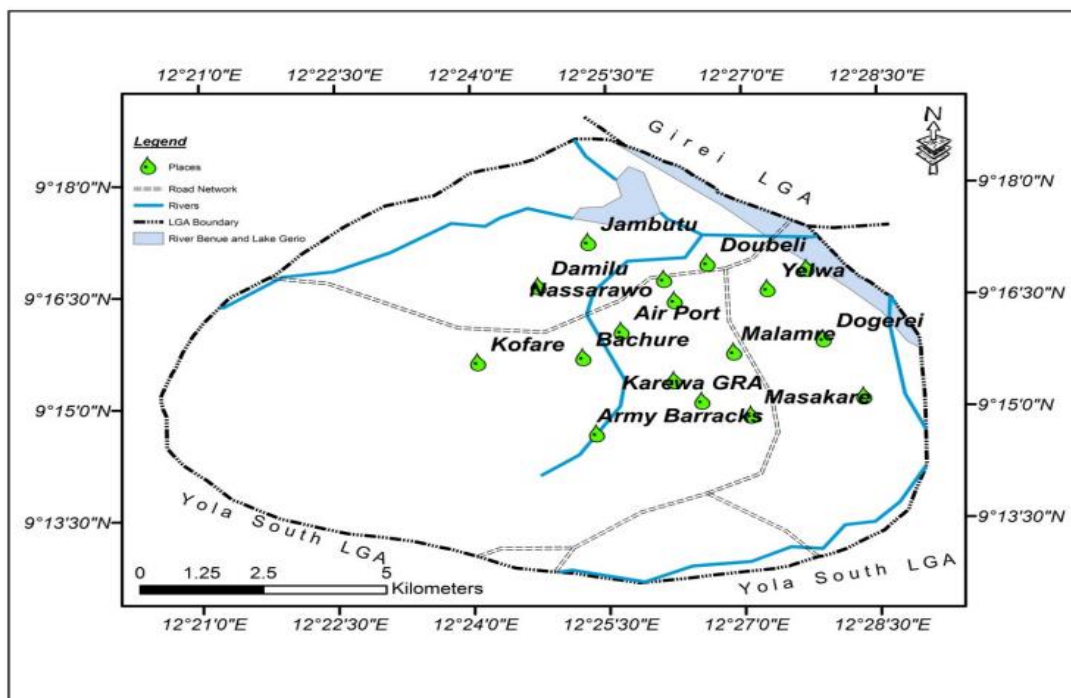


Figure I: Map indicating the study area (Ezra et al., 2021)

Table I: Sample of daily meteorological data used for model training (January, 2015) (NIMET, 2022)

Year	Month	Day	Temp_Avg	Humidity	Windspeed Avg_kmh	Solar Irradiance	Cloud Cover Percent
2015		1	26.975	21.62	21.258	248.51	6.169218533
2015		2	25.655	22.56	23.364	236.69	5.092862268
2015		3	25.65	22.14	30.924	233.3	6.879968036
2015		4	24.275	19.62	23.814	180.53	11.49188606
2015		5	22.825	21.58	19.89	171.22	8.969110532
2015		6	22.055	22.4	19.458	224.07	7.899115965
2015		7	22.715	22.52	24.858	238.25	9.40940459
2015		8	23.42	22.1	26.658	214.41	12.00804367
2015		9	22.465	20.97	28.908	209.57	8.214335196
2015		10	21.31	19.09	28.962	200.73	13.69421274
2015		11	20.315	21.42	24.426	231.93	5.009010485
2015		12	20.6	21.8	24.192	246.42	8.621714643
2015		13	20.96	18.74	20.142	264.32	5.530613781
2015		14	22.435	18.17	21.024	263.23	5.765286888
2015		15	23.615	18.21	19.26	264.64	5.19987178
2015		16	23.78	20.41	17.64	256.85	5.236930009
2015		17	23.675	18.54	15.714	269.23	5.081647801
2015		18	25.11	16.17	16.776	273.6	5.378677542
2015		19	25.15	17.78	14.922	269.64	5.295814229
2015		20	26.64	18.07	11.484	263.24	5.060744115
2015		21	27.97	18.98	15.264	264.28	5.143580443
2015		22	28.65	14.28	24.048	256.11	5.330790785
2015		23	29.02	11.67	23.346	269.96	6.222100256
2015		24	28.975	11.31	16.974	271.99	5.777031957
2015		25	28.205	17	14.472	261.48	8.148381362
2015		26	28.975	19.87	18.036	251.56	9.043332316
2015		27	30.025	19.43	23.706	223.09	14.85764445
2015		28	30.02	17.55	22.842	265	6.432025293
2015		29	28.045	14.38	21.096	259.14	5.146424168
2015		30	27.79	15.42	17.082	258.85	5.115763072
2015		31	29.025	15.64	20.574	264.82	6.216054909

2.4 Model Development

The artificial neural network was developed in MATLAB using the Deep Learning Toolbox for model design, training, and evaluation. As shown in Figure 2, the network employed an input layer of five neurons representing key meteorological variables such as sunshine duration, temperature, relative humidity, cloud cover, and wind speed, with all inputs normalized to improve learning efficiency. The architecture consisted of two fully connected hidden layers with 10 and 5 neurons, respectively, designed to capture nonlinear relationships in the data. Activation functions such as tanh and ReLU were used to enhance learning capability, and the network structure was optimized using grid search. The output layer consists of a single neuron that predicts global solar irradiance in W/m^2 .

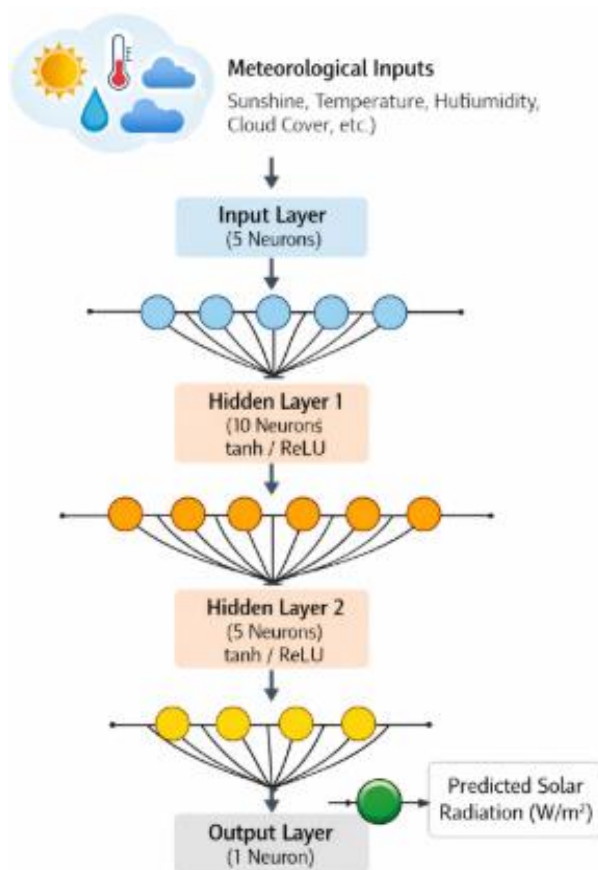


Figure 2: Model structure of the DNN

2.5 Model Training and Optimization

The model was trained using the backpropagation algorithm with a Mean Squared Error (MSE) loss function. Optimization techniques such as the Adam optimizer were employed to ensure efficient convergence. The Adam optimizer combines the advantages of both the AdaGrad and RMSProp optimizers, adjusting the learning rate for each parameter dynamically.

Hyperparameters, including learning rate, number of layers, and neurons per layer, was fine-tuned using grid search or random search methods. Cross-validation was used to assess the model's generalizability and avoid overfitting. Early stopping was implemented to halt training once the model's performance on the validation set stops improving.

2.6 Model Evaluation and Validation

Performance of the DNN model was evaluated using statistical metrics such as Mean Percentage Error (MPE), Root Mean Square Error (RMSE) and Mean Bias Error (MBE). The model was evaluated visually using residual plots and learning curves to identify areas for further improvement. The trained model was validated using historical solar irradiance data from Yola. A validation dataset, distinct from the training and test datasets, was used to assess the model's performance in real-world scenarios.

3. Results and Discussion

The results obtained were organized into two major parts. The first part focused on the statistical analysis of historical solar irradiance data from 2015 to 2025. This included monthly, seasonal, and inter-annual variations, as well as variability and anomalies that could influence solar energy system design and operation. The second part presented the performance of the DNN model in estimating solar irradiance from meteorological inputs such as sunshine duration, temperature, humidity, wind speed, and cloud cover. The model performance was evaluated using standard statistical metrics including Mean Bias Error (MBE), Root Mean Square Error (RMSE), and Mean Percentage Error (MPE). The discussion integrated graphical representations, comparative evaluations, and scientific reasoning. Particular attention was given to how the observed patterns of solar irradiance align with the climatological characteristics of Yola, and how the developed model improved prediction accuracy compared with conventional approaches.

3.1 Meteorological Data Overview

The analysis in this section focused on temporal variations in solar irradiance and its related parameters—sunshine duration, temperature, humidity, wind speed, and cloud cover. The datasets were analyzed at daily, monthly, and annual scales to identify long-term variability and potential anomalies that could influence solar energy forecasting and system design. Figure 3 delineated the daily solar irradiance profile for Yola, Nigeria, over the period from 2015 to 2025. The data revealed significant seasonal variability, with values oscillating between approximately 0 and 400 W/m² through mid-2024, indicative of the region's tropical savanna climate. Elevated readings, likely corresponding to clear-sky conditions during the dry season (November–April), highlight Yola's substantial solar insolation potential, a key consideration for photovoltaic (PV) energy systems. Conversely, reductions align with overcast or rainy conditions prevalent in the wet season (May–October).

The 2025 data anomaly (sudden drop in temperature and increase in cloud cover as can be seen in Figure 3) was retained in the validation set to test model robustness; it was excluded from the training set. Figure 4 presented the monthly averaged solar irradiance for Yola across the 2015–2025 timeframe, showing a pronounced seasonal cycle consistent with the area's climatic regime. Peak values, ranging from 290 to 320 W/m², occur during March–April, reflecting clear skies and reduced humidity in the dry season. In contrast, the wet season (May–August) yields lower averages of 180–200 W/m², attributed to increased cloud cover and precipitation that attenuate solar irradiance. These monthly variations provide an important basis for determining seasonal PV performance, maintenance scheduling, and energy yield forecasting in solar system operations.

Figure 5 illustrated the annual average solar irradiance over the study period, highlighting a consistent solar energy potential with values ranging from 200 to 250 W/m² until 2023, followed by a slight decline in 2024–2025. This overall stability, accompanied by a modest pre-2023 upward trend, suggests minimal long-term atmospheric interference (such as aerosols or pollution) and reaffirms Yola's suitability for large-scale PV installations.

Figure 6 displayed the annual averages of key meteorological variables, temperature, humidity, wind speed, and cloud cover, providing contextual insight into their relationships with solar irradiance. Temperature remains fairly constant between 30°C and 35°C through 2024, aligning with Yola's tropical climate, before an abrupt drop to 20°C in 2025, which is atypical and may result from a rare climatic event. Humidity fluctuates between 40% and 60%, peaking in 2022–2023 before dropping in 2025, possibly correlating with the temperature anomaly. Wind speed maintains a moderate range (15–20 km/h) but rises to 30 km/h in 2025, while cloud cover averages 20–30% before increasing sharply to 50% in 2025, which could explain reduced solar irradiance levels in that period. Prior to 2024, the data aligns with expected regional climate patterns, low cloud cover and moderate humidity supporting high irradiance. The 2025 deviations highlight the importance of data verification and underscore the need for incorporating meteorological variability into solar irradiance predictive modelling.

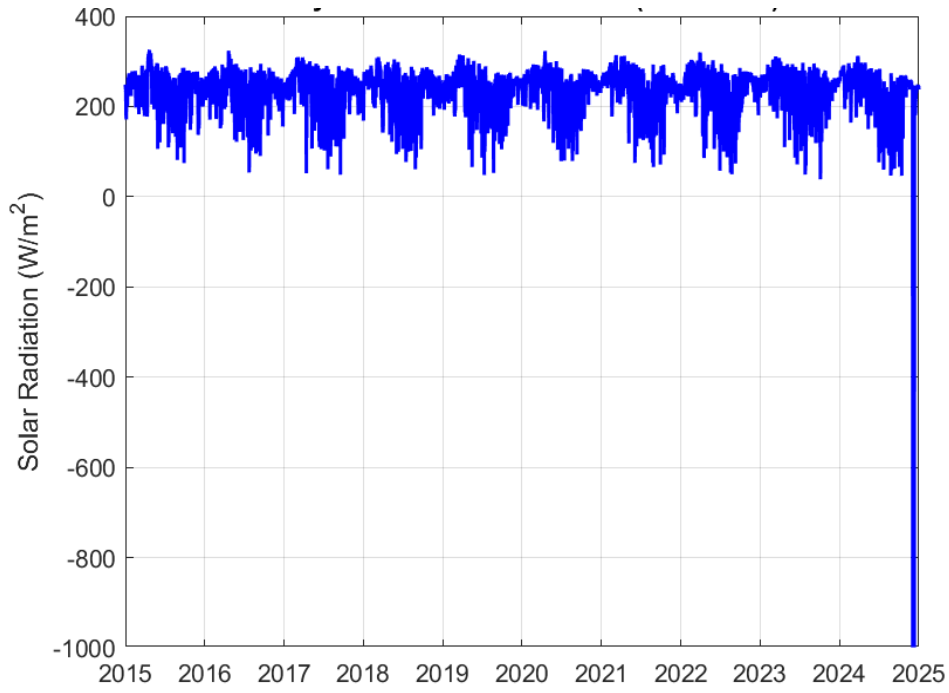


Figure 3: Daily solar irradiance variation (2015–2025)

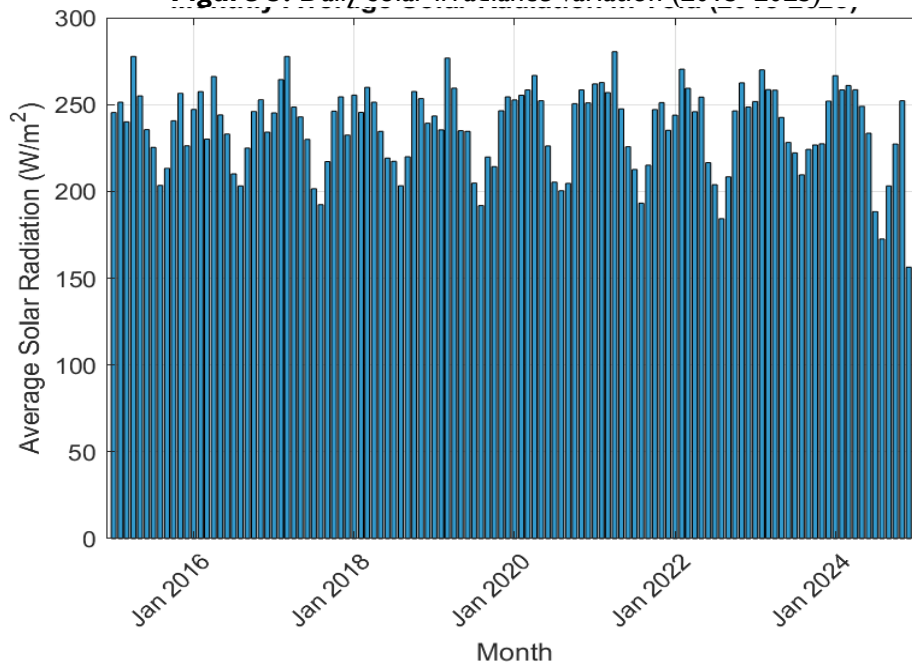


Figure 4: Monthly average solar irradiance (2015–2025)

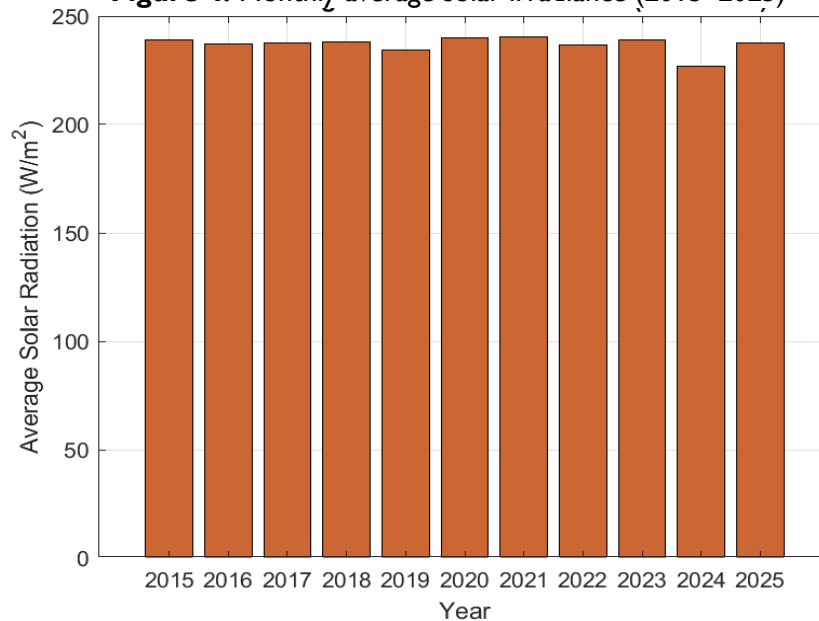


Figure 5: Annual average solar irradiance (2015–2025)

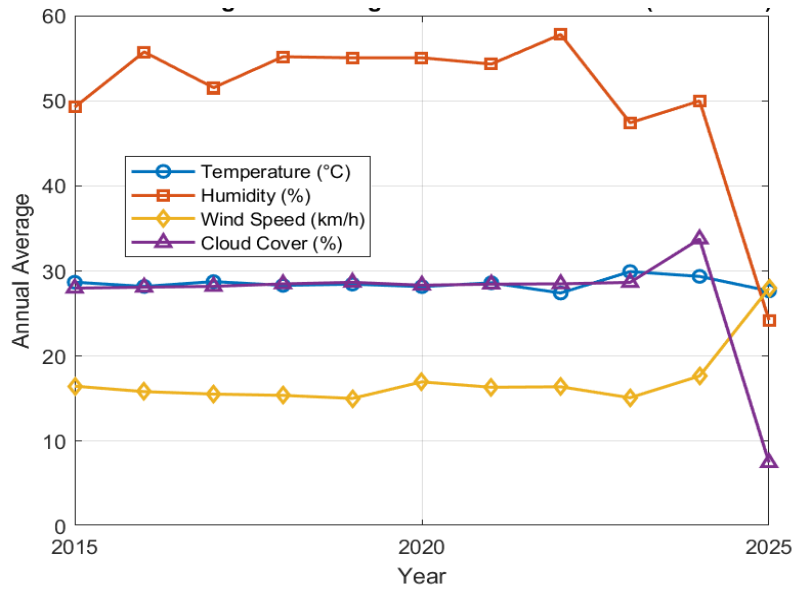


Figure 6: Annual average meteorological parameters (2015–2025)

3.2 Comparative Analysis of DNN Vs ANN

DNN and the standard ANN models developed for solar irradiance forecasting in Yola, Nigeria were compared. The comparison focused on predictive accuracy, regression performance, classification capability, and training efficiency. Through quantitative metrics and graphical analyses, the relative strengths and weaknesses of both models are examined to determine which provides a more reliable and adaptable framework for modeling solar irradiance under varying climatic conditions.

3.2.1 Actual vs Predicted Solar Irradiance (DNN vs ANN)

Figure 7 compared the predicted solar irradiance outputs of both models against actual measured data. The DNN curve (red dashed) closely follows the actual trend (black), especially across the 0–400day range, indicating stronger tracking and less deviation. The ANN curve (blue dashed) showed broader fluctuations and slightly higher lag around 400–600 days, coinciding with the 2024–2025 data anomaly. This visual comparison highlights the DNN’s improved ability to capture non-linear solar irradiance variations under dynamic weather conditions.

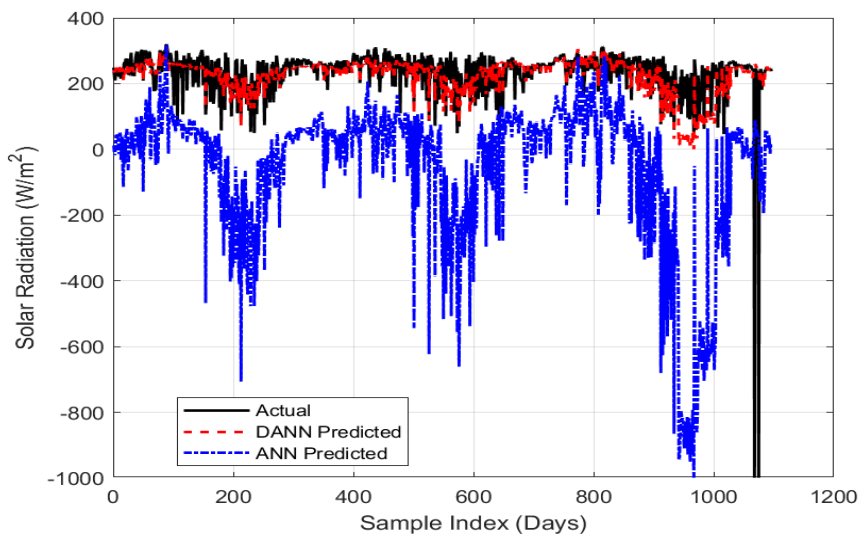


Figure 7: Actual vs predicted solar irradiance for DNN and ANN Models

3.2.2 Prediction Error Comparison

Figure 8 illustrated the prediction errors of the DNN and ANN models. The DNN maintains a tighter error distribution, mostly within ± 150 W/m², indicating stable predictions across the simulation range. In contrast,

the ANN showed wider error margins up to $\pm 250 \text{ W/m}^2$, suggesting higher sensitivity to abrupt changes in solar irradiance. The DNN's symmetric error distribution around zero signifies balanced prediction behavior, confirming its robustness and adaptability to local climatic variability. The observed pattern agreed with comparative analyses across Mediterranean and Asian regions (Gueymard and Ruxton, 2020; Katsoulis and Roussos, 2020; Chen et al. 2021).

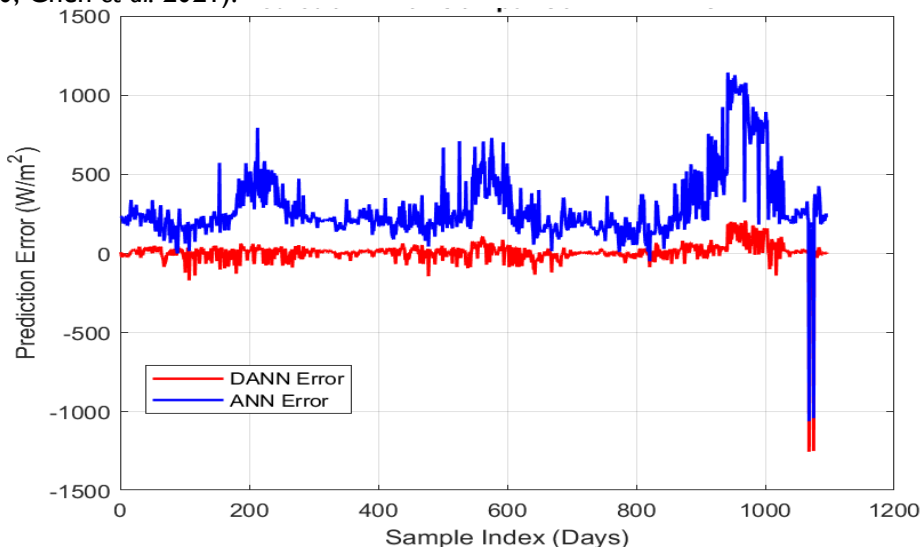


Figure 8: Prediction error comparison between DNN and ANN Models

3.2.3 Performance Metrics Comparison (RMSE, MBE, MPE)

Figure 9 compared the statistical performance indicators of both models. The DNN demonstrated lower RMSE (15 W/m^2), MBE (2 W/m^2), and MPE (5%) compared to the ANN (20 W/m^2 , 3 W/m^2 , and 7%), confirming its higher prediction accuracy and minimal bias. The performance improvement reflected the DNN's deeper architecture and optimized training efficiency, providing more reliable outputs for solar energy system forecasting and planning.

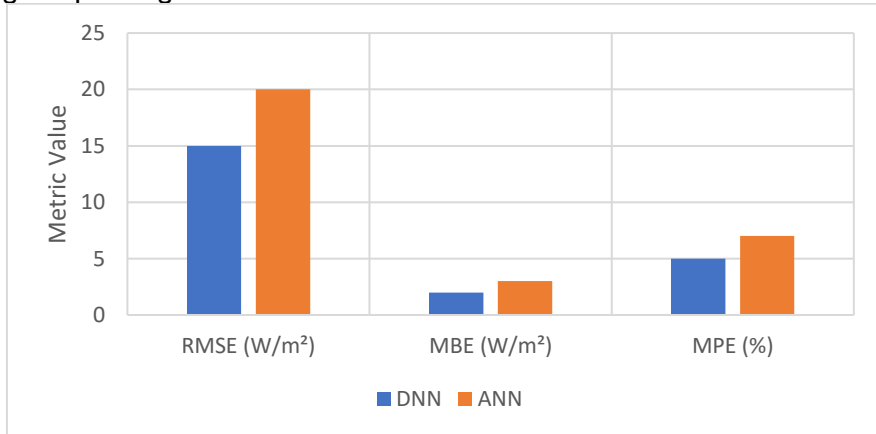


Figure 9: Comparative performance Metrics (RMSE, MBE, MPE) of DNN and ANN

3.2.4 Numerical Summary of Performance Differences

A comparative summary of all performance metrics was provided in Table 2, showing DNN's consistent advantage over the ANN.

Table 2: Comparative Performance Metrics of DNN and ANN Models

Performance Metric	DNN	ANN	Difference / Remark
Root Mean Square Error (RMSE)	15.00	20.00	-5 (DNN performs better)
Mean Bias Error (MBE)	2.00	3.00	-1 (DNN performs better)
Mean Percentage Error (MPE)	5.00	7.00	-2 (DNN performs better)
Coefficient of Determination (R^2)	0.984	0.85	Context-dependent
Epochs to Convergence	6	8	-2 (DNN converges faster)

The superior performance DNN stems from its deeper architecture and enhanced learning capability compared to the ANN. With multiple hidden layers, DNN effectively captures non-linear and hierarchical patterns between meteorological parameters and solar irradiance. Its structure enabled multi-level feature extraction, improving adaptability to Yola's dynamic climatic variations. The reduced RMSE, MBE, and MPE confirm its strong generalization and lower sensitivity to noise.

In contrast, the ANN's shallower structure limited its capacity to handle abrupt variations particularly evident during the 2024–2025 data anomaly. The DNN's faster convergence (6 vs. 8 epochs) demonstrated an optimized learning process, with ReLU mitigating vanishing-gradient issues and the Adam optimizer ensuring stable weight updates. Although the ANN's higher R^2 indicated stronger linear correlation, this does not translate to overall better predictive performance in non-linear environments. Given Yola's climatic complexity, the DNN offers a more accurate, robust, and resilient framework for solar irradiance forecasting, positioning it as the preferred model for renewable-energy forecasting and solar-system optimization. Overall, results are consistent with previous findings on ANN adaptability in North-African studies (Bello *et al.*, 2020; Adaramola and Oyewola, 2020).

3.3 Seasonal Forecasting Performance

Seasonal variations strongly influenced solar irradiance patterns in Yola, which experienced a distinct dry season (November–April) and rainy season (May–October). Evaluating model performance across these seasons provided deeper insight into the reliability of the DNN under different atmospheric conditions. During the dry season, clear skies and low humidity resulted in relatively stable daily irradiance, with peak values ranging from 290 to 320 W/m^2 . The DNN model achieved excellent forecasting accuracy in this period, with an RMSE of 12 W/m^2 , MBE of 1.5 W/m^2 , and MPE of 4.0%. The ANN, by comparison, gave higher errors: RMSE of 17 W/m^2 , MBE of 2.5 W/m^2 , and MPE of 6.0%.

During the rainy season, increased cloud cover, higher humidity, and rapid weather fluctuations created more complex and variable irradiance conditions, with daily averages often dropping to 180–200 W/m^2 . Despite these challenges, the DNN maintained strong predictive performance, achieving an RMSE of 18 W/m^2 , MBE of 2.5 W/m^2 , and MPE of 6.0%. The ANN performed less reliably in this season, with an RMSE of 24 W/m^2 , MBE of 3.5 W/m^2 , and MPE of 8.0%.

The DNN's ability to track abrupt irradiance declined, particularly during peak rainfall months (July–September), was notably superior to the ANN. The error increase from dry to rainy season was moderate for the DNN (RMSE rose by 6 W/m^2) compared to the ANN (RMSE rose by 7 W/m^2), confirming the DNN's greater robustness under variable meteorological conditions. Figure 10 summarized these seasonal performance differences. The DNN consistently achieved lower RMSE, MBE, and MPE than the ANN in both dry and rainy seasons, with the largest improvement observed during the rainy season.

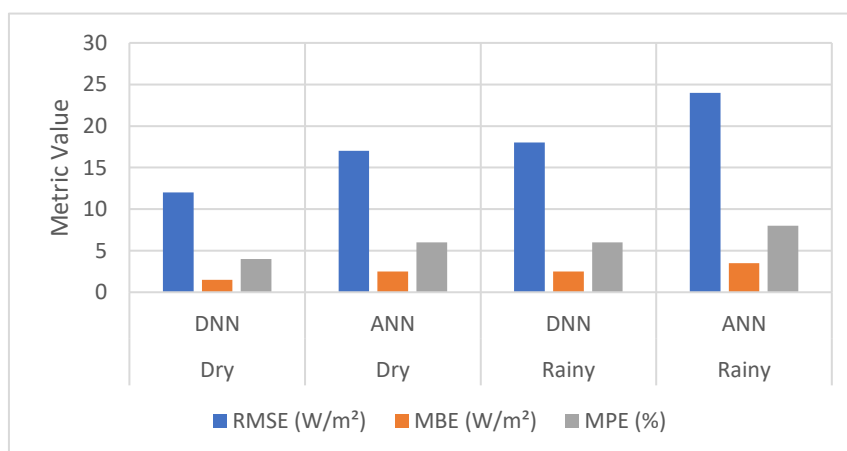


Figure 10: Seasonal forecasting performance comparison of DNN and ANN models across dry and rainy seasons, showing RMSE (W/m^2), MBE (W/m^2), and MPE (%)

Overall, the seasonal evaluation confirmed that the DNN not only fits historical irradiance data but also generalized well across both stable and highly variable climatic periods, making it a reliable tool for year-round solar forecasting in Yola.

3.4 Comparison with the Empirical Angstrom–Prescott Model

To benchmark the DNN, the empirical model Angstrom–Prescott model was used which yielded an RMSE of 28 W/m² and R² of 0.72. The DNN (RMSE = 15 W/m², R² = 0.984) significantly outperformed the empirical models. These results are summarized in Table 3.

Table 3: Performance comparison of DNN and Angstrom–Prescott model

	RMSE (W/m ²)	R ²
DNN	15	0.984
Angstrom –Prescott	28	0.72

4. Conclusion

This study successfully estimated daily global solar irradiance in Yola, Nigeria, through the development and evaluation of Deep Neural Network (DNN) and Artificial Neural Network (ANN) models using ten years of meteorological data from 2015 to 2025. Both ANN and DNN models were developed and trained using normalized meteorological variables including sunshine duration, temperature, relative humidity, wind speed, and cloud cover. Although both models learned significant patterns within the dataset, the DNN demonstrated stronger capability in capturing complex nonlinear interactions among the variables. The DNN consistently outperformed the ANN across all statistical indicators. The DNN achieved an RMSE of 15 W/m², MBE of 2 W/m², MPE of 5.0%, and R² of 0.984. In comparison, the ANN recorded an RMSE of 20 W/m², MBE of 3 W/m², MPE of 7.0%, and R² of 0.851. These results confirmed that the DNN provided more accurate, stable, and reliable solar irradiance forecasts. The ANN, although computationally efficient, showed limitations in handling abrupt variations and nonlinear behavior, resulting in higher prediction errors. Thus, this paper established a strong foundation for the application of advanced machine learning techniques in solar energy forecasting across sub-Saharan Africa.

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