

# Predicting Photovoltaic Power Production Using Artificial Neural Approach with Focus on Four Photovoltaic Module Technologies

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*Abstract: Accurate prediction of photovoltaic (PV) module power output is essential for optimal design and performance of solar systems. The power output of PV modules is influenced by various factors, including the size and number of solar cells, the angle and orientation of the installed module, and prevailing weather conditions. This paper focuses on developing an accurate Artificial Neural Network (ANN) model to estimate the power output of PV modules. Data from four different photovoltaic module technologies were used for this purpose. The dataset was further divided into two sub-databases: one for sunny days and the other for cloudy days, considering varying environmental conditions. The experiment was conducted in the desert area of Ghardaïa, Algeria. The developed neural approach was compared with classical models, such as multi-linear regression (MLR) and analytical methods. The findings revealed a consistent correlation coefficient exceeding 99% for all tested modules and weather conditions, indicating a strong agreement between predicted and monitored power outputs. Furthermore, the ANN model outperformed the compared methods, demonstrating its superiority in accurately estimating PV power outputs.*

*Keywords: ANN; PV module; power output; conventional models; desert area*

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## 1 Introduction

Photovoltaic (PV) power generation has seen significant growth worldwide. According to statistics from the International Energy Agency (IEA), global PV installed capacity has increased by more than 30 GW per year on average since 2010. In 2021, the total generating capacity has been increased by 22% to reach a record of 179 TWh [1]. This exponential trend encouraged many countries to adopt strategies and policies for the development of the PV sector. The production costs of solar energy have also decreased significantly over the years, making it a competitive source of energy. Overall, the growth of solar energy is expected to continue in the coming years, driven by factors such as technological advancements, government supports, reduction costs, and increasing demand for clean energy [2].

Hence, several governments are adopting solar energy to reduce their carbon footprint and energy cost. In Algeria, energy policies emphasize diversifying energy sources and integrating solar energy into the energy mix to minimize dependence on conventional energies (oil and gas) and extend their exploitation. An ambitious roadmap has been developed, targeting the gradual integration of renewable energies, particularly in desert regions, with plans to install 15,000 MW of PV capacity by 2035, including an annual addition of 1,000 MW [3]. Accurately predicting the power output of PV modules is important for designing, installing, and maintaining solar power systems. Accurate estimates ensure peak efficiency, maximize energy yield, and optimize return on investment. In this context, various methods have been used for PV power prediction [4] [5] which are summarized as follows:

- Analytical Models: These models use mathematical equations to predict PV module performance based on parameters like solar radiation, temperature, and module efficiency. Their accuracy depends on model complexity and data availability.
- Empirical Models: These models rely on statistical analyses of historical data to estimate PV performance under different conditions.
- Artificial Intelligence (AI) and Machine Learning (ML) Algorithms: These advanced methods analyze large datasets to predict PV power output, incorporating a wide range of variables such as weather conditions, module characteristics, and operating parameters, to generate highly accurate predictions.

This work belongs to the third category of PV power prediction. With the growing interest in using artificial intelligence in the field of solar energy, many researches dealing with the estimation of the PV module output through AI approaches can be found in the literature. Ghenai *et al.* [6] performed ANN model for bifacial solar PV system power and energy forecasting. They revealed that the developed model is extremely precise with an improvement of the monthly power of the bifacial PV modules from 10.87 to 21.54%. The coefficient of correlation exhibits also enhancement from 99.14 to 99.382%. In the work of Kallio and Siroux [7], a comparison study between multiple linear regression (MLR) model and ANN approach was carried out for predicting the photovoltaic output of solar micro-grid system. Comparative analysis revealed that the ANN approach achieved significantly better performance than MLR, with lower errors (MAE, RMSE, MSE) and a higher coefficient of determination (COD). Abdel-Nasser *et al.* [8] developed forecasting models for PV power using deep LSTM–RNN architectures and compared them with traditional ANN models. Their results showed that ANN still performs competitively in capturing nonlinear PV behavior under varying weather conditions, especially with reduced computational complexity. Aazam and Lee [9] proposed a day-ahead PV power forecasting framework that integrates ANN and deep learning models with weather classification. Their study highlighted the

effectiveness of ANN in scenarios with limited training data and fluctuating environmental inputs.

As demonstrated in prior research, AI methods play a crucial role in predicting PV module performance. Moreover, recent advances in intelligent modeling techniques such as artificial neural networks, deep learning, and ensemble systems have confirmed wide applicability across various fields, beyond renewable energy forecasting. For example, Abramov et al. [10] proposed a dynamic modeling framework to monitor and forecast pandemic-related statistics, highlighting the value of predictive models in public health. In the domain of smart transportation, object detection using deep learning was applied to electric vehicle infrastructure, where Tadity et al. [11] successfully used a YOLOv8s-based model to detect charging sockets with high precision. Furthermore, robust modeling strategies for uncertain, incomplete data streams were introduced in the OSSEFS framework [12], which combined fuzzy logic with ensemble learning to handle missing values in real-time systems. Earlier work by Pozna et al. [13] modeled cognition processes through observation-based systems, demonstrating the role of theoretical modeling in intelligent systems. In the biomedical field, deep learning models have been used to estimate vitamin D deficiency using only CBC test data, as shown in [14], proving that even minimal input features can yield high prediction accuracy when nonlinear models are applied. These studies emphasize the versatility and power of such modeling approaches, supporting their future application in solar energy area.

However, most previous studies on predicting PV module output have been limited in scope, focusing on a single PV technology, a single type sky condition, or using extremely complex models, even though they have successfully used artificial neural networks and other AI techniques to predict PV production. Moreover, little research has been conducted on how to tune the basic structures of artificial neural networks to ensure reliable performance in various module types and weather scenarios. This study is motivated by the need to fill these gaps by developing a lightweight yet accurate ANN model that is practical, adaptable, and easy to deploy. The modeling approach is chosen based on its proven ability to learn nonlinear relationships, while our design ensures its suitability for real-world solar energy predicting tasks.

The main contributions of this work compared to existing studies include:

- The development of separate ANN models for sunny and cloudy conditions, enabling the model to better adapt to atmospheric variability.
- A comparative analysis across four distinct PV module technologies (monocrystalline, polycrystalline, thin-film, and triple junction), which is not commonly addressed together in prior work.
- The use of a simple ANN architecture (with only one hidden layer and two input features) that is suitable for real-time deployment and low-resource environments.

- A comparative performance evaluation using identical inputs and conditions for ANN, multiple linear regression (MLR), and an analytical model, to ensure fair benchmarking.

The manuscript is structured as follows: Section 2 outlines an overview of the collected data and the proposed approach for power output prediction. Section 3 presents the key findings and simulation results. Finally, the paper ends with a comprehensive conclusion based on the outcomes of the study.

## 2 Material and Methods

### 2.1 System Monitoring and Database

The experiment was conducted at the Applied Research Unit in Renewable Energies (URAER) situated in Ghardaïa, located in the northern region of Algeria's desert, at coordinates (32.3° N, 3.8° E, 450 m asl). The site experiences a desert and arid climate, and the solar potential of Ghardaïa was examined from four years of data [15] [16]. Based on the Koppen-Geiger climate classification [17], Ghardaïa falls under the category of arid hot and dry (BWh) climate. The test bench and PV system monitoring is shown in the Fig. 1. It consists of solar measurement station for recording solar irradiance, weather station for measuring air temperature, PV current and voltage sensors and Agilent data-logger for data recording. Four PV modules with different technologies were measured, and their technical specifications are shown in Fig. 2; all parameters are measured with 5 min time intervals.

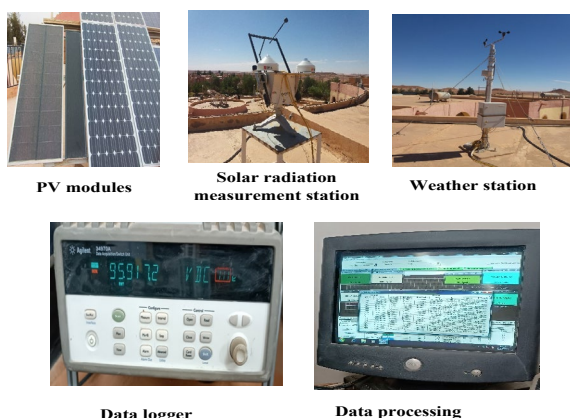


Figure 1  
Test bench and PV system monitoring

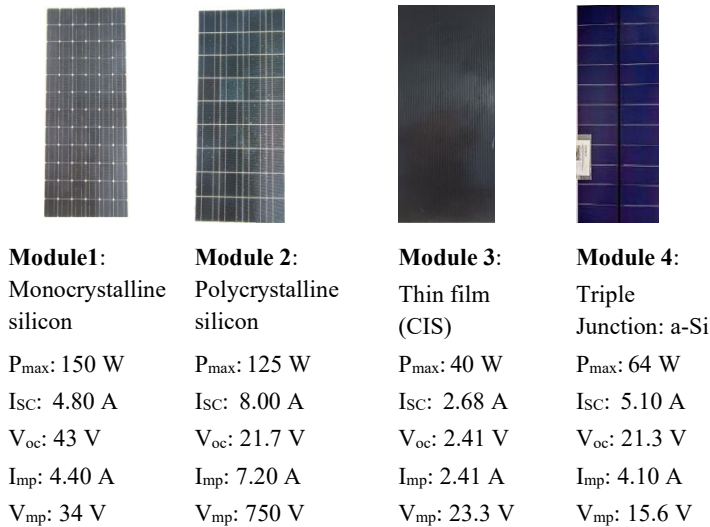


Figure 2

Specifications of the four PV modules at STC

Before data processing starts, the measured data is checked. Undeniably, during the measuring process many errors may happen. These errors result from various anomalies (power cuts, bad instrument calibration, soiling, etc.) and can significantly compromise the database if left unchecked, especially when there is a substantial lack of data. From the recorded dataset, two subsets were extracted: the first contains data meeting cloudy-day conditions, and the second comprises data satisfying sunny-day conditions. The extraction of cloudy and sunny days is done through a visual inspection of solar irradiance components: diffuse (DHI), direct (DNI) and global (GHI) irradiances [18]. Under overcast conditions, diffuse and global irradiance dominate, while direct irradiance becomes negligible.

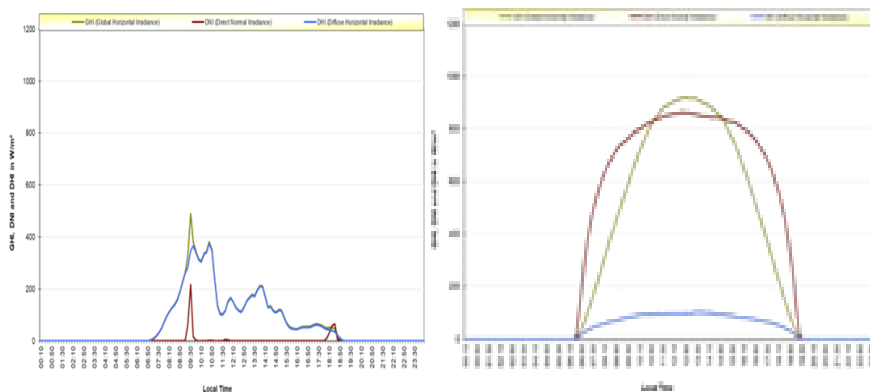


Figure 3

Distinguishing between cloudy and sunny days through visual analysis of solar radiation components

The inverse scenario occurs during sunny conditions, characterized by minimal diffuse irradiance as well as high levels of direct and global irradiances. The cloudy days subset contains 39,600 samples, whereas the sunny day subset comprises 32,400 samples. Fig. 3 shows an example of visual inspection of cloudy and sunny days.

## 2.2 Artificial Neural Networks Modeling

Artificial neural networks (ANNs) are powerful computational models inspired by the organization and operation of the neural networks in the human brain (Fig. 4). ANNs are constructed by interconnected “neurons,” or nodes, arranged in layers. Each neuron receives input signals, performs a computation, and produces an output signal. The strength of the signal transmission is determined by the weights attached to the connections between neurons [19]. ANNs are trained using large datasets and a learning algorithm that adjusts the weights based on the desired outputs. ANNs can develop complex models, classify data, generate predictions, and deal with a variety of problems according to this training process. They have been successfully implemented in a variety of applications, including time series prediction, pattern recognition, natural language processing, and image and speech recognition [20]. ANNs are a useful and important tool in machine learning and artificial intelligence research because of their capacity to learn from data, generalize novel examples, and adapt to new information. Fig. 4 illustrates an example of ANN architecture which mimics the biological human brain:

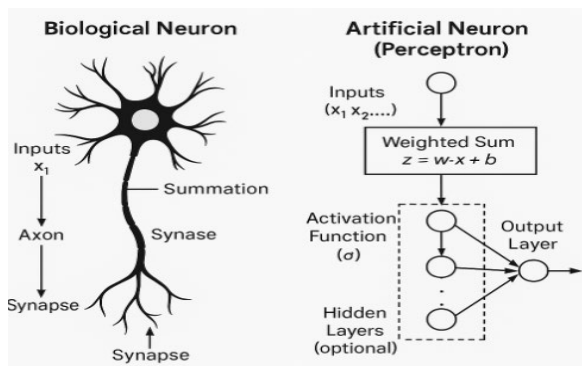


Figure 4

General ANN structure draws inspiration from biological human brain [19]

According to the bibliographic review, multilayer perceptron (MLP) feed- forward neural network structure is the most used architecture in the field of solar energy forecasting [21]. In MLP structure, the neurons are organized to form multiple layers. The number of layers typically ranges from three to four including an input layer, an output layer, and one or two hidden layers. The flow of information propagates unidirectionally from the input to the output layers. The input layer

consists of neurons equal to the dimension of the input space, while the output layer contains a single neuron for the predicted value. Finally, one or more hidden layers contain a variable number of neurons.

In this work, the power outputs of PV modules are predicted based on the MLP architecture. As illustrated in Fig. 5, the network comprises: an input layer processing two meteorological variables (solar irradiance  $G$  and air temperature  $T$ ), a single hidden layer, and an output layer generating a power prediction ( $P$ ) of PV modules.

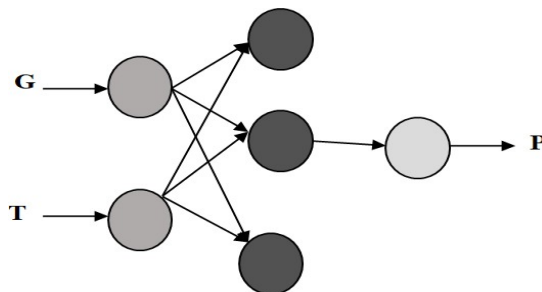


Figure 5

MLP architecture for PV power prediction

Hence, the goal is to find a relationship, which can be useful for the prediction of the power produced according to the solar irradiance and the air temperature. This relationship can be expressed as:

$$\hat{P} = f(G, T) \quad (1)$$

Where:  $f$  is an approximate function.

On the other hand, it is also possible to express the previous equation as follows:

$$\hat{P}(t) = w^T \cdot g(W \cdot x(t) + b) \quad (2)$$

where  $x(t) = [G(t), T(t)]^T$  is the input vector,  $W$  and  $b$  are the hidden layer weights and biases, and  $w$  are the output layer weights.

The input vector  $x(t)$  is expressed as:

$$x(t) = \begin{bmatrix} G(t) \\ T(t) \end{bmatrix} \quad (3)$$

The weight matrix ( $W$ ) is given as:

$$W = \begin{bmatrix} w_{1,1} & w_{1,2} \\ w_{m,1} & w_{m,2} \end{bmatrix} \quad (4)$$

The bias vector ( $b$ ) is given as:

$$b = \begin{bmatrix} b_1 \\ \vdots \\ b_m \end{bmatrix} \quad (5)$$

The output weight vector ( $w$ ) is given as:

$$w = \begin{bmatrix} w_1 \\ \vdots \\ w_m \end{bmatrix} \quad (6)$$

Prior to ANN model optimization, input/output data undergoes preprocessing. The main aim of this step is to normalize the data into dimensionless forms, allowing network efficiency, while guaranteeing reliable and robust results. The normalization is implemented by the following transformation:

$$y = y_{min} + (x - x_{min})(x_{max} - x_{min})^{-1}(y_{max} - y_{min}) \quad (7)$$

Where:  $x$ ,  $x_{min}$ ,  $x_{max}$ ,  $y_{min}$  and  $y_{max}$  is the original data and  $y$  is the corresponding scaled variables.

Consequently, two distinct ANN models have been developed separately under cloudy days and sunny days, to estimate power output from four PV module types. Each ANN model was trained using a feedforward architecture composed of two input neurons (for irradiance and temperature), one hidden layer with three neurons, and one output neuron.

To ensure robust and generalizable learning, each sub-database (cloudy and sunny) was divided into three sets: 60% for training, 15% for validation (used during training for early stopping to prevent overfitting) and 25% for testing (used only after training to evaluate final performance).

The optimization problem consists of minimizing the loss function, defined as the mean squared error (MSE) between the predicted and the actual outputs, by adjusting the network's weights and biases. The Levenberg-Marquardt algorithm is used to iteratively solve this nonlinear least-squares problem without constraints [22]. It is particularly appropriate for this task as it efficiently handles nonlinear least-squares problems, making it suitable for training feedforward neural networks. The linear function is employed in the output layer in order to produce continuous output values while a hyperbolic tangent sigmoid transfer function is used for the input and hidden layers given by:

$$y = \frac{2}{1 + e^{-2(\sum_{i=1}^N w_i x_i + b)}} - 1 \quad (8)$$

Where:

$x_i$ : Scalar input

$w_i$ : Weight for input  $i$

$b$ : Bias term

$y$ : Output of the neuron after applying the activation

The initial weights and biases of the ANN model were randomly initialized as part of the training process. To assess the effect of randomness on model stability, the

training was repeated many times using different random seeds, and the average performance metrics were reported.

Early stopping was applied using the validation set to avoid overfitting. Convergence of the ANN model was ensured through early stopping, monitored on the validation set. The training process terminated when the validation error failed to improve for three consecutive evaluations ( $\text{max\_fail} = 3$ ). In practice, convergence was consistently achieved in under 200 epochs for all datasets, well below the maximum of 1000 epochs set in the training parameters. Once convergence was reached, the final evaluation of model performance was conducted using the independent test set, which had not been involved in either training or validation.

After the completion of the network training, it becomes ready to evaluate the generated PV power output. The trained network was implemented in a MATLAB 2016 software to predict power outputs for the four studied PV module technologies.

### 2.2.1 Modeling Steps

The following steps summarize the procedure used to develop and evaluate the ANN model:

- **Step 1 Data Preprocessing:** The input variables (solar irradiance  $G$  and temperature  $T$ ) and output variable (power  $P$ ) were normalized using Equation (3) to ensure efficient network learning.
- **Step 2 Network Architecture:** A feed-forward neural network with two input neurons, one hidden layer of three neurons, and one output neuron was adopted (see Fig. 5). The activation functions used are described in Eq. (4).
- **Step 3 Training:** The training process was conducted using the Levenberg-Marquardt algorithm to minimize the mean squared error (Equation (1)). Data was split into 60% for training, 15% for validation, and 25% for testing. Early stopping was applied using validation performance.
- **Step 4 Model Evaluation:** The model performance was evaluated using normalized root mean square error (nRMSE), normalized mean absolute error (nMAE), and the correlation coefficient  $r$ , as defined in Equations (5), (6), and (7). These metrics were applied to compare predicted and measured power values on the test set.

Fig. 6 flowchart resumes the different steps of modeling.

However, this study focuses on developing a practical ANN model for real-time power output estimation in operational photovoltaic systems. By utilizing only commonly monitored environmental variables, the proposed model can be easily integrated into existing solar monitoring infrastructures, including those in remote locations.

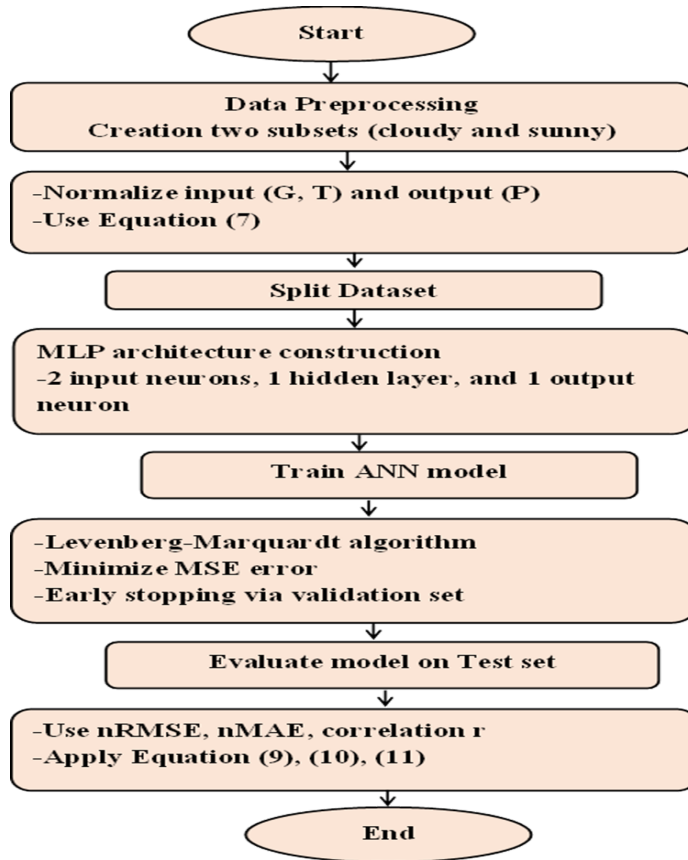


Figure 6  
Flowchart of ANN model implementation

### 2.3 Model Performance

The ANN models were evaluated using three metrics: normalized root mean square error (nRMSE), normalized mean absolute error (nMAE), and correlation coefficient ( $r$ ), defined as [16] [23]:

$$nRMSE = \frac{\sqrt{\frac{1}{N} \sum_{i=1}^N (e_i - m)^2}}{\text{mean}(m_i)} \quad (9)$$

$$nMAE = \frac{1}{N} \sum_{i=1}^N \frac{|e_i - m_i|}{\text{mean}(m_i)} \quad (10)$$

$$r = \frac{\sum_{i=1}^N (m_i - \bar{m})(e_i - \bar{e})}{\sqrt{\sum_{i=1}^N (m_i - \bar{m})^2 (e_i - \bar{e})^2}} \quad (11)$$

Where:  $e$  and  $m$  represent the predicted and measured values, respectively.

### 3 Results and Discussion

#### 3.1 ANN Model Assessment

Multiple ANN architectures were systematically evaluated, with the optimal configuration selected through rigorous error analysis. Thereby, the optimized configuration consists of two neurons in the input layer, three neurons in the hidden layer, and one neuron in the output layer. For each subset (cloudy-days and sunny-days), distinct data samples were allocated: one for model training and a separate, unseen sample for testing. This approach helps prevent data leakage and provides a reliable assessment of the ANN's performance.

Figs. 6-9 display a comparison between the predicted outputs of the ANN model and the actual measured data of the power outputs generated by the four PV module technologies. For each PV module, the comparison is showcased for both cloudy and sunny days. Specifically, four days have been selected to represent each type of subset, allowing for a comprehensive evaluation of the ANN model's performance across different scenarios. This approach ensures a thorough assessment of the model's accuracy and robustness under varying environmental conditions.

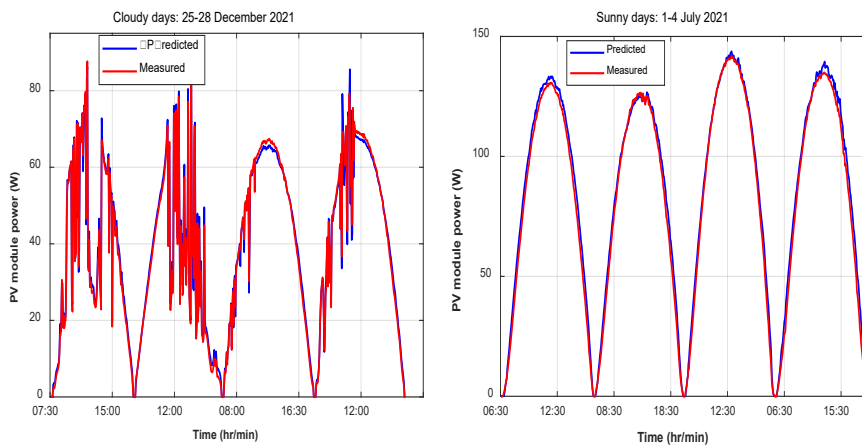


Figure 6

Comparison of measured and predicted power output for PV module 1 under cloudy and sunny days

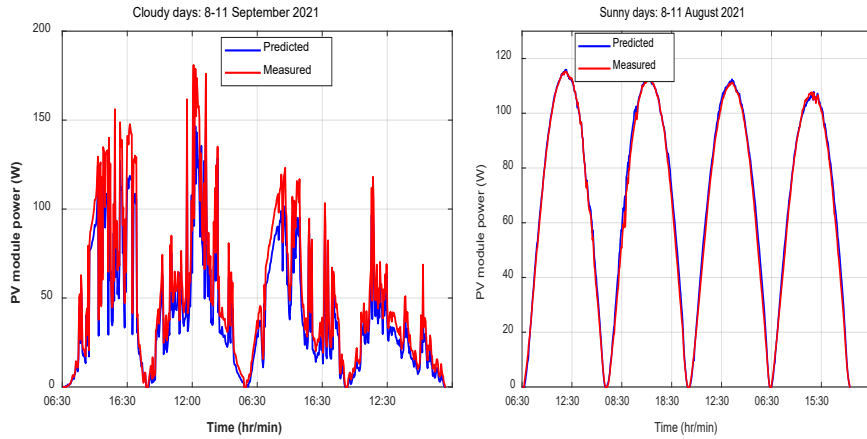


Figure 7

Comparison of measured and predicted power output for PV module 2 under cloudy and sunny days

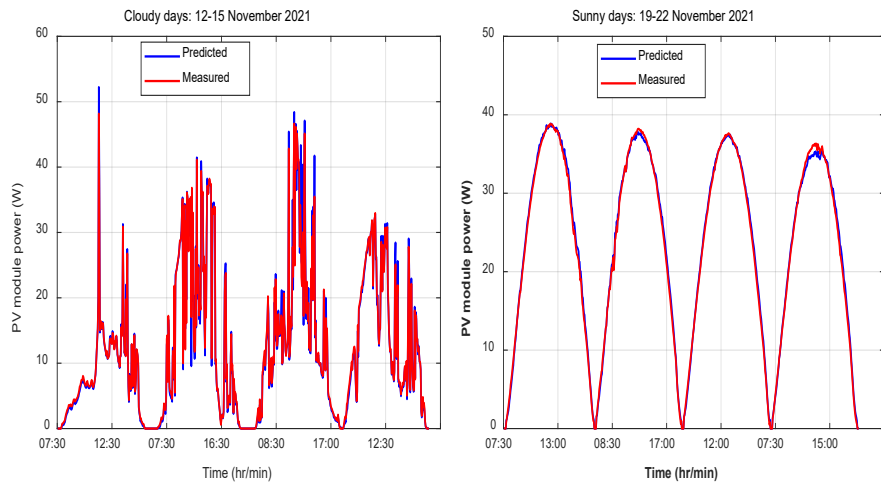


Figure 8

Comparison of measured and predicted power output for PV module 3 under cloudy and sunny days

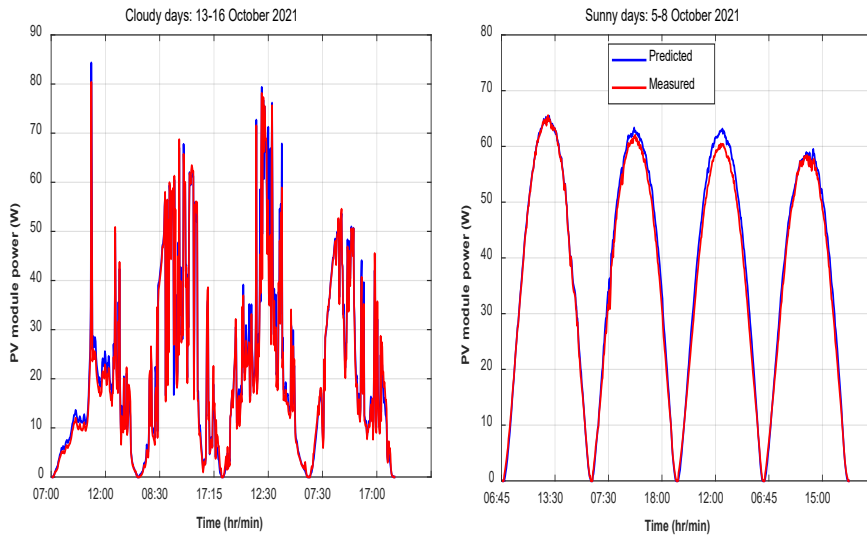


Figure 9

Comparison of measured and predicted power output for PV module 4 under cloudy and sunny days

The figures demonstrate excellent concordance between measured and ANN-predicted power outputs across both cloudy and sunny conditions. This consistent agreement validates the model's robust performance in accurately estimating PV module output under all sky conditions. Also, the ANN model performance was evaluated using three statistical metrics: normalized root mean square error (nRMSE), normalized mean absolute error (nMAE) and correlation coefficient ( $r$ ). These scores quantitatively compare measured versus predicted energy outputs across all four PV module technologies. The evaluation outcomes are reported in Table 1 and Table 2.

Table 1

Comparison between measured and ANN predicted energy on cloudy days

		Cloudy days			
		Module 1	Module 2	Module 3	Module 4
1 <sup>st</sup> day	Mean daily measured energy (Wh/day)	333	280	164	154
	Mean daily estimated energy (Wh/day)	324	270	166	141
	nRMSE (%)	5.47	6.99	6.65	7.80
	nMAE (%)	1.45	4.24	3.62	5.53
	$r$ (%)	99.63	99.88	99.84	99.38
2 <sup>nd</sup> day	Mean daily measured energy (Wh/day)	311	471	155	270

	Mean daily estimated energy (kWh/day)	299	462	153	267
	nRMSE (%)	6.68	11.48	10.52	9.95
	nMAE (%)	5.16	5.24	4.77	8.35
	r (%)	98.58	99.20	99.11	98.85
3 <sup>rd</sup> day	Mean daily measured energy (Wh/day)	391	517	148	258
	Mean daily estimated energy (Wh/day)	390	503	150	243
	nRMSE (%)	4.06	5.06	5.14	6.89
	nMAE (%)	2.52	3.07	3.53	5.48
	r (%)	99.76	99.73	99.71	99.50
4 <sup>th</sup> day	Mean daily measured energy (Wh/day)	423	450	297	239
	Mean daily estimated energy (Wh/day)	418	453	313	238
	nRMSE (%)	6.73	5.01	7.20	7.41
	nMAE (%)	3.56	2.96	5.88	5.60
	r (%)	99.38	99.74	99.84	99.49

Table 2

Comparison between measured and ANN predicted energy on sunny days

		Sunny days			
		Module 1	Module 2	Module 3	Module 4
1 <sup>st</sup> day	Mean daily measured energy (Wh/day)	948	785	268	430
	Mean daily estimated energy (Wh/day)	918	778	264	429
	nRMSE (%)	3.95	1.95	2.41	1.58
	nMAE (%)	3.25	1.46	2.04	1.25
	r (%)	99.92	99.94	99.30	99.96
2 <sup>nd</sup> day	Mean daily measured energy (Wh/day)	917	774	256	414
	Mean daily estimated energy (kWh/day)	876	748	255	397
	nRMSE (%)	5.17	4.54	2.17	4.68
	nMAE (%)	4.47	3.48	1.83	4.26
	r (%)	99.87	99.84	99.90	99.90
3 <sup>rd</sup> day	Mean daily measured energy (Wh/day)	909	762	257	415
	Mean daily estimated energy (Wh/day)	864	738	254	392
	nRMSE (%)	5.44	3.93	2.00	6.50

	nMAE (%)	5.01	3.29	1.68	6.06
	r (%)	99.89	99.88	99.93	99.90
4 <sup>th</sup> day	Mean daily measured energy (Wh/day)	852	720	244	388
	Mean daily estimated energy (Wh/day)	826	705	242	375
	nRMSE (%)	4.56	3.55	3.03	4.35
	nMAE (%)	3.74	2.83	2.57	3.68
	r (%)	99.82	99.85	99.86	99.84

From these tables, the following findings can be drawn:

- The correlation coefficient exceeding 99% indicates a high-level of agreement between the measured and estimated PV power energy, even in cloudy conditions,
- The nRMSE and nMAE scores fall within acceptable performance ranges for all tested PV module technologies,
- The results suggest that the ANN model performs better in predicting energy outputs on sunny days, which aligns with the statistical errors obtained and the actual energy production.

The results presented above are further supported by additional evidence illustrated in Fig. 10 and Fig. 11. These scatterplots display the relationship between the measured and estimated power outputs for the four PV modules on both sunny and cloudy days. These figures offer valuable visual insights into the model's performance and provide additional support for the previously reported statistical test results. For both cases, the points are closely aligned along a clear trend line. This indicates a strong correlation between the measured and estimated power outputs, further reinforcing the accuracy of the ANN model's predictions under clear and overcast weather conditions.

Indeed, it is important to highlight that the classification of days into distinct categories of sunny and cloudy contributes significantly to the enhancement of the ANN-based models. This approach proves superior compared to using a single database containing all days without differentiation. Segregating the data based on weather conditions, the ANN models can better adapt to the specific characteristics and patterns associated with each type of day.

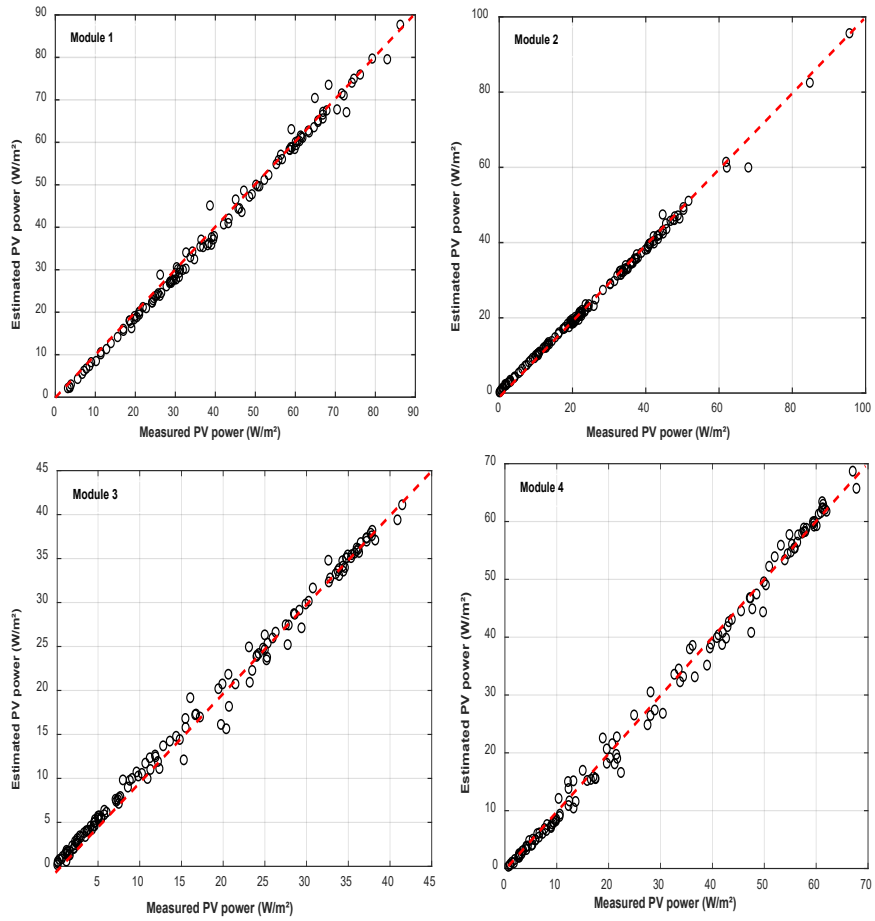


Figure 10  
Scatter plot between measured and estimated PV power on cloudy days

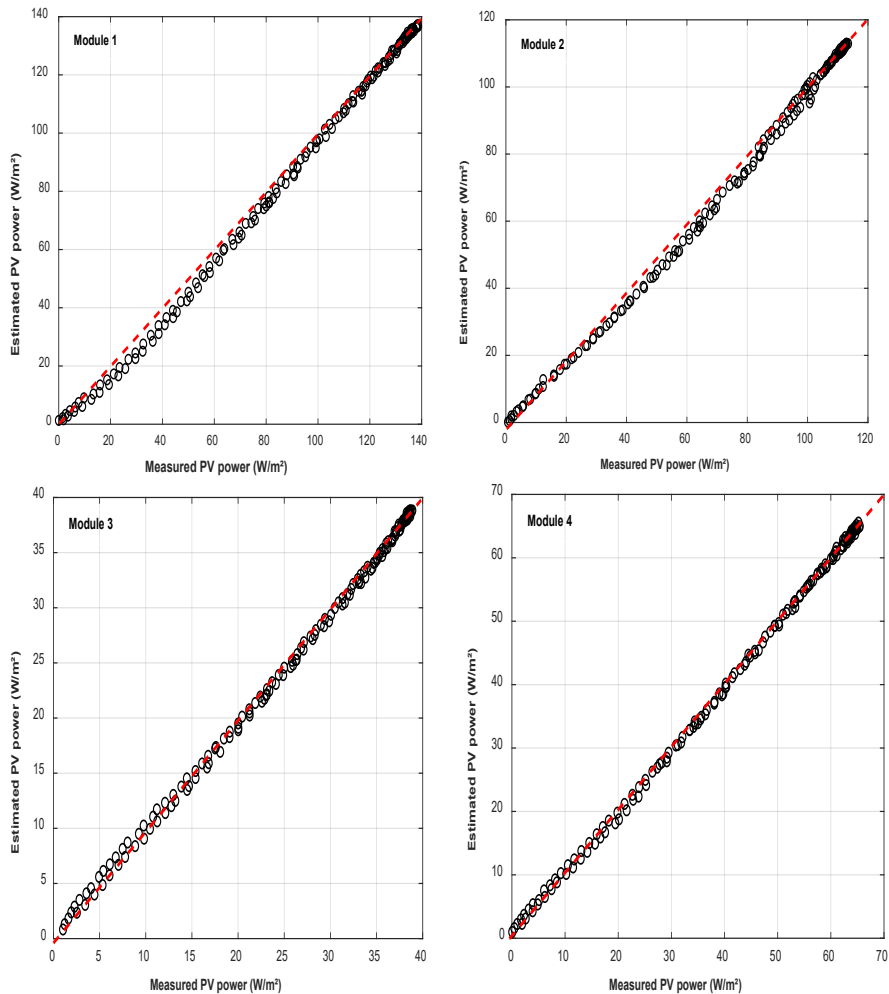


Figure 11

Scatter plot between measured and estimated PV power on sunny days

## 3.2 Comparative Study

The developed neural models were benchmarked against two conventional approaches to identify their strengths and weaknesses. A concise overview of each model is provided below.

### 3.2.1 Multiple Linear Regression Model (MLR)

Multiple linear regression is a statistical technique that extends simple linear regression to model the relationship between a dependent variable and two or more

independent variables. The primary goal of MLR model is to find the best-fitting linear equation that explains how the variations in the dependent variable are associated with the variations in multiple independent variables. In our case and for the estimation of the PV power output, the following expression is used [16]:

$$P(G, T) = \alpha + \beta_1 G + \beta_2 T + \varepsilon \quad (8)$$

Where:  $\alpha$ ,  $\beta_1$ ,  $\beta_2$  are coefficients to be determined and  $\varepsilon$  is the error.

### 3.2.2 Analytical Model

The analytical model for PV power output can be expressed by the simplified expression as follow [24]:

$$P(G, T) = \frac{G}{G_{ref}} P_{ref} (1 - \gamma(T - T_{ref})) \quad (9)$$

Where:  $\gamma$  is the maximum power correction factor for temperature; subscript “ref” designates standard testing conditions ( $G_{ref}=1000 \text{ W/m}^2$  and  $T_{ref} = 25 \text{ }^\circ\text{C}$ ).

To ensure a fair comparison, all models were trained on the same input variables (solar irradiance and temperature) and tested on the same data partitions. The simulation results and the comparison between models are depicted in Fig. 12. The assessment of models has been conducted in terms of the normalized root mean square error (nRMSE), which serves as a key metric for evaluating their performance.

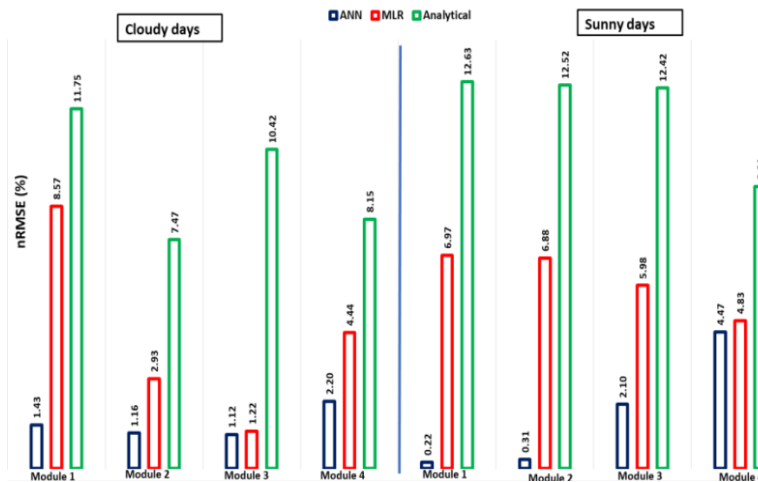


Figure 12

Comparison between performed ANN, MLR and analytical models

From the above Fig., it is evident that the ANN approach outperforms both the MLR and analytical models for both cloudy and sunny days. The improvement of the ANN model, in terms of nRMSE, compared to the MLR and analytical models, is

approximately 83.3% and 87.8%, respectively, for PV module 1 on cloudy days. On sunny days, this improvement increases to about 96.8% and 98.2% when compared to the MLR and analytical models, respectively. Consistent with PV module 1, the comparison of the ANN model with the MLR model demonstrates noteworthy improvements in nRMSE for the other PV modules as well. The analysis yields the following observations:

- During cloudy days, the nRMSE improvement against the MLR model is approximately 60.4% for module 2, 8.19% for module 3, and 50.45% for module 4.
- When compared to the analytical model, the nRMSE improvement is about 84.47% for module 2, 78.50% for module 3, and 73.0% for module 4.
- For the case of sunny days, the nRMSE improvement against the MLR model is approximately 95.4% for module 2, 64.8% for module 3, and 7.45% for module 4.
- When compared to the analytical model, the nRMSE improvement is about 97.52% for module 2, 83.09% for module 3, and 51.4% for module 4.

The findings demonstrate consistent superiority of the ANN model over both MLR and analytical approaches in predicting power output across all PV module types and sky conditions.

### 3.2.2 Comparison with Literature

Several studies have demonstrated the effectiveness of lightweight ANN architectures in PV power forecasting. Durrani et al. [25] combined irradiance forecasting with MLP networks to predict photovoltaic yield in grid-connected plants and reported strong predictive accuracy. A study in Algeria [26] compared feed-forward, cascade-forward, and Elman neural networks using only basic meteorological inputs; ANN models significantly outperformed linear regression in both accuracy and stability. Other work [27] employed FFNNs trained on hourly data (irradiance, temperature, and PV output), achieving correlation coefficient values up to 0.998 for sunny days, and 0.93 under cloudy conditions. More recently, Youssef et al. [28] compared MLP, LSTM, and modular neural-network models, finding that a modular ANN model offered near-LSTM accuracy with lower structural complexity. In comparison, our ANN-based model achieves similar or better predictive accuracy using a minimal architecture with competitive nRMSE and correlation metrics, Table 3 summarizes selected studies, focusing on model types, reported accuracy, error metrics, and model characteristics.

Table 3  
Comparison between measured and ANN predicted energy on sunny days

Study	Model Type	Input variable	R <sup>2</sup> (%)	RMSE / nRMSE	Notes
Durrani et al. [25]	MLP	Irradiance, Temperature	~98%	RMSE $\approx$ 2.5	Applied in grid-connected PV systems; trained on real plant data
Bouzidi et al. [26]	FFNN, CFNN, Elman	Irradiance, Temperature	97–99%	RMSE $\approx$ 2–3	Models tested in Algerian desert using minimal weather inputs
El Mghouchi et al. [27]	FFNN	Irradiance, Temperature	93–99.8%	nRMSE $\approx$ 3–7%	Accuracy evaluated under both sunny and cloudy days
Youssef et al. [28]	MLP	Historical PV & weather	~98%	RMSE $\approx$ 1.8	Modular ANN matched LSTM performance with lower complexity
This work	MLP	Irradiance, Temperature	> 99%	nRMSE < 5% (sunny), <8% (cloudy)	Simple, classified by sky condition

## Conclusion

This study developed and evaluated an artificial neural network (ANN) model for photovoltaic power output prediction across four PV module technologies. To train this model effectively and capture diverse relationships between input features and power output, a comprehensive database comprising meteorological parameters and PV module characteristics has been used. In order to ensure robust learning, the database was partitioned into two distinct subsets corresponding to cloudy and sunny day conditions.

The results demonstrated superior performance of the developed ANN model, achieving exceptional accuracy in power output estimation across all PV module technologies. Notably, the correlation coefficient exceeded 99% for all scenarios and weather conditions, indicating a strong agreement between predicted and monitored power outputs. Moreover, evaluation through nRMSE and nMAE scores revealed that the ANN model's predictions fall within acceptable performance ranges, confirming its reliability. Comparative analysis with conventional methods

demonstrated the ANN's superior predictive performance, proving its ability for PV output estimation.

The developed ANN model is simple, enabling fast processing and low resource usage, making it suitable for real-time energy management, particularly in large photovoltaic farms or regions with limited connectivity or computing capacity. Future extensions of this work could explore alternative nonlinear models, such as deep learning architectures, ensemble fuzzy systems and combined approaches, which have proven effective in complex prediction tasks in diverse fields.

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