EVOLUTION IN ELECTRICAL AND ELECTRONIC ENGINEERING
e-ISSN: 2756-8458

EEEE

Vol. 6 No. 2 (2025) 302-311
https://publisher.uthm.edu.my/periodicals/index.php/eeee

Application of Artificial Neural Network (ANN) for Solar Photovoltaic Power Forecasting

Nazmi Tohid[1], Mimi Fasyalini Ramli[1*]

[1] *Department of Electrical Engineering, Faculty of Electrical and Electronic Engineering, Universiti Tun Hussein Onn Malaysia, 86400, Batu Pahat, Johor, MALAYSIA*

*Corresponding Author: fasyalini@uthm.edu.my
DOI: https://doi.org/10.30880/eeee.2025.06.02.037

Article Info

Received: 26 June 2025
Accepted: 22 August 2025
Available online: 30 October 2025

Keywords

Solar Photovoltaic (PV), Artificial Neural Network (ANN), Power Forecasting, Renewable Energy, MATLAB

Abstract

The integration of renewable energy sources, particularly solar photovoltaic (PV) systems, is crucial in the global fight against climate change and the reduction of dependence on fossil fuels. However, the variability in environmental conditions makes accurate forecasting of PV system power output challenging. This project investigates the application of Artificial Neural Networks (ANN) to predict PV system power output using historical and real-time environmental data. Data were collected over 20 days at Lorong Haji Idris, Parit Raja, Batu Pahat, Johor, with measurements taken five times daily. The ANN model effectively addresses the nonlinear relationships and complexities of PV performance. Statistical metrics such as Mean Squared Error (MSE) were used to validate the model's accuracy. The findings show that the ANN model achieved high accuracy with R = 0.98661, MSE = 5.37 W^2, and RMSE = 2.32 W, with most predictions within ±5% of measured values. In comparison, the calculation method produced higher errors wih MSE = 26.89 W^2 and RMSE = 5.19 W, confirming that ANN is more reliable for PV power forecasting.

1. Introduction

Renewable energy sources are becoming a more popular substitute for traditional energy sources. Renewable energy sources are a sustainable choice due to their naturally replenished and have little impact on the environment. These sources of power are considered to almost limitless, unlike fossil fuels, which are limited. These sources also very crucial to reduce the carbon emissions of greenhouse gases and reliance on fossil fuels while making energy more accessible. There are still problems such as the need for energy storage systems, which will increase the initial cost will and inconsistent sunlight availability will be an issue. As economies of scale grow and technology improves, renewable energy is becoming more important to struggle against climate change and the development of sustainable energy.

Solar energy, also known as photovoltaic (PV) energy, is a well-known type of renewable energy that converts sunlight into electricity. This happens with photovoltaic cells, which are also called solar cells. Solar PV systems come in carry size from huge solar power plants to small as rooftop installations. Advances in solar technology have made PV energy much more widely expanded and affordable. It is now applied in many buildings from residential, commercial and industrial. Solar energy is a competitive and sustainable energy source in many parts of the world today. It has played a big role in the shift to a greener and more sustainable energy landscape [1][2].

To manage energy effectively, it is necessary to be able to accurately predict the amount of power photovoltaic cells can produce. This can be achieved by the help of the Artificial Neural Network (ANN), which are used as predictive tools. ANN are a part of Artificial Intelligence (AI) and machine learning, especially deep learning. They are computer models that are operate in the way human brain works [3]. These systems can

Evolution in Electrical and Electronic Engineering Vol. 6 No. 2 (2025) p. 302-311

make complex calculations to predict power output without relying on preset equations or variable assumptions. The goal of this project is to make solar energy forecasting more accurate and reliable by using ANN technology [4].

PV systems produce electricity by directly converting light into electricity using semiconductor materials such as silicon. When these cells are exposed to light, they generate electricity which is called photovoltaic effect. The efficiency of the PV system is highly influenced by environmental factors such as ambient temperature, module temperature, and solar irradiance. The non-linear relationship across these factors makes PV power output estimation accuracy challenging.

Conventional methods used theoretical formula to calculate output power by involving climate parameters, such as temperature coefficients, irradiance adjustment factor and NOCT (Nominal Operating Cell Temperature). Nonetheless, because of partial shading, soiling and the influence of the weather, this approach commonly does not capture the variations in the system over time. To address this issue, several authors have employed ANN to make forecasts.

Mittal et al. [5] show that by adjusting to changing input conditions, shown that ANN models performed better in PV prediction than equivalent electrical models. In case studies for PV plant power prediction, Stoyanov and Draganovsk [6][7] demonstrate that the use of ANN showed lower forecasting errors than conventional methods. Similarly, Zarkov et al. [8][9] emphasized the benefit of ANN over regression-based models in the forecasting of solar radiation. Lastly, Brenna et al. [10] applied neural networks to predict solar radiation and load power consumption, this shows the ANN's adaptability to work with nonlinear and dynamic energy datasets.

In order to find patterns between input variables like module temperature and solar irradiance and output power values, ANN are trained using historical datasets. Their ability to learn from complex data makes them suitable for solar forecasting tasks. However, training technique and input data quality will have a significance impact on model accuracy. To further enhance the model performance, studies also recommend adding other environmental variables like wind speed and humidity

2. Methodology

2.1 System Overview

The study utilized a 50W polycrystalline PV module shown in Fig.1 was installed at Lorong Haji Idris, Parit Raja, Batu Pahat, Johor. The system was set up in an open area to ensure optimal sunlight exposure with minimal shading throughout the measurement period. The datasheet for PV Module 50W is tabulated in Table 1 while the flowchart used in this project is presented in Fig. 2.

Fig 1: *Solar Panel Polycrystalline 50W*

Table 1 *Datasheet for PV Module 50W*

Specification	**Value**
Model	BH-50WP
Solar Cell	Polycrystalline
Maximum Power (Pmax)	50W
Maximum Voltage (Vmp)	18.6V
Maximum Current (Imp)	2.69A
Open Circuit Voltage (Voc)	22.6V
Short Circuit Current (Isc)	2.92A
Dimension	540 x 690 x 30mm
Operating Temperature	-40°C to +85°C
Standard Test Condition	1000W/m^2, AM 1.5 , 25°C
Maximum System Voltage	1000V
Max Series Fuse Rating	15A
Output Tolerance	± 3 %
Pmax Temperature Coefficient (%/°C)	-0.44
Voc Temperature Coefficient (%/°C)	-0.30
Isc Temperature Coefficient (%/°C)	+0.05
NOCT (°C)	45±2

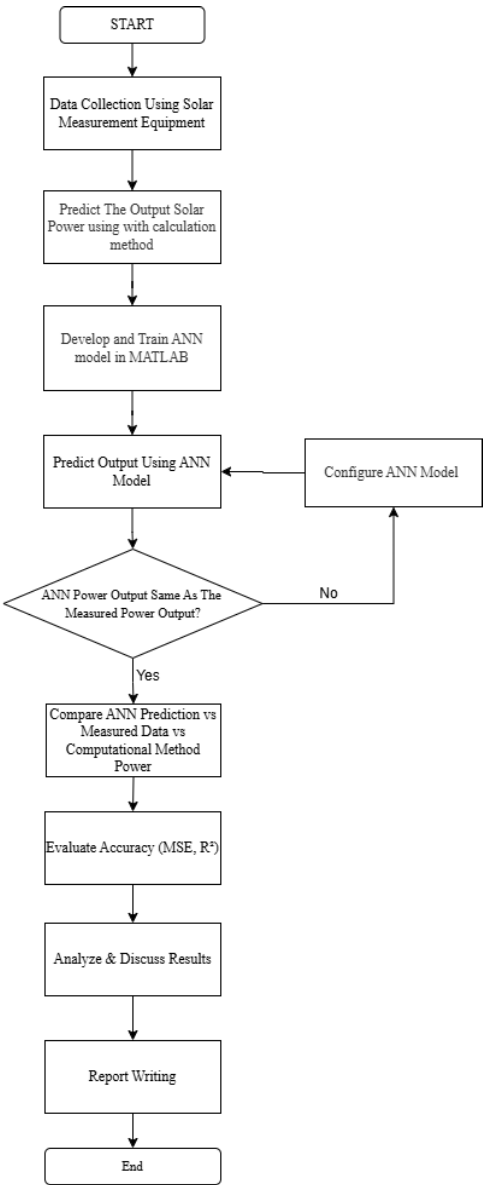


Fig. 1 *Flowchart of the system*

Evolution in Electrical and Electronic Engineering Vol. 6 No. 2 (2025) p. 302-311

2.2 Data Collection

Data were collected from February 1 to February 20, 2025. Measurements were recorded five times daily at 9:00 AM, 11:00 AM, 1:00 PM, 3:00 PM, and 5:00 PM to capture variations in environmental conditions and power output throughout the day.
The following parameters were measured by:

- Solar Irradiance (W/m^2): Parallel to the PV module, the solar irradiance is measured by using a solar power meter
- PV Cell Temperature (°C): The cell temperature is measured by using a digital thermometer
- Ambient Temperature (°C): The ambient temperature is measued by using online weather data from weather.my
- Real Power Output (W): Determined by connecting an Elejoy solar panel multimeter straight to the terminals of the PV module.

2.3 Calculation Method

PV systems output power can be predicted using calculation methods. Environmental factors such as cell temperature, ambient temperature and sun irradiation are critical when assessing PV power generation. The 30W rated power specified in the datasheet serves as a vital point of reference for this prediction method.

The following formulas, that allow for the effects of cell temperature, irradiance and the derating factor, were used to calculate the predicted power output using the calculation method in this paper. To determine the module temperature, the following formula can be use:

$$Tcell = Tambience + \frac{NOCT - 20\deg C}{\frac{800W}{m^2}} \quad (1)$$

$Tambience$ = Temperature Ambience
$NOCT$ = Nominal Operating Cell Temperature
G = Solar Irradiance

The following formula can be used to determine the power derating factor that caused by the cell temperature effect:

$$ftemp_p = 1 + \left[\frac{Pmax}{100\%}\right] \times (Tmod - Tstc) \quad (2)$$

where,
$Pmax$ = Maximum power of a PV module
$Tstc$ = PV cell temperature under STC (°C)

The power output for the module can be defined by :

$$Pmax = Pmaxstc \times fmm \times fdegrad \times ftemp_p \times fg \times fclean \times funshade \quad (3)$$

where,
fmm = Mismatch factor (dimensionless)
$fdegrad$ = LID and ageing combined factor (decimal)
$ftemp_p$ = Factor that takes into consideration the impact of temperature on power (dimensionless)
fg = Irradiance based factor (dimensionless)
$fclean$ = Factor that indicates the effect of dirt buildup (dimensionless)
$funshade$ = Factor resulting from the panel's shading (dimensionless)

The irradiance factor can be calculated by using formula:

$$fg = \frac{G}{1000} \quad (4)$$

where,
G = Solar irradiance in W/m^2
fg = Irradiance factor, which adjusts irradiance to the value of the standard test condition (STC) of $1000W/m^2$

Next, the formula to calculate the LID aging (decimal factor) is:

$$fdegrade = fLID\ X\ fage \quad (5)$$

where,
$fLID$ = The factor that accounts for degradation caused by light
$fage$ = Factor that shows how ageing can affects the module.

2.4 ANN Configuration

The modelling for ANN was designed in MATLAB's Neural Network Fitting Tool (nftool). The architecture of this network is based on:

- Two hidden layers with 20 and 10 neurons
- Levenberg-Marquardt training algorithm
- Dataset split: 80% training, 10% validation, and 10% testing

The input parameters were solar irradiance, PV cell temperature, and ambient temperature, while the output was the predicted PV power. Regression analysis and Mean Squared Error (MSE) were used to assess the model's performance. MSE and regression, as shown in Equations (6), were used to assess the performance of the ANN predicted value. MSE is a helpful metric for evaluating predictive models that allows to precisely calculate the variance between the measured solar power's expected and actual values. The MSE formula can be found as follows:

$$MSE = \frac{1}{NT\ D}\sum_{TD=1}^{NT\ D}((Target - ANN\ Prediction))^2 \quad (6)$$

where,
$NT\ D$ = the total number of training data
TD = the number of training data
The formula for regression,

$$R^2 = \frac{[N\sum XY - (\sum X)(\sum Y)]^2}{(N\sum X^2 - (\sum X)^2)(N\sum Y^2 - (\sum Y)^2)} \quad (7)$$

where,
N = total number of training data
X = data on the x-axis (target values)
Y = data on the y-axis (prediction values)

2.5 One-Day Ahead Forecasting Power Output

The historical data for solar irradiance and module temperature were averaged over the previous 20 days at 1 PM during peak sunlight to forecast the anticipated environmental conditions for the following day,21st February 2025. The average values were also input into the trained ANN model to predict the solar power output. Two main parameters that this project aims to predict are cell temperature and solar irradiance. The forecast uses a moving average method for solar irradiance, specifically utilizing data from the previous 20 days during the hours of greatest sunlight. By using this formula, the value for average irradiance can be calculated by:

$$Gavg = \frac{\sum n = 1,2,3 \ldots (G1 + G2 + G3 + \cdots . + Gn)}{n} \quad (8)$$

where,
n = total number of data used
G = Irradiance
The formula used to determine the average cell temperature are:

$$Tcell\_avg = \frac{\sum n = 1,2,3 \ldots (T1 + T2 + T3 + \cdots . + Tn)}{n} \quad (9)$$

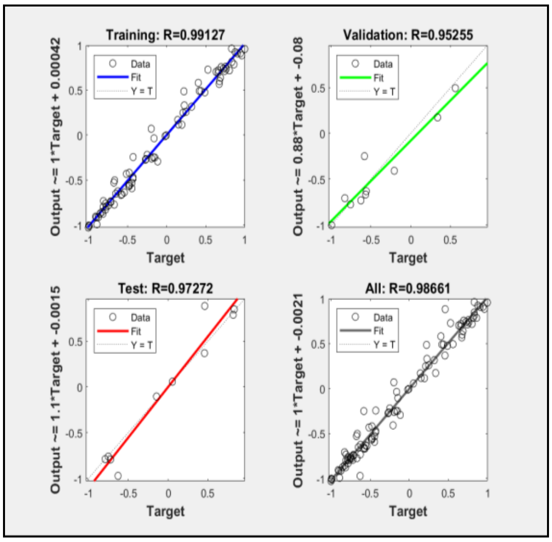
where
n = Total number of data used

T = Cell's temperature

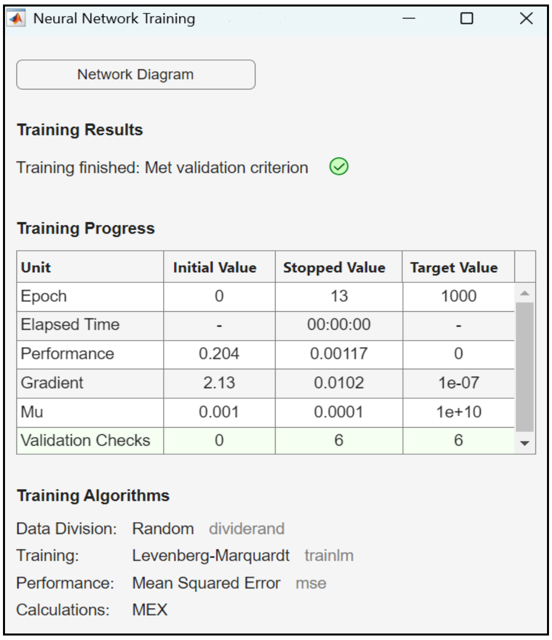
3. Results and Discussions

3.1 ANN Model Performance

Fig. 3 shows the ANN Regression & Training Results from the current project. The ANN model achieved a regression coefficient (R) of 0.98661 and a low MSE of 5.3701 W^2, indicating a strong correlation between the predicted and measured power outputs. The ANN predictions closely matched the measured data, especially during peak sunlight hours, demonstrating the model's ability to handle dynamic environmental changes.



(a)



(b)

Fig 3: (*a) ANN Regression and (b) Training Results*

3.2 Measured Power Solar Output

Table 1 shows the actual power output from the PV module was measured using a multimeter configured to display power directly that were collected for 20 days of observation. We used this data to do comparison with the ANN so that we could determine the percentage error and MSE error based on the real data and ANN predicted data.

Table 2 *Output Power Collected Data*

Date	Measured Output Power				
	9:00 AM	11:00 AM	1:00 PM	3:00 PM	5:00 PM
1-Feb	21.77	16.17	24.07	9.17	0
2-Feb	22.05	30.18	23.17	12.38	6.88
3-Feb	25.2	27.84	28.94	13.25	1.52
4-Feb	19.71	14.09	4.74	9.19	4.57
5-Feb	18.83	27.63	30.7	8.62	5.76
6-Feb	4.03	32.34	29.74	3.47	4.72
7-Feb	23.38	27.36	32.05	6.92	5.37
8-Feb	13.33	19.95	8.66	8.51	3.62
9-Feb	12.17	26.92	29.05	9.43	2.11
10-Feb	18.99	30.96	23.71	5.54	2.45
11-Feb	13.84	20.23	27.57	3.17	2.85
12-Feb	7.07	7.58	12.03	4.12	3.76
13-Feb	6.18	29.96	28.47	20.14	6.21
13-Feb	24.02	31.42	27.38	8.02	1.79
15-Feb	8.61	20.59	30.2	16.41	5.45
16-Feb	7.28	13.08	14	6.13	2.85
17-Feb	13.71	30.24	7.15	3.14	0.08
18-Feb	17.38	28	9.4	3.6	1.67
19-Feb	14.6	32.97	28.76	3.07	0.1
20-Feb	9.42	4.24	25.72	24.55	0.18

3.3 Predicted ANN Power Solar Output

Based on the environmental input parameters, such as temperature and solar irradiance, that were gathered over the course of 20 days of observation, Table 3 displays the anticipated power output from the Artificial Neural Network (ANN) model. To teach the ANN about the nonlinear relationships between these environmental factors and the PV system's output power, we used historical data. Furthermore, the predicted values demonstrate that the ANN is capable of handling minor variations in environmental inputs, such as variations in temperature and irradiance brought on by moving clouds or unpredictable weather conditions. The ANN's performance demonstrates that even in the presence of varying conditions, the model has learnt from the training data and can predict power output with accuracy.

Table 3 *Output Power by ANN*

Date	Power Output (ANN)				
	9:00 AM	11:00 AM	1:00 PM	3:00 PM	5:00 PM
1-Feb	17.6605	18.71546	25.94508	9.872376	0.734598
2-Feb	16.04942	29.67222	25.79143	14.07741	7.486158
3-Feb	24.40674	27.25549	29.14854	15.21975	0.912881
4-Feb	16.8413	14.5173	5.300143	7.979106	4.472033
5-Feb	17.70474	27.12811	27.99661	10.20002	7.346793
6-Feb	4.826162	29.15286	28.62915	5.01646	5.742684
7-Feb	23.55455	27.45323	31.65846	11.68516	8.550298
8-Feb	9.520362	12.80018	8.787888	7.940183	4.629474
9-Feb	12.62152	28.58389	29.4072	6.937474	2.306838
10-Feb	19.47382	30.41632	25.39726	7.645041	2.891544
11-Feb	16.64921	15.95894	26.05808	5.185579	2.956011
12-Feb	6.810305	7.41472	13.30513	4.927254	4.010614

13-Feb	6.113696	29.2799	29.97025	21.58938	7.640728
13-Feb	26.66323	29.16947	28.77486	8.500826	1.900573
15-Feb	8.070894	23.55434	29.2914	19.83553	4.855318
16-Feb	7.548251	12.82942	9.749896	7.171248	4.848129
17-Feb	9.466785	29.19139	7.209627	4.398506	0.268286
18-Feb	17.25297	22.70044	9.298397	4.128427	2.366901
19-Feb	11.9354	29.36093	22.01038	2.742135	0.687001
20-Feb	9.881903	4.304956	26.72268	24.98113	0.966958

3.4 PV Power Output Comparison

The study's analysis demonstrates the pros and cons in predicting solar PV power output by using ANN as comparison to conventional calculation techniques. When compared to the actual measured power values, it was confirmed that the ANN model consistently produced predictions that were substantially closer to the actual output. From Fig 4, the mean squared error and root mean squared error percentage for the ANN model was significantly lower than that of the calculation method. The calculation method produced higher deviations due to its reliance on static coefficients and inability to adapt to real-time variations. The ANN, however, successfully accounted for dynamic environmental factors, resulting in more accurate power predictions.

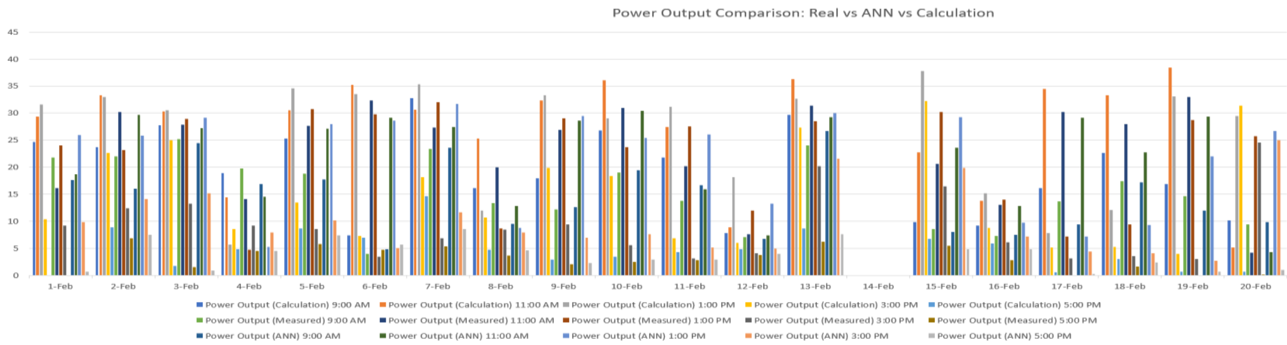


Fig 4: *Graph for Power Output Comparison*

Comparison of MSE and RMSE Error performance between ANN and calculation prediction is presented in Table 4. Based on Table 4, the comparison between the calculation method and the ANN model, the ANN demonstrates enhanced performance with significantly fewer errors. The calculation method showed an RMSE of 5.19 W, whereas the ANN model acquired an RMSE of around 2.32 W, representing a reduction of nearly fifty percent in error magnitude. This highlights the advantages of the ANN model for learning complicated nonlinear relationships and reacting to changes in solar irradiance and temperature conditions more efficiently than the formula approach.

Table 4 *Comparison of MSE and RMSE Error Performance Between ANN and Calculation Prediction*

Method	MSE	RMSE
Calculation	26.8865 W^2	5.1852 W
ANN	5.3701 W^2	2.3173 W

3.5 One-Day Ahead Forecasting

The predicted power output for the subsequent day was derived using the average values calculated from Equations (8) and (9). The ANN predicted value had a percentage error of 6.61% relative to the actual measured data. Table 4.8 provides a comprehensive comparison of the calculation method, actual data, one-day-ahead ANN prediction, and the corresponding percentage error. The provided inputs to forecast the next day's power output are:

- Average Solar Irradiance: 854.58 W/m^2
- Average Cell Temperature: 50.47°C
- Average Cell Temperature: 31°C

Table 5 *Comparison for One-Day Ahead Power Output*

Date	Parameter			PV Power Output			
21 Feb 2025	Irradiance	Cell Temperature	Ambient Temperature	Calculation	Measured Data	1 Day Ahead	Percentage Error
	854.8	50.47	31	27.76	24.49	22.87	6.61%

On February 21, 2025, the calculated PV output was 27.76W, the observed output was 24.49W, and the one-day ahead ANN prediction was 22.87W with a 6.61% error. Due to preset derating factors that do not account for environmental variations, the calculation method barely overestimated the output power. The ANN's ability to adjust to nonlinear changes in temperature and irradiance is demonstrated by the fact that its predicted value is closer to the measured value. This indicates that, in comparison to the conventional calculation method, the ANN model provides higher accuracy in short-term PV power forecasting.

4. Conclusion

The ANN model to predict solar photovoltaic (PV) power output using environmental input data, such as sun irradiance, ambient temperature, and cell temperature, was the main goal of this project. Data gathered over a 20-day period in MATLAB was used to train and test the ANN model. The performance of the ANN model was then contrasted with a conventional calculation technique that used Mean Squared Error (MSE) and percentage error as evaluation criteria. The study successfully demonstrated the potential of ANN-based forecasting as a trustworthy method for predicting solar energy. It provides an effective method for improving grid integration, energy planning, and system efficiency in solar photovoltaic applications.

Acknowledgement

The authors would like to give huge thanks to the Faculty of Electrical and Electronic Engineering, Universiti Tun Hussein Onn Malaysia, for the facilities provided during the completion of this project

Conflict of Interest

Author declare that there is no conflict of interest regarding the publication of the paper.

Author Contribution

Muhammad Nazmi bin Tohid confirms sole responsibility for the following: study conception and design, data collection, analysis and interpretation of results, and manuscript preparation.

References

[1] Karthikeyan, V., et al. "Reducing PV Module Temperature with Radiation-Based PV Module Incorporating Composite Phase Change Material." *Journal of Energy Storage*, vol. 29, June 2020, p. 101346, https://doi.org/10.1016/j.est.2020.101346. Accessed 14 Apr. 2020.

[2] Jãmi'at al-Imärät al-'Arabiyah al-Muttahidah and Institute of Electrical and Electronics Engineers, 5th International Conference on Renewable Energy: Generation & Application: Mon to Wed, Feb 26-28, 2018, CIT Building.

[3] R. Ramakumar and J. E. Bigger, "Photovoltaic systems," Proceedings of the IEEE, vol. 81, no. 3, pp. 365-377, Mar. 1993, doi: https://doi.org/10.1109/5.241491.

[4] IEEE Control Systems Society, Dongbei da xue, Chinese Association of Automation. Technical Committee on Control and Decision of Cyber Physical Systems, IEEE Singapore Section. Industrial Electronics Chapter, Chongqing da xue, and Institute of Electrical and Electronics Engineers., Proceedings of the 30th Chinese Control and Decision Conference (2018 CCDC): 09-11 June 2018, Shenyang, China.

[5] G. de Freitas Viscondi and S. N. Alves-Souza, "A Systematic Literature Review on big data for solar photovoltaic electricity generation forecasting," Sustainable Energy Technologies and Assessments, vol. 31, pp. 54-63, Feb. 2019, doi: 10.1016/j.seta.2018.11.008.

[6] Mittal, M., Bora, B., Saxena, S., & Gaur, A. M. (2018). Performance prediction of PV module using electrical equivalent model and artificial neural network. Solar Energy, 176, 104-117.

[7] Stoyanov, L., & Draganovsk, I. (2021, July). Application of ANN for forecasting of PV plant output power-Case study Oryahovo. In 2021 17th Conference on Electrical Machines, Drives and Power Systems (ELMA) (pp. 1-5). IEEE.

Evolution in Electrical and Electronic Engineering Vol. 6 No. 2 (2025) p. 302-311

[8] Z. Zarkov, L. Stoyanov, I. Draganovska, V. Lazarov, "The Comparison of different approaches for solar radiation forecasting using Artificial Neural Network", Electrical Engineering Faculty Conference (BulEF), 2019.
[9] Z. Zarkov, L. Stoyanov, I. Draganovska, and V. Lazarov, "A comparison of various methods for solar radiation forecasting using Artificial Neural Networks," presented at the *Electrical Engineering Faculty Conference (BulEF)*, 2019.
[10] S. Assahout, H. Elaissaoui, A. El Ougli, B. Tidhaf, and H. Zrouri, "An MPPT algorithm for photovoltaic pumping systems based on neural networks and fuzzy logic," *International Journal of Power Electronics and Drive Systems (IJPEDS)*, vol. 9, no. 4, pp. 1823–1833, 2018