African Scholars Multidisciplinary Journal (ASMJ), Vol.8, June 2024. Pg.90-96

CHARACTERIZATION OF PHOTOVOLTAIC YIELDS IN SOUTHERN REGION OF NIGERIA (A CASE STUDY OF DELTA STATE)

OVUAKPORAYE DENNIS OKUKU[1*], BENJAMIN AKINLOYE[2]
[1,2]Department of Electrical and Electronics Engineering, Federal University of Petroleum Resources, Effurun, Delta State, Nigeria.
dennis.okuku.7782@gmail.com

Abstract
This study examines the characterization of photovoltaic yields in Delta State, Nigeria, using Artificial Neural Networks (ANN) to analyze and predict solar energy production. This study utilized experimental data to assess the impact of environmental factors such as sunlight intensity, humidity, and temperature on solar panel efficiency. The ANN was trained with data collected over 365 days to predict photovoltaic outputs. Compared to traditional modeling techniques, the ANN model demonstrated superior accuracy and robustness, achieving a coefficient of determination (R^2) of 99.9%. The study underscored the potential of ANN in minimizing the need for costly physical experiments by accurately simulating and predicting photovoltaic yields based on historical data. Key findings revealed seasonal variations in photovoltaic outputs, with lower yields associated with cooler temperatures and higher rainfall. These insights are vital for optimizing the design and deployment of solar energy systems in tropical climates, highlighting the practical applications of ANN in enhancing renewable energy solutions. This study, contributes significantly to the field by providing a reliable, cost-effective method for improving solar energy efficiency and guiding future technological and policy decisions in the energy sector.
Keywords: Photovoltaic yields, performance analysis, ANN, sun intensity, humidity, temperature

1. Introduction

The Southern region of Nigeria, with its abundant solar resources, presents a significant potential for harnessing photovoltaic (PV) energy. As the country seeks to diversify its energy mix and enhance sustainable development, understanding the performance and yield of PV systems in this region becomes crucial [1]. Characterization of photovoltaic yields involves assessing various factors such as solar irradiance, temperature variations, and local environmental conditions that influence the efficiency and output of PV installations. This study aims to provide a comprehensive analysis of these factors, offering valuable insights into optimizing PV system performance and contributing to the broader adoption of solar energy in Southern Nigeria. By characterizing the photovoltaic yields, this research will aid in identifying the most suitable locations for PV deployment, inform policy decisions, and support the development of resilient energy infrastructure in the region [2].

Nigeria, as the most populous country in Africa, faces considerable energy challenges. The national grid is often unreliable, and many areas experience frequent power outages. This has led to a significant reliance on fossil fuels, which are not only unsustainable but also contribute to environmental degradation. In this context, solar energy presents a viable alternative that can help address these challenges [11]. The Southern region, with its high levels of solar radiation, is particularly well-suited for the deployment of PV systems. Photovoltaic technology converts sunlight directly into electricity using semiconducting materials that exhibit the photovoltaic effect. The efficiency and yield of these systems depend on several factors, including the amount of solar radiation received, temperature, shading, and the technology used [7]. By characterizing the PV yields in the Southern region of Nigeria, this study aims to provide insights that can optimize the deployment and performance of solar energy systems. This study present the results obtained from the characterization of the photovoltaic yields in the Southern region of Nigeria, with Specific emphasis in Delta state.

1.1 Global Perspective on Photovoltaic Systems

Globally, photovoltaic technology has seen rapid advancements and widespread adoption. Countries like Germany, China, and the United States have invested heavily in solar energy, recognizing its potential to provide clean, renewable power. Studies have shown that the efficiency of PV systems can be significantly influenced by local climatic conditions [3]. For instance, high temperatures can reduce the efficiency of PV modules, while dust and shading can lead to substantial energy losses [12].

1.2 Photovoltaic Potential in Nigeria

Nigeria has considerable solar energy potential, with an average solar radiation level of about 5.5 kWh/m²/day. This potential is particularly high in the Northern and Southern regions [4]. The country receives an average of 6.25 hours of sunshine per day, which translates to significant solar energy potential throughout the year. This solar irradiance makes Nigeria one of the most favorable locations for solar energy exploitation in the world. Previous studies have highlighted the viability of solar energy in Nigeria, but there is a need for region-specific data to inform deployment strategies. The Southern region, with its unique climatic conditions, requires detailed analysis to fully understand its photovoltaic potential [5].

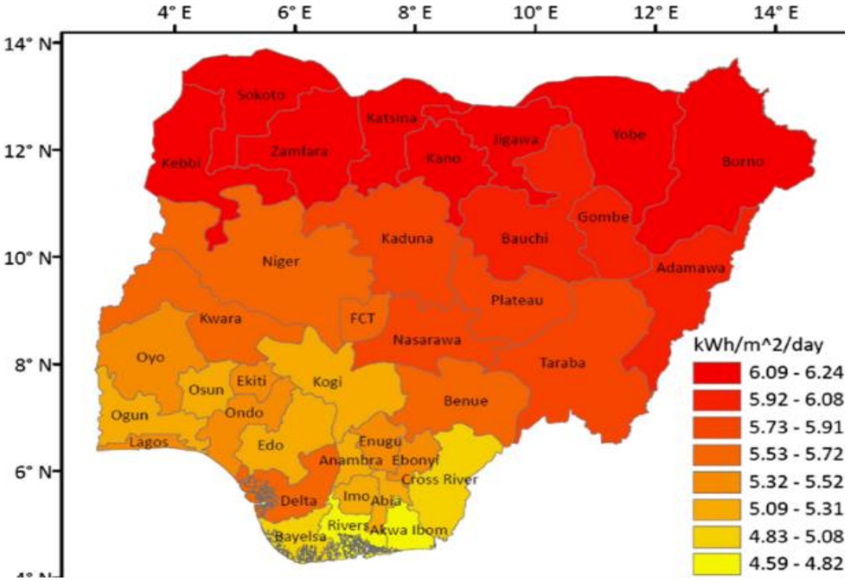

Fig. 1: Map of Nigeria indicating the solar radiation level [13]

1.3 Factors Influencing PV Performance

Several factors influence the performance and yield of PV systems:

(i) *Solar Irradiance*: The primary factor affecting PV performance is the amount of solar irradiance received. Regions with higher solar radiation levels will generally produce more electricity from the same PV system.

(ii) *Temperature*: PV modules typically lose efficiency as temperatures increase. Understanding the temperature profile of the Southern region is crucial for accurate yield estimation.

(iii) *Shading*: Even partial shading can cause significant reductions in PV output. The impact of shading from buildings, trees, and other structures must be considered.

(iv) *Dust and Pollution*: Dust accumulation on PV panels can block sunlight and reduce efficiency. The Southern region's environmental conditions, including humidity and pollution levels, need to be studied.

(v) *Technology and Installation:* Different PV technologies such as the monocrystalline, polycrystalline, and thin-film, have varying efficiencies. Installation angles and system configurations also play a role in overall performance.

2. The Unified Artificial Neural Networks

Artificial Neural Networks (ANNs) serve diverse purposes such as classification, data mining, pattern recognition, image compression, and process modeling [6]. These algorithms mimic the functioning of the human brain using interconnected neurons as their basic components [8].

Neurons within an ANN are interconnected processing elements arranged in layers. Each connection between neurons is assigned a weight, adjusted by a training algorithm that computes these weights. Each neuron then calculates a weighted sum based on input variables. A transfer function determines the output of neurons based on these weighted sums. Setting up an ANN involves defining inputs, network type, topology, training method, and transfer functions. ANNs model relationships between input and output vectors without assuming deterministic relationships.

ANNs utilize various types of connections for data transfer, with the multilayer perceptron (MLP) being the most common. MLPs are feed-forward ANNs where data flows from input to output through multiple hidden layers without feedback loops. These hidden layers constitute the core computation model of the network. MLPs can learn complex relationships between input and output patterns, offering precise approximations and quick adaptation between constant and non-constant input values. The error Back-Propagation (BP) algorithm is widely used for training MLPs [9], adjusting network weights based on the gradient of network error. Cross-validation techniques, such as k-fold cross-validation, are employed during ANN development to assess model generalization using independent data sets and estimate mean squared error (MSE). MSE results guide the selection of optimal ANN parameters, including training algorithm, number of hidden layers and neurons, and transfer functions.

In selecting ANN parameters, options range from gradient descent with momentum and weight decay to the Levenberg–Marquardt algorithm for training algorithms [10]. Topology choices typically involve one or two hidden layers, supported by the universal approximation theorem. Linear functions are preferred for output layers, whereas non-linear functions like sigmoid or hyperbolic tangent are chosen for hidden layers due to their suitability for BP algorithm application and management of non-linearity issues [11]. The process of designing neural networks involves several steps:

(i) Data collection and preprocessing
(ii) Configuring the neural network
(iii) Initializing and training the model with the training subset
(iv) Evaluating ANN performance with the validation subset

3. Study Framework

The strategy employed in this study integrates various research components using scientifically proven techniques, including artificial intelligence. Centered on the experimental study of how weather variations affect the voltage generated by solar panels, this study utilized scientifically designed experimental analysis. Artificial Neural Networks (ANNs), expert systems, and advanced statistical and mathematical models were developed and tested to analyze the data from the weather monitoring system for a period of 365 days. The study data which meticulously measured the impact of various environmental conditions on solar panel performance were collected through a series of structured experiments. The experimental data include measurements of factors such as sunlight intensity, temperature, and humidity. This approach ensured that the study was grounded in reliable empirical evidence, enhancing the robustness of the research findings.

Table 1.0: Process Parameters and Their Levels

Factor	**Range**	**Coded Low**	**Coded High**	**Mean**	**Std. Dev.**
Sun Intensity (W/m^2)	1000-26477	-1 ↔ 1000.00	+1 ↔ 20000.00	11273.70	8466.63
Humidity (%rh)	20-90	-1 ↔ 20.00	+1 ↔ 89.00	55.87	28.06
Temp (^oC)	19-38	-1 ↔ 23.00	+1 ↔ 34.00	28.57	5.29

Photovoltaic voltage yields as presented in table 2.0 are critical indicators of the performance and efficiency of solar panels. These yields represent the electrical potential generated by the PV cells under various conditions and are influenced by factors such as solar irradiance, temperature, and panel orientation. Understanding and analyzing these numerical values are essential for designing and optimizing PV systems to ensure they deliver the expected power output and efficiency. Accurate predictions and measurements of voltage yields help in enhancing the reliability and performance of solar energy systems, thereby contributing to the broader adoption of renewable energy sources.

Table 2.0: Excerpt of Voltage Yield for 365 Days

Std	Run	Sun Intensity (W/m^2)	Humidity (%rh)	Temperature (^oC)	Solar Output Voltage (V)
90	1	20000	20	23	15.27
149	2	20000	20	23	15.27
24	3	26477	55	29	17.5
323	4	20000	20	23	15.27
262	5	26477	55	29	17.6
283	6	26477	55	29	17.4
173	7	10500	55	38	13.84
188	8	10500	55	38	13.84
315	9	10500	55	38	13.84
204	10	26477	55	29	17.5

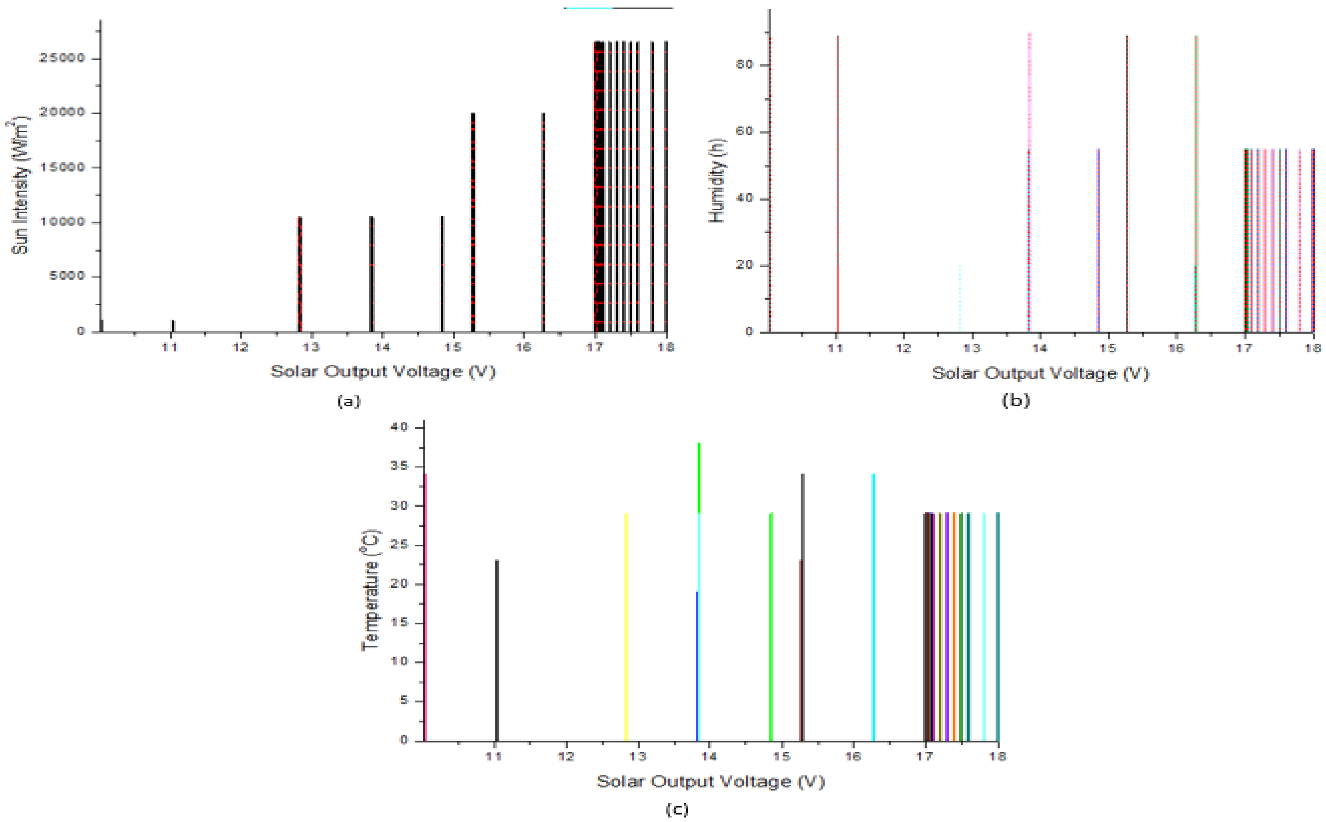

Fig.2: Solar Voltage Yield for 365 Days

The experimental results show that the open circuit voltage, short-circuit current, and maximum output power of solar cells increase with the increase of light intensity. Therefore, it can be seen from Fig. 2(a) that the greater the light intensity, the better the power generation performance of the solar cell. Also, Fig. 2(b) and (c) show the variation of humidity and temperature to output voltage characteristics for 365 days. As relative humidity decreases, the output power increases. The output power of solar cell decreases with increase in temperature

As presented in table 3.0, several key numerical values were obtained that highlight the effectiveness of the model. These numerical results confirm the ANN model's capability to provide accurate, reliable, and quick predictions for solar PV yield, supporting better energy management and planning.

Table 3.0: Excerpt of Predicted Solar Photovoltaic Yield Using ANN

	Factor 1	Factor 2	Factor 3	Response 1 Solar Voltage		
Run	Sun Intensity (W/m^2)	Humidity (%rh)	Temp (°C)	Experimental (V)	ANN Trained (V)	Error (V)
1	20000	20	23	15.27	15.27046	-0.00046
2	20000	20	23	15.27	15.27046	-0.00046
3	26477	55	29	17.5	17.28531	0.214693
4	20000	20	23	15.27	15.27046	-0.00046
5	26477	55	29	17.6	17.28531	0.314693
6	26477	55	29	17.4	17.28531	0.114693
7	10500	55	38	13.84	13.84008	-8.07E-05
8	10500	55	38	13.84	13.84008	-8.07E-05
9	10500	55	38	13.84	13.84008	-8.07E-05
10	26477	55	29	17.5	17.28531	0.214693

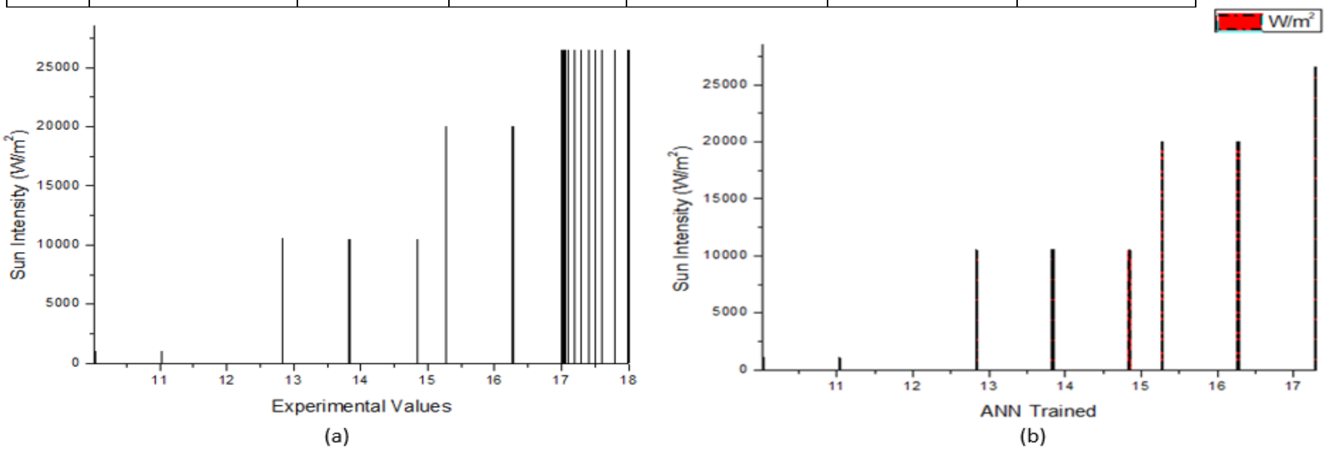

Fig. 3: Predicted Solar Photovoltaic Yield Using Sun-Intensity for Experimental Values and ANN

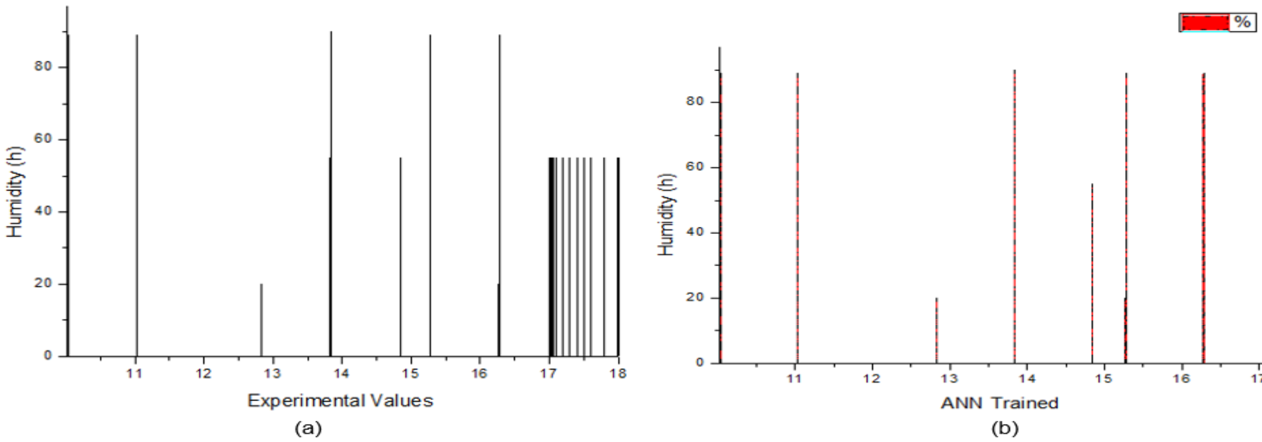

Fig. 4: Predicted Solar Photovoltaic Yield Using Humidity for Experimental Values and ANN

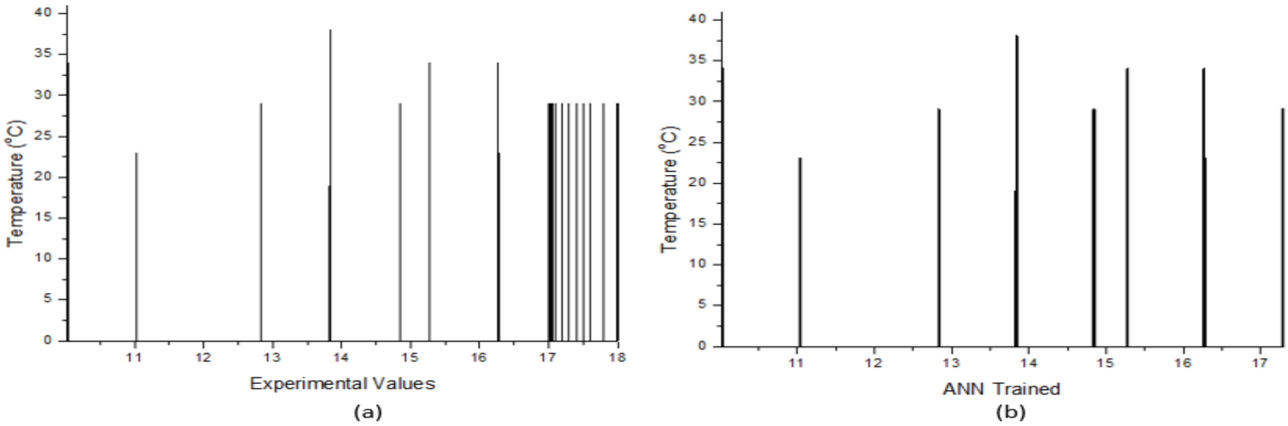

Fig. 5: Predicted Solar Photovoltaic Yield Using Temperature for Experimental Values and ANN

Figure(s) 3,4 and 5 show a comparison of the Predicted Solar Photovoltaic Yield for sun-intensity, humidity and temperature variation for both experimental values and ANN. Based on the computed values of the correlation coefficient (R) as presented in Table 3.0 and observed in Figure(s) 3,4 and 5, it was concluded that the network has been accurately trained and can be employed to predict the solar photovoltaic yield.

Table 4.0: Average Monthly Solar Photovoltaic Yield For 2021

Jan	**Feb**	**March**	**April**	**May**	**June**
15.7790	15.1039	13.7406	13.8927	13.2603	12.5047
July	**Aug**	**Sept**	**Oct**	**Nov**	**Dec**
11.3532	11.3494	12.5973	13.0832	15.0947	15.3584

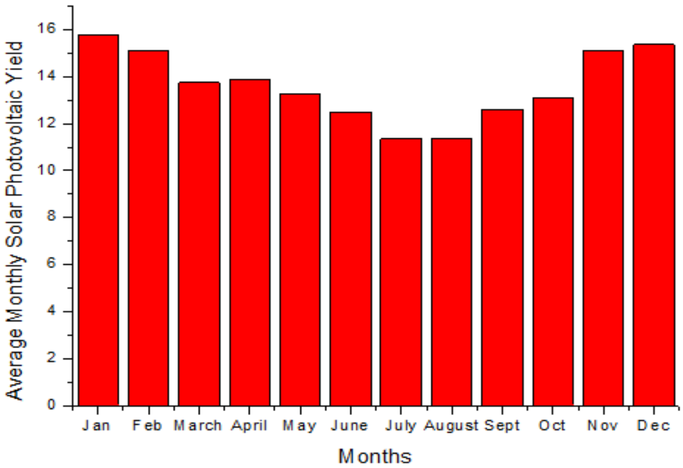

Fig.: 6: Average Monthly Solar Photovoltaic Yield For 2021

From table 4.0 as presented in Fig. 6, show the average yearly voltage yield, which was a key finding from the research. It is seen that the months of July and August yielded the lowest voltages at 11.3532 and 11.3494 volts, respectively, suggesting that lighter appliances are advisable during these periods. Conversely, the months of January, February, November, and December recorded the highest yields, with voltages of 15.7790, 15.1039, 15.0947, and 15.3584 volts, respectively. This information is crucial for properly sizing solar panel systems for homes, as relying solely on the high-yield months for system capacity can lead to undercharging during seasons with lower voltage gains.

4. Conclusion

This study demonstrated the capability of Artificial Neural Networks (ANN) in characterizing and optimizing photovoltaic yields using data from Delta State, Nigeria. By validating previous research and offering new insights, the study highlighted ANN's superior accuracy in predicting solar energy outputs under various conditions. The findings confirmed ANN as a powerful tool for analyzing and predicting solar panel performance, outperforming traditional methods like Response Surface Methodology. With a high coefficient of determination, the ANN model proved efficient and reliable in handling complex datasets. The research has significant implications for solar energy system design and optimization, particularly in regions similar to Delta State, and suggests that advanced AI technologies can enhance renewable energy production and sustainability. This study contributes to academic knowledge and provides practical insights for future technological and policy advancements in the energy sector, promoting efficient and reliable solar energy systems globally.

5. RECOMMENDATION

Future studies should explore integrating AI techniques like support vector machines and deep learning models, investigate diverse environmental variables, expand geographic scope, develop real-time predictive models, and conduct economic analysis for large-scale solar installations.

6. References

[1] Ju-Young Kim, Gyu-Yeob Jeon, Won-Hwa Hong (2009). The Performance And Economical Analysis Of Grid-Connected Photovoltaic Systems in Daegu, Korea. *Applied Energy*, Vol. 86: 265–272

[2] Pablo Ferrada, Francisco Araya, Aitor Marzo, Edward Fuentealba, 2015. Performance analysis of photovoltaic systems of two different technologies in a coastal desert climate zone of Chile. *Solar Energy*, Vol 114: 356-363

[3] Hussein A. Kazem, Jabar Yousif, Miqdam T. Chaichan, Ali H.A. Al-Waeli (2019). Experimental and Deep Learning Artificial Neural Network Approach for Evaluating Grid-Connected Photovoltaic Systems. *International Journal of Energy Research*, Vol. 43: 8572-8591

[4] Y. Ueda *et al*.(2006). Performance Ratio and Yield Analysis of Grid Connected Clustered PV Systems in Japan, *IEEE 4th World Conference on Photovoltaic Energy Conference*, Waikoloa, HI, USA, pp. 2296-2299

[5] Ruifeng Yan, Tapan Kumar Saha, Paul Meredith, Shane Goodwin (2013). Analysis of Yearlong Performance of Differently Tilted Photovoltaic Systems in Brisbane, Australia. *Energy Conversion and Management*, Vol 74: 102-108

[6] C. Renno, F. Petito, A. Gatto, (2015). Artificial Neural Network Models for Predicting the Solar Radiation as Input of a Concentrating Photovoltaic System. *Energy Conversion and Managemen*t, Vol. 106: 999-1012

[7] I. U. Khalil *et al*, (2020). Comparative Analysis of Photovoltaic Faults and Performance Evaluation of its Detection Techniques, in *IEEE Access*, vol. 8, pp. 26676-26700

[8] A. Gupta, P. Kumar, R. K. Pachauri and Y. K. Chauhan, (2014). Performance Analysis of Neural Network and Fuzzy Logic Based MPPT Techniques for Solar PV Systems, *6th IEEE Power India International Conference (PIICON)*, Delhi, India, pp. 1-6

[9] S. A. Binti Jumaat, F. Crocker, M. H. Abd Wahab and N. H. Binti Mohammad Radzi, (2016). Investigate the Photovoltaic (PV) Module Performance Using Artificial Neural Network (ANN), *IEEE Conference on Open Systems (ICOS)*, Langkawi, Malaysia, pp. 59-64

[10] J. Perez-Alonso, M. Perez-Garcı, M. Pasamontes-Romera, A.J. Callejon-Ferre, (2012). Performance Analysis and Neural Modelling of a Greenhouse Integrated Photovoltaic System. *Renewable and Sustainable Energy Reviews*, Vol. 16: 4675-4685

[11] Samuel Ikemba *et al*., (2024). Analysis of Solar Energy Potentials of Five Selected South-East Cities In Nigeria Using Deep Learning Algorithms. *Sustainable Energy Research*, vol. 11(2): 1-26

[12] A. Adiyabat and K. Kurokawa, (2002). Performance Analysis of Portable Photovoltaic Power Generation Systems Based on Measured Data in Mongolia, *Conference Record of the Twenty-Ninth IEEE Photovoltaic Specialists Conference,* New Orleans, LA, USA, pp. 1664-1667

[13] C. Nwokocha, U. Okoro, I. Usoh Chizomam (2018). Photovoltaics in Nigeria – Awareness, attitude and expected benefit based on a qualitative survey across regions. *Renewable Energy*, 116:176-182