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Accurate Method for Solar Power Generation Estimation for Different PV (Photovoltaic Panels) Technologies

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Abstract: In 2023, solar photovoltaic energy alone accounted for 75% of the global increase in renewable capacity. Moreover, this natural energy resource is the one that requires the least investment, which makes it accessible to developing countries. Increasing return on investment in these regions requires a particular evaluation of environmental parameters influencing PV systems performance. Higher temperatures decrease PV module efficiency and, as a result, their power output. Additionally, fluctuations in solar irradiance directly impact the energy generated by these systems. Consequently, it is essential for investors to improve accurate predictive models that assess the power generation capacity of photovoltaic systems under local environmental conditions. Therefore, accurate estimation of maximum power generation is then crucial for optimizing photovoltaic (PV) system performances and selecting suitable PV modules for specific climates. In this context, this study presents an experimental comparison of three maximum power prediction methods for four PV module types (amorphous silicon, monocrystalline silicon, micromorphous silicon, and polycrystalline silicon) under real outdoor conditions. Experimental data gathered over the course of a year are analyzed and processed for the four PV technologies. Three different methods taking into account environmental parameters are presented and analyzed. The first estimation method utilizes irradiance as the primary input parameter, while two additional methods incorporate ambient temperature and PV module temperature for enhanced accuracy. The performance of each method is evaluated using standard statistical metrics, including the root mean square error (RMSE) and coefficient of determination (R^2). The results demonstrate the effectiveness of all three methods, with RMSE values ranging from 1.6 W to 3.8 W and R^2 values consistently above 0.95. The most appropriate method for estimating PV power output is determined by the specific type of photovoltaic module and the availability of meteorological parameters. This study provides valuable insights for selecting an appropriate maximum power prediction method and choosing the most suitable PV module for a given climate.

Keywords: photovoltaic modules; maximum power prediction; outdoor conditions; irradiance; temperature

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1. Introduction

Global annual investments in photovoltaic (PV) solar panels are anticipated to approach USD 500 billion by 2024, surpassing total expenditures across all other energy generation technologies [1]. This exceptional financial investment underscores the growing recognition of solar energy as a cornerstone of global renewable energy initiatives. As nations strive to transition towards sustainable energy solutions, solar energy emerges not only as a viable alternative but also as a strategic asset that can significantly contribute to energy independence and security. In many developing countries, where energy demands often outpace supply, solar energy is not only abundant but also represents the most economically advantageous method of energy generation.

Maximizing return on investment in these regions necessitates a meticulous evaluation of environmental parameters influencing PV system performance. Among these parameters, solar irradiance is particularly critical, alongside ambient temperature and the temperature of the PV module itself, as all significantly affect solar panel efficiency. Increased temperatures, prevalent in numerous developing nations, can reduce the efficiency of photovoltaic modules and, consequently, their total power output. Additionally, fluctuations in solar irradiance directly impact the energy generated by these systems. Therefore, it is essential for investors in these areas to obtain highly accurate predictive models that assess the power generation capacity of photovoltaic systems under local environmental conditions. Such models are vital for accurate energy output predictions, guiding the economic feasibility and anticipated returns on investment in solar energy initiatives.

The precise forecasting of peak PV power output is crucial for enhancing energy production and evaluating the performance of solar energy systems in real-world scenarios. This predictive ability is essential for maximizing the performance of photovoltaic systems, especially in varied climatic conditions where temperature, irradiance, and weather variations substantially influence energy production. Advanced mathematical models are essential in this process, offering strong frameworks for simulating and predicting PV module performance based on diverse environmental factors [2–4]. These models provide more accurate power output predictions and evaluate the long-term behavior and degradation patterns and reliability of photovoltaic systems. The current body of research includes various approaches for predicting the maximum power of photovoltaic systems, each tackling the intricate relationships between climatic factors and module performance [5–7].

This increasing recognition of solar energy's potential underscores the need for robust analytical frameworks to accurately predict PV system performance. Understanding the intricate dynamics of how environmental factors interact with photovoltaic technology is essential for optimizing energy production. To this end, researchers have begun focusing on the development of advanced predictive models that incorporate multiple variables; these models not only facilitate a better understanding of energy generation patterns but also allow for real-time adjustments based on fluctuating conditions. By integrating diverse datasets and employing sophisticated algorithms, these predictive frameworks enhance the predictive accuracy of energy output forecasts, thereby empowering investors to make informed decisions that align with local resource availability and climatic conditions.

Recent studies have further advanced the field of photovoltaic (PV) power forecasting by exploring diverse methodologies aimed at improving prediction accuracy and efficient techniques for estimating photovoltaic cell and module parameters. Muhammad et al. [8] introduced an approximation and correction technique while they focused on determining the ideality factor from the shunt resistance curve [9]. Giorgi et al. [10] examined the influence of weather data on PV power forecasting, comparing traditional statistical methods with artificial neural networks (ANNs) to highlight the advantages of using advanced modeling techniques. In a complementary approach, Gaboitaolelwe et al. [11] conducted a comprehensive review of machine learning techniques used for predicting PV power output, synthesizing various strategies and their effectiveness in enhancing prediction performance. Building on this foundation, Alrashidi et al. [12] proposed innovative hybrid data-driven models that integrate multiple ML approaches to improve forecasting precision. Additionally, Ait Abdelmoula et al. and Tercha et al. [13,14] introduced forecasting methodologies that combine feature engineering with stacked machine learning models, further refining prediction accuracy.

Expanding the exploration of advanced techniques, Miraftabzadeh et al. [15] investigated the use of transfer learning with deep neural networks to improve the accuracy of day-ahead PV power predictions, demonstrating the potential of deep learning to significantly enhance forecasting accuracy. In a similar vein, Scott et al. [16] assessed the effectiveness of various machine learning algorithms for forecasting PV generation systems, showcasing improvements in predictive performance through innovative applications.

Sagingalieva et al. [17] introduced quantum machine learning techniques, underscoring the emerging potential of this novel field to enhance prediction capabilities in PV systems.

Furthering the discourse on current methodologies, Alcañiz et al. [18] undertook a comprehensive analysis of the literature on machine learning techniques applied to PV power forecasting with the aim of identifying research gaps and opportunities for future advancements, offering a comprehensive overview of the field's evolution and remaining challenges. Finally, Tucci et al. [19] focused on regional PV power generation forecasting using machine learning models, addressing the limitations posed by insufficient plant-specific data.

In addition to these machine learning approaches, neural networks gained widespread traction for solar power prediction due to their ability to capture intricate nonlinear patterns in data. For instance, Shuvho et al. employed neural networks to accurately predict solar irradiance levels at grid-connected photovoltaic power plants [20], while Fentis et al. and Rana et al. utilized them for short-term forecasting [21,22]. Sharifzadeh et al. conducted a comprehensive review of machine learning methodologies for renewable energy modeling, identifying neural networks as a particularly promising approach [23]. Moreover, support vector machines (SVMs) were also effectively applied to solar power prediction, especially in conjunction with optimization algorithms. Li et al. showcased the improved performance of a novel multi-verse optimizer algorithm (HIMVO) in tuning SVM parameters for accurate PV power forecasting [24].

However, despite these advancements, existing methods still exhibited significant limitations. Advanced machine learning techniques, including deep neural networks and hybrid models, often require extensive computational resources and large datasets to achieve high accuracy. These models struggled to generalize across different geographic regions or varying climatic conditions, necessitating continuous retraining on expansive datasets. Additionally, many approaches relied on intricate feature engineering and detailed weather data, which may not always be available or reliable, particularly in regions with less developed meteorological infrastructure, thereby hindering practical implementation.

In contrast, this research focuses on addressing these limitations by proposing a simpler yet highly effective approach grounded in real-world measurements. By utilizing readily available data from PV systems and minimizing computational demands, this method enables accurate predictions of power output for various PV module types without compromising performance. This approach leverages operational data to ensure practical and reliable predictions, making it particularly well-suited for environments with limited resources or incomplete weather data. This contribution emphasizes how the use of real measurements can enhance forecasting accuracy while maintaining simplicity, thereby facilitating the more efficient and accessible integration of PV systems into the grid.

This work makes several key contributions to the field of PV power prediction. We address the existing gap in photovoltaic power prediction by utilizing a comprehensive experimental dataset that has been carefully processed and filtered to cover four distinct PV module technologies: amorphous silicon (Amor), monocrystalline silicon (Mono), micromorphous silicon (Micro), and polycrystalline silicon (Poly). Building on a significant experimental study conducted over more than one year, we develop precise prediction methods for estimating the maximum power output of each technology. The proposed prediction model utilizes three primary parameters: solar irradiance, ambient temperature, and module temperature. By incorporating these factors, the model accounts for atmospheric conditions, leading to more reliable power output estimates. The results demonstrate the high reliability of our methods, with R^2 values ranging from 0.95 to 0.99, thereby providing valuable information for the design, optimization, and performance assessment of PV systems.

The remainder of this manuscript is organized to systematically present our research methodology, findings, and analysis. Following this introduction, Section 2 provides a comprehensive review of related work and establishes the motivation behind this study, examining current research in PV power prediction methods and identifying existing gaps

in the literature. Section 3 introduces our methodological framework, detailing the systematic three-phase approach encompassing data collection, prediction method development, and validation strategies. Section 4 then describes the materials and methods employed, including our experimental setup at the UDES facility, the data acquisition system, and the specifications of the four different PV technologies examined, along with the detailed mathematical formulation of our three prediction methods. The experimental results are presented in Section 5, where we analyze the annual maximum power measurements for each PV module type and evaluate the accuracy of our prediction methods using statistical metrics. Section 6 provides a comprehensive discussion of our findings, examining the relationships between power output and various environmental parameters while comparing the effectiveness of our three prediction methods and analyzing their practical implications for different PV technologies. Finally, Section 7 concludes the paper by summarizing our key findings, their significance for PV system design and operation, and suggesting directions for future research.

2. Related Work and Motivation of This Study

Table 1 provides a comprehensive survey of techniques used to predict the maximum power output of photovoltaic modules. The findings suggest that neural networks, particularly deep learning models, are promising for accurate predictions. However, the optimal method selection is influenced by factors such as data availability, computational resources, and desired accuracy.

Table 1. Comparative Analysis of PV Module Maximum Power Prediction Methods.

Author(s)	Methodology	Key Findings
Yadav et al. (2024) [25]	ANN, MLR	ANNs outperform MLRs in predicting PV module maximum power. Solar radiation and air temperature are key influencing factors.
Varanasi et al. (2024) [26]	ANN-PSO, SVR, K-means clustering	ANN-PSO with K-means clustering outperforms SVR for short-term forecasting.
Verma et al. (2016) [27]	ANN, MLR, Regression techniques	ANNs consistently outperform other models in predicting solar power generation.
Miraftabzadeh et al. (2023) [15]	Deep learning (LSTM, RNN)	Deep learning methods show promise in solar power prediction but require extensive computational resources.
Kaaya et al. (2022) [2]	Review	Discusses various solar power forecasting methods, including statistical and machine learning approaches.
Iheanetu KJ. (2022) [3]	Review	Reviews various machine learning techniques used for PV power prediction.
Zhang et al. (2017) [4]	Similar day approach	Proposes a method for predicting solar power output based on historical weather patterns.
Yang et al. (2021) [7]	Kalman filter	Uses a Kalman filter to enhance the precision and reliability of solar power predictions.
Zhang et al. (2021) [6]	Transformer, K-means clustering	Uses transformers and K-means for power prediction, not directly related to solar power generation.
Kumpanalaisatit et al. (2022) [5]	Review	Analyzes the efficiency in the context of systems of agrivoltaic, not directly related to power prediction.
Giorgi et al. (2014) [10]	Statistical methods	Investigates the impact of weather data on solar power forecasting using statistical methods.
Gaboitaolelwe et al. (2023) [11]	Review	Reviews various machine learning techniques used for solar power forecasting.
Alrashidi et al. (2023) [12]	Hybrid data-driven models	Introduces novel hybrid data-driven models for the accurate prediction of short-term solar power generation.
Abdelmoula et al. (2022) [13]	Feature engineering, stacked machine learning	Proposes a method using advanced feature engineering techniques and machine learning models for solar power prediction.
Tercha et al. (2024) [14]	Machine learning	Employs machine learning techniques to forecast temperature and solar irradiance for photovoltaic systems.
Miraftabzadeh et al. (2023) [15]	Deep learning (transfer learning)	Uses transfer learning and deep neural networks for day-ahead PV forecasting.
Scott et al. (2023) [16]	Machine learning	Uses machine learning to forecast photovoltaic generation.

3. Methodology Framework

3.1. Overview of the Methodological Approach

This research employs a systematic experimental methodology to develop and validate three distinct methods for predicting PV module power output. Our approach combines rigorous experimental data collection with analytical modeling to ensure reliable and reproducible results. The methodology framework encompasses comprehensive data acquisition, model development, and validation procedures, all designed to ensure the robustness of our findings across different PV technologies and environmental conditions.

3.2. Phase 1: Data Collection and Processing

The foundation of our methodology rests on a comprehensive data acquisition system implemented at the UDES facility. Our system collects high-frequency measurements at 5 min intervals over a complete one-year period, ensuring the capture of seasonal variations and environmental fluctuations. The collected data undergo systematic filtering and validation processes to eliminate anomalies and ensure data quality. Raw data processing includes compensation for measurement uncertainties and environmental variations, resulting in a clean, reliable dataset for analysis.

3.3. Phase 2: Development of Prediction Methods

This study develops three complementary methods for power prediction, each building upon the previous one with increasing complexity and accuracy. The first method establishes a linear relationship between power output and solar irradiance, providing a foundational approach for basic predictions. The second method enhances prediction accuracy by integrating module temperature effects with irradiance measurements, accounting for thermal influences on PV performance. The third method incorporates ambient temperature data, further refining the prediction model to account for environmental conditions more comprehensively.

3.4. Phase 3: Validation and Analysis

Our validation process employs multiple statistical metrics to ensure the reliability of our predictions. We utilize root mean square error (RMSE) and coefficient of determination (R^2) as primary validation metrics, supplemented by cross-validation across different PV technologies. The analysis includes performance comparison under varying environmental conditions and a comprehensive reliability assessment of each prediction method. This multi-faceted validation approach ensures the robustness of our findings across different operational scenarios.

3.5. Methodological Considerations

3.5.1. Data Quality Assurance

Our methodology incorporates rigorous data quality assurance protocols throughout the research process. This includes regular calibration of measuring instruments, implementation of systematic uncertainty analysis, and continuous monitoring of data quality. We employ multiple validation checks during data collection and processing to ensure measurement accuracy and reliability, establishing a solid foundation for our subsequent analysis.

3.5.2. Model Development Framework

The model development process follows a structured approach to ensure scientific rigor and practical applicability. We carefully select appropriate mathematical models based on established physical principles and empirical observations. The framework includes systematic parameter optimization procedures and continuous model refinement based on experimental results. This iterative approach allows us to develop models that balance complexity with practical utility.

3.5.3. Validation Strategy

Our validation strategy encompasses multiple layers of verification to ensure the reliability and generalizability of our results. We employ comprehensive statistical validation methods to assess model performance across different operating conditions. The strategy includes cross-technology performance assessment to verify model applicability across different PV technologies. Temporal analysis of prediction accuracy ensures model reliability over extended periods, while comparative analysis with existing methods validates our approach against established benchmarks.

4. Materials and Methods

4.1. Experimental Data Acquisition

This study utilizes an experimental dataset collected at the Solar Equipment Development Unit in Bouismail, Algeria (UDES). As shown in Figure 1, the UDES facility features a dedicated outdoor PV module characterization bench. The data acquisition system continuously records voltage, current, irradiance, and temperature at five-minute intervals. Importantly, the system collects data from four distinct PV module technologies with high accuracy. For reference, Table 2 provides the electrical specifications of the PV modules in Standard Test Conditions (STC); more details on this experimental characterization bench are explained in our previous work [28,29].

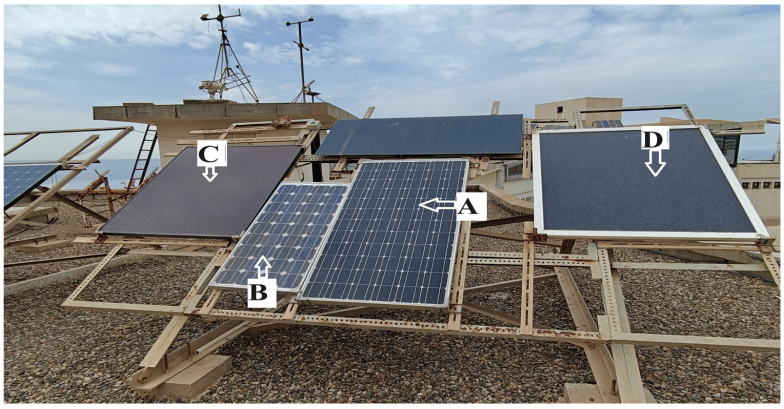


Figure 1. Outdoor test bench for characterizing photovoltaic modules at UDES, Algeria. (**A**) Si monocrystalline (c-Si), (**B**) Si polycrystalline (p-Si), (**C**) Si amorphous (a-Si), and (**D**) Si micromorphous (µm-Si).

Table 2. Specifications of the PV modules in the manufacturer's datasheets at STC conditions.

Specifications	Values of Modules Parameters at STC			
	m-Si	**p-Si**	**a-Si**	**µm-Si**
Maximum power (P_{max})	185 W	135 W	100 W	110 W
Open-circuit voltage (V_{oc})	43.2 V	22.3 V	40.9 V	87 V
Short-circuit current (I_{sc})	5.76 A	8.2 A	3.85 A	1.98 A
Maximum power voltage (V_{mpp})	36 V	17.5 V	30.7 V	64 V
Maximum power current (I_{mpp})	5.14 A	7.71 A	3.25 A	1.76 A
Temperature coefficient of power	−0.1 to −0.3 %/°C	−0.2 to −0.4 %/°C	−0.3 to −0.5 %/°C	−0.4 to −0.6 %/°C
Response time to fluctuating irradiance	Slowest response time (seconds)	Moderate response time (seconds)	Fast response time (milliseconds)	Fast response time (milliseconds)
Degradation rate	Lowest degradation (around 0.1% per year)	Low degradation (around 0.25% per year)	Moderate degradation (around 0.5% per year)	Relatively high (around 1% per year)

The characterization of the PV modules was conducted using a custom-built outdoor test bench. The bench consisted of a platform where the modules were mounted, along with a Kipp and Zonen pyranometer and a silicon reference solar cell for measuring solar

irradiation. Solar panel temperature was monitored using PT100 sensors placed at the center of the module's rear side. An electronic load (PVPM) is used to obtain the I-V curves of the PV panels. Data acquisition was performed using a computer, with measured parameters (current, voltage, temperature, and irradiance) saved for subsequent analysis using a locally developed code. The measurement uncertainties for voltage, current, irradiance, and temperature are approximately ±0.5 V, ±0.01 A, ±10 W/m^2, and ±0.5 °C, respectively.

The dataset employed in this study represents a one-year period recorded in 2022; the selected period for this analysis was chosen due to the exceptional quality of our experimental data collected during this time. The data are rigorously filtered and sorted to eliminate anomalies and potential errors, ensuring the reliability of the obtained results. The measurements are conducted only during daylight hours, from 9 a.m. to 5 p.m., totaling 8 h per day. The data acquisition interval for each photovoltaic module is 10 min. Since our characterization bench is equipped with a data acquisition system for five modules, with a two-minute interval between each module, the complete measurement cycle for all modules takes approximately 10 min.

Therefore, on a daily basis, we obtained approximately 48 measurements per module (8 h/10 min/module). This theoretically gives us a total of approximately 1440 measurements per month. However, it is important to note that several factors can explain the discrepancy between this theoretical number and the actual number of recorded data points: Power outages and interruptions. Power failures or technical issues can lead to data loss. Weather conditions: Adverse weather conditions (clouds, rain) can cause temporary interruptions in measurements. System maintenance: Maintenance interventions can also disrupt data acquisition. Taking these factors into account, we estimate that an average of approximately 1000 data points per month is realistic for our experimental setup. This rich dataset offers valuable insights due to the concurrent variations in irradiance and ambient temperature, enabling the development of reliable prediction models for PV module maximum power output. Figure 2 presents the recorded values of ambient temperature Ta (°C) and irradiation G (W/m^2) throughout the selected period. According to this figure, the measured irradiation exhibited values ranging from 200 to 1100 W/m^2, while the average ambient temperature remained approximately 30 °C throughout the year. Figure 3 provides a comparative analysis of the measured efficiency of the four module types over a 12-month period.

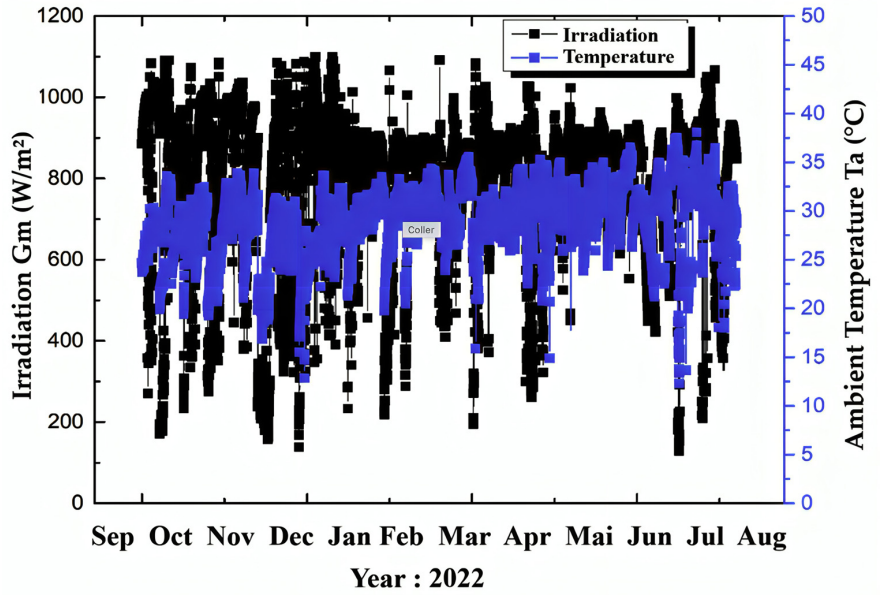


Figure 2. Measured solar irradiation and ambient temperature data for 2022.

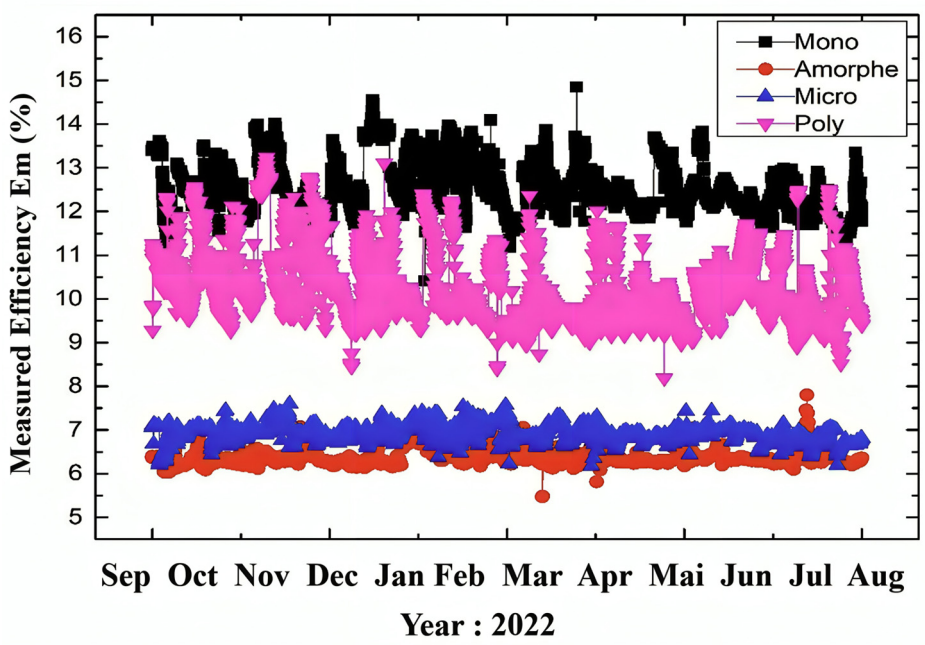


Figure 3. The measured efficiency of the four module types for the year 2022.

4.2. Proposed Methods

4.2.1. First Method (Linear Relationship)

The simplest and quickest method involves establishing a linear relationship between the measured maximum power output of the photovoltaic modules ("Pm") and the measured irradiance ("Gm"). This relationship using experimental data is considered linear, as found by [30]. This relationship can be expressed as Pm = f(Gm), and a fitting procedure can be employed to derive an equation of the following form:

$$Pm = \alpha \times Gm + \beta \quad (1)$$

4.2.2. Second Method (Based on the Maximum Power Modeling)

The effects of heat on electron flow within photovoltaic modules are very important to know. Increased temperature can influence the bandgap energy of the semiconductor material, leading to changes in carrier concentration and mobility. Additionally, elevated temperatures can affect the diffusion length of charge carriers, impacting the overall efficiency of the module. These factors will be incorporated into the two next methods in order to enhance their theoretical basis and improve the ability to accurately estimate the performance of photovoltaic modules under varying temperature conditions.

In this second method, the dependence of the measured maximum power ("Pm") on the two parameters, measured irradiance ("Gm") and measured PV module temperature ("Tm"), is represented by Pm = f (Gm, Tm). This relationship is modeled using the Curve Fit application in Matlab R2014a, as shown in Figure 4. This application provides an adaptable interface that enables interactive adjustment of curves and surfaces to fit the data while displaying graphical representations, as conducted by Ioan Viorel Banu et al. [31] and Michael Koehl et al. [32]. The choice of Curve Fit in MATLAB for model development is based on its robust capabilities for nonlinear regression analysis and its widespread use in scientific research. MATLAB's Curve Fit toolbox offers a user-friendly interface and a variety of fitting functions, making it well-suited for tasks involving complex data modeling. While other software packages and programming languages can be used for data fitting, MATLAB's Curve Fit tool provides several advantages, including:

- Extensive function library: A wide range of fitting functions to choose from, including polynomial, exponential, and trigonometric models. Interactive interface: A graphical user interface that simplifies the process of fitting data and exploring different models.

- Integration with other MATLAB tools: Seamless integration with other MATLAB functions and toolboxes for data analysis and visualization.

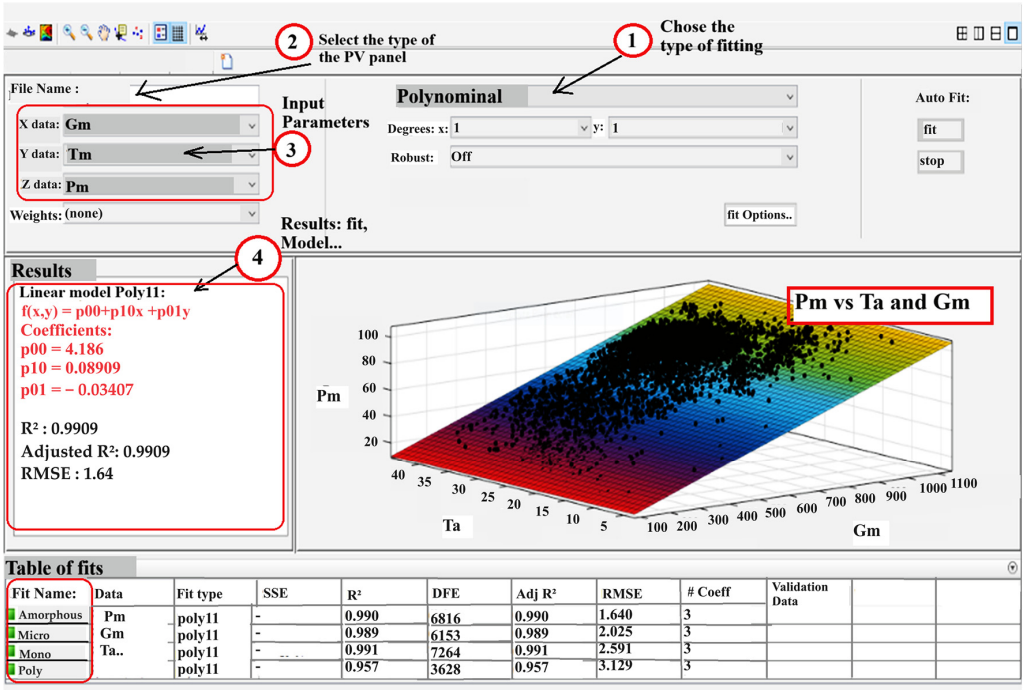


Figure 4. PV Module Maximum Power Model using Curve Fit in MATLAB.

MATLAB's Curve Fit tool is a suitable and effective choice for our research, providing a reliable and versatile platform for developing and evaluating our PV power estimation model. Figure 4 shows an example of data analysis interface for studying photovoltaic (PV) panel performance. At the top of the interface, users can select the type of fitting (marked as 1) and the PV panel type (marked as 2). The input parameters section (marked as 3) allows selection of data variables Gm (solar irradiance), Tm (module temperature), and Pm (power output) for analysis. The results section (marked as 4) displays a polynomial model fit with statistical metrics including R^2 value of 0.9909 and RMSE of 1.64, indicating a very good fit. The right side features a 3D surface plot showing the relationship between Pm versus Ta and Gm, with actual data points scattered around the fitted surface. The bottom table summarizes different fitting results for various types of analysis (amor, micro, mono, poly), each showing high R^2 values above 0.95, demonstrating strong correlation across all fits. The interface includes control buttons at the top for various analysis functions and fitting options accessible through the "fit Options" button on the right.

4.2.3. Third Method (Based on Measured Maximum Power and Measured Temperature)

This third method is very similar to the previous one, except that the measured PV module temperature ("Tm") is replaced with the measured ambient temperature ("Ta") for all module types. The dependence of the measured maximum power ("Pm") on the measured irradiance ("Gm") and the measured PV module temperature ("Tm") is represented by Pm = f(Gm, Tm). This relationship is also modeled using the CURVE FIT application in MATLAB.

4.3. Statistical Evaluation of Model Performance

The performance and adequacy of the proposed models are evaluated using the root mean square error (RMSE) metric, a statistical measure of the differences between predicted and observed values. Smaller RMSE values indicate a better fit for the observed data. The coefficient of determination (R^2) represents the proportion of the variability in the observed

data that is accounted for by the model. R^2 values close to 1 indicate a strong relationship between the proposed model's predictions and the observed values. The relative error (*Er Relative)* expresses the error as a percentage of the observed values. Lower relative error values indicate a better fit to the observed data. These metrics are commonly employed in the literature for evaluating and comparing different models [33]:

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(X_P - X_O)^2} \quad (2)$$

$$R^2 = 1 - \frac{\sum_{i=1}^{N}(X_P - X_O)^2}{\sum_{i=1}^{N}(X_O - \overline{X}_O)^2} \quad (3)$$

$$ERrelative = \left|\frac{H_C - H_M}{H_M}\right| \quad (4)$$

5. Results

Annual Maximum Measured Power of PV Modules

Figure 5 presents a comparison of the measured power over a one-year period for the four PV modules. This power is measured depending on meteorological parameters under real-world conditions. To gain insights into the maximum power output generation capabilities of each PV module type, Table 3 compares the measured maximum power values (Pm) in watts with the power under STC (Pstc) in watt provided by the manufacturer of each PV module. The relative error (ERpm) calculation is also presented in this table. It is observed that the maximum power output values of the three PV modules (micromorphous silicon, amorphous silicon, and monocrystalline silicon) are close to those given by the manufacturer under standardized test conditions compared to the relative error values found ("1.188", "2.011", and "3.959", respectively, for amorphous, mono-, and polycrystalline). In contrast, the polycrystalline silicon module exhibits a significant relative error of "6.493" due to module degradation, as all four modules are not installed simultaneously.

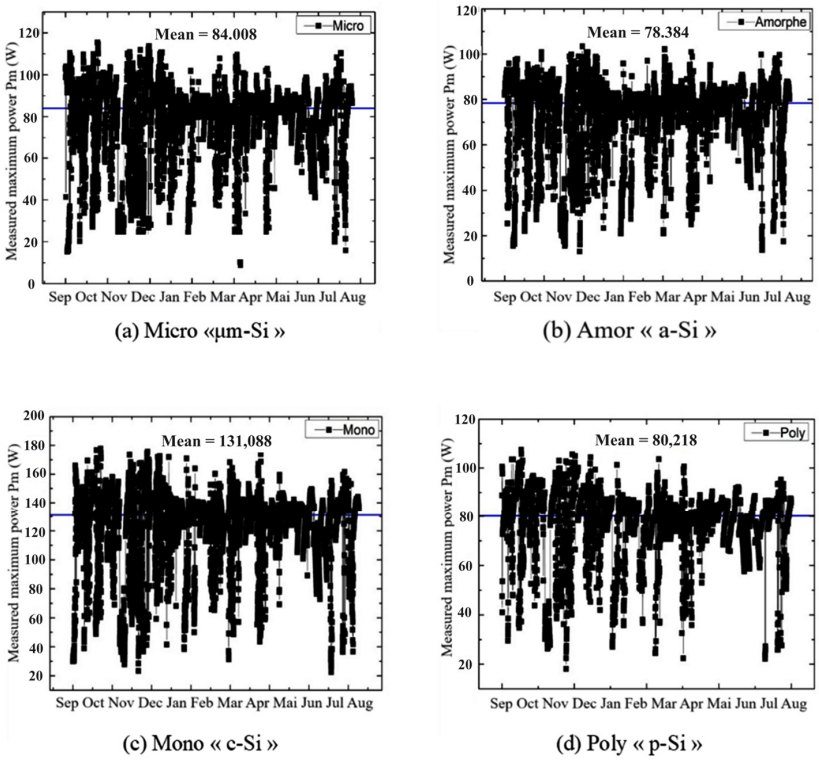


Figure 5. Comparison of the maximum power measured for the four PV modules over a one-year period.

Table 3. Comparison of Measured Maximum Power and STC Power for Four PV Modules.

	STC Power (W) at 1000 W/m^2	Measured Maximum Power (W)	Relative Error ErPm (%)
Micro [µm-Si]	110	108.693	1.188
Amorphous [a-Si]	100	97.989	2.011
Mono [c-Si]	185	177.675	3.959
Poly [p-Si]	115	107.533	6.493

6. Discussion

6.1. Relationship Between Power and Irradiance: First Method Pm (G)

This first method explored the relationship between the power generated by each PV module ("Pm") and the measured solar irradiance ("Gm"). As depicted in Figure 6, this relationship exhibited a linear trend for all PV module types, indicating a strong dependence of the generated power on the irradiation level. The coefficient of determination (R^2) exceeded 0.95 for all PV modules, and the root mean square error (RMSE) remained below 3.8. These findings validated the reliability of the data fitting technique. Table 4 presents a comparison of the coefficients 'α', 'β', R^2, and RMSE for each PV module type.

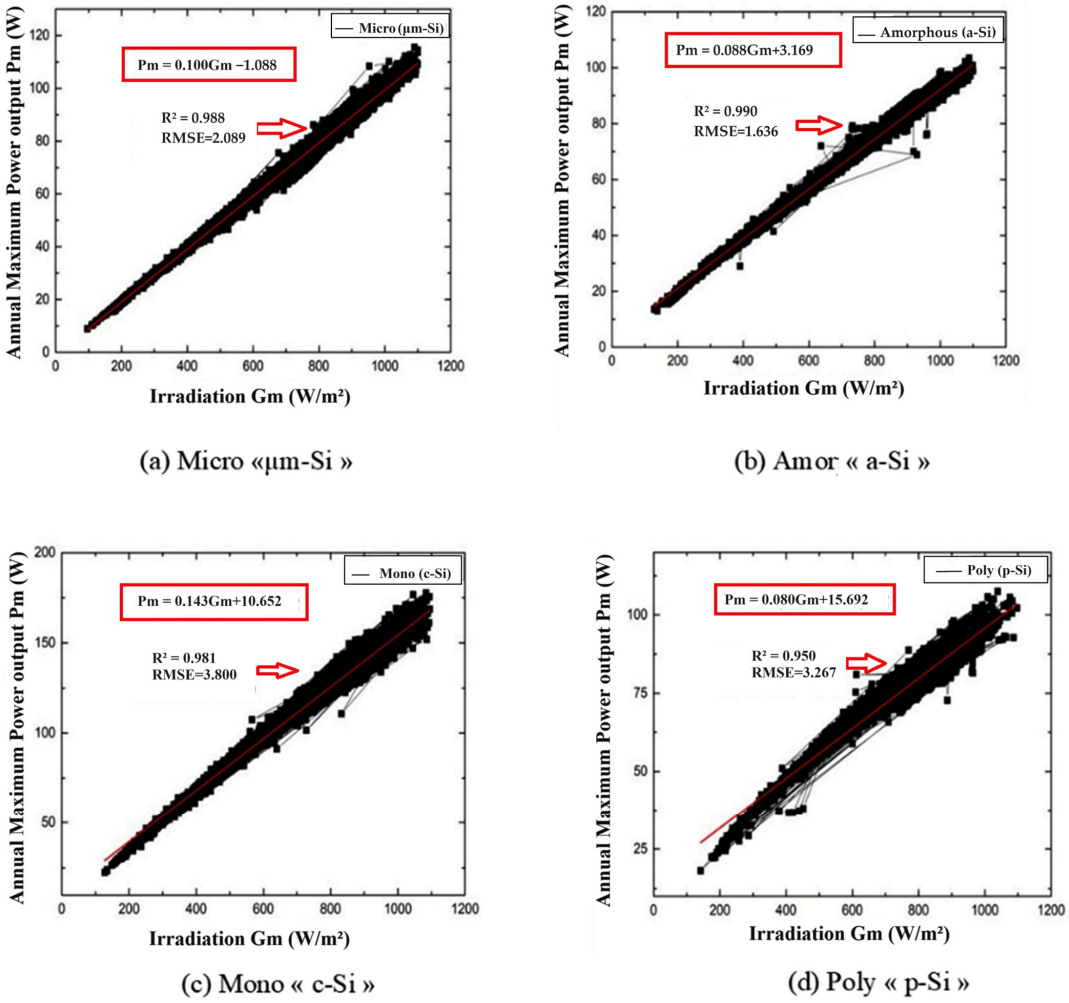


Figure 6. Annual Power Output "Pm" as a Function of Irradiation "Gm" for the Four PV Modules.

Table 4. Comparison of the coefficients 'α' and 'β', R^2, and RMSE for each PV module type using the first method.

	Micro [µm-Si]	Amorphous [a-Si]	Mono [c-Si]	Poly [p-Si]
α	0.100	0.088	0.143	0.079
β	1.054	3.177	10.652	15.77
R^2	0.988	0.99	0.981	0.95
RMSE	2.089	1.636	3.8	3.267

6.2. Power Estimation Considering Irradiance and Module Temperature: Second Method Pm as a Function of (Gm, Tm)

To further enhance the accuracy of estimating the maximum power generated by PV modules, the dependence on module temperature is incorporated. Figure 7 illustrates this relationship: Pm = f(Gm, Tm), obtained using the Curve Fit function for the four PV module types.

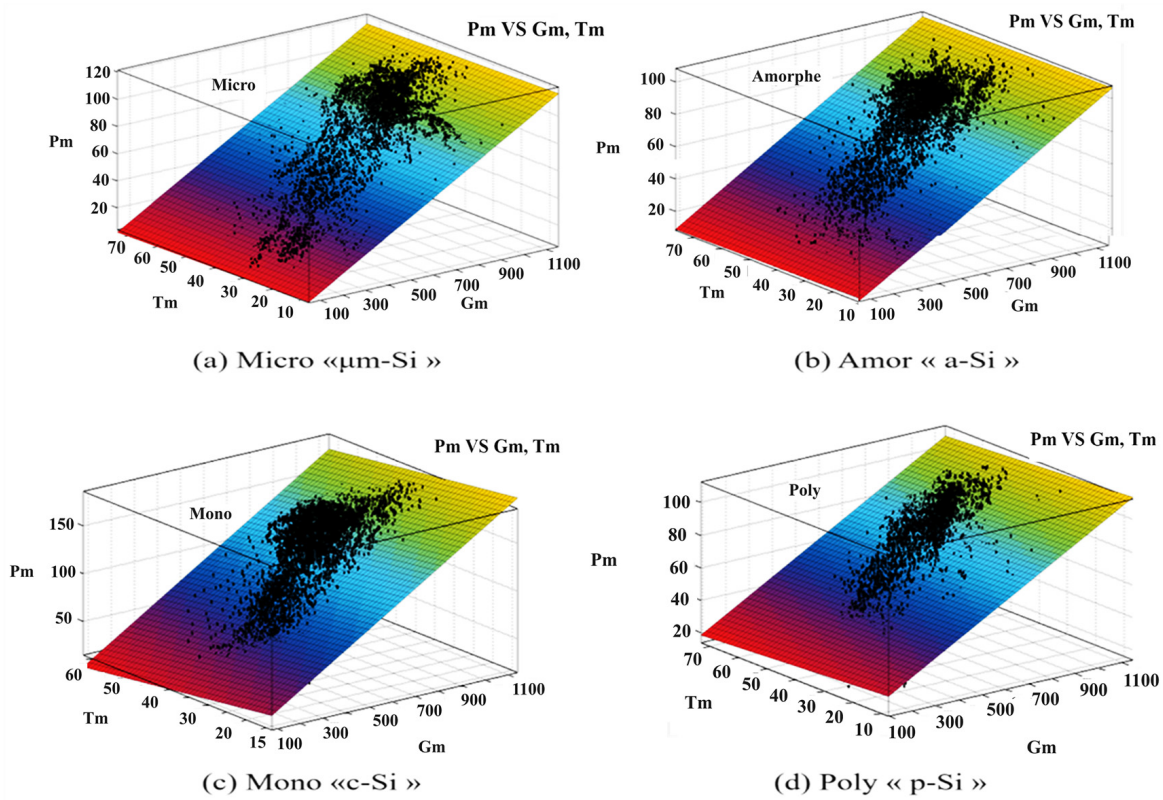


Figure 7. Curve Fit-Based Estimation of Maximum Power (Pm) with Irradiance (Gm) and PV Module Temperature (Tm).

To validate the reliability of this fitting method, the results of the estimated power data ("calculated") as a function of the real power ("measured") are plotted in Figure 8. A linear relationship is observed with an R^2 value exceeding 0.95 and an RMSE value below 3.03, validating the efficacy and robustness of the proposed method in comparison to the first method. Table 5 summarizes all the fitting equations obtained for the four PV module types, along with the calculation of R^2 and RMSE errors.

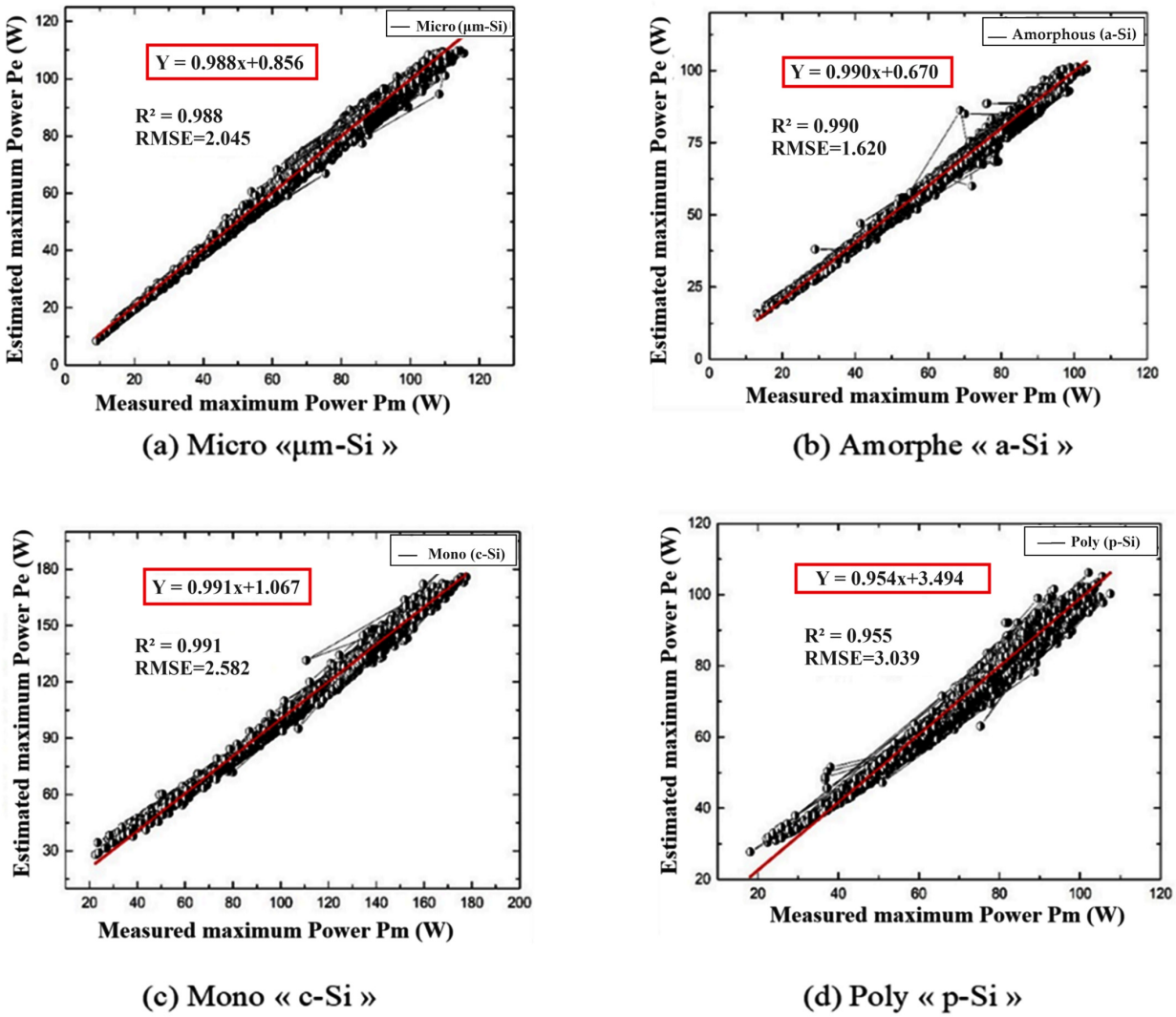


Figure 8. Estimated maximum power data (Pe) as a function of the measured maximum power (Pm) using the second method.

Table 5. Fitting equations were obtained for the four PV module types using the second method.

	Pm = f(Gm, Tm)	R^2	RMSE
Micro [µm-Si]	Pm = 0.2191 + 0.1013 × Gm − 0.03552 × Tm	0.988	2.045
Amorphous [a-Si]	Pm = 3.974 + 0.0896 × Gm − 0.0264 × Tm	0.990	1.620
Mono [c-Si]	Pm = 24.85 + 0.1572 × Gm − 0.562 × Tm	0.991	2.582
Poly [p-Si]	Pm = 18.76 + 0.08314 × Gm − 0.1135 × Tm	0.955	3.039

6.3. Power Estimation Considering Irradiance and Ambient Temperature: Third Method with Pm as a Function of (Gm, Ta)

This third method introduces the influence of ambient temperature 'Ta.' Figure 9 illustrates this relationship: Pm = f(Gm, Ta), obtained using the Curve Fit function for the four PV module types. To validate the reliability of this fitting method, the estimated power data ("calculated") is plotted against the actual power ("measured") in Figure 10. A linear relationship is observed with an R^2 value exceeding 0.957 and an RMSE value below 3.06, further confirming the reliability of this proposed method. Table 6 provides all the fitting equations obtained for the four PV module types, and Table 7 summarizes the comparison of the three proposed power estimation methods.

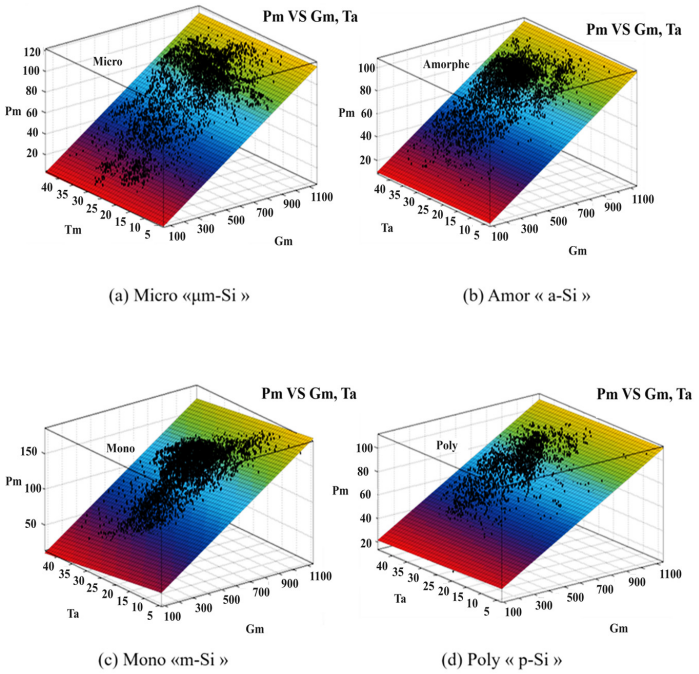


Figure 9. Curve Fit-Based Estimation of Maximum Power (Pm) with Irradiance (Gm) and Ambient Temperature (Ta).

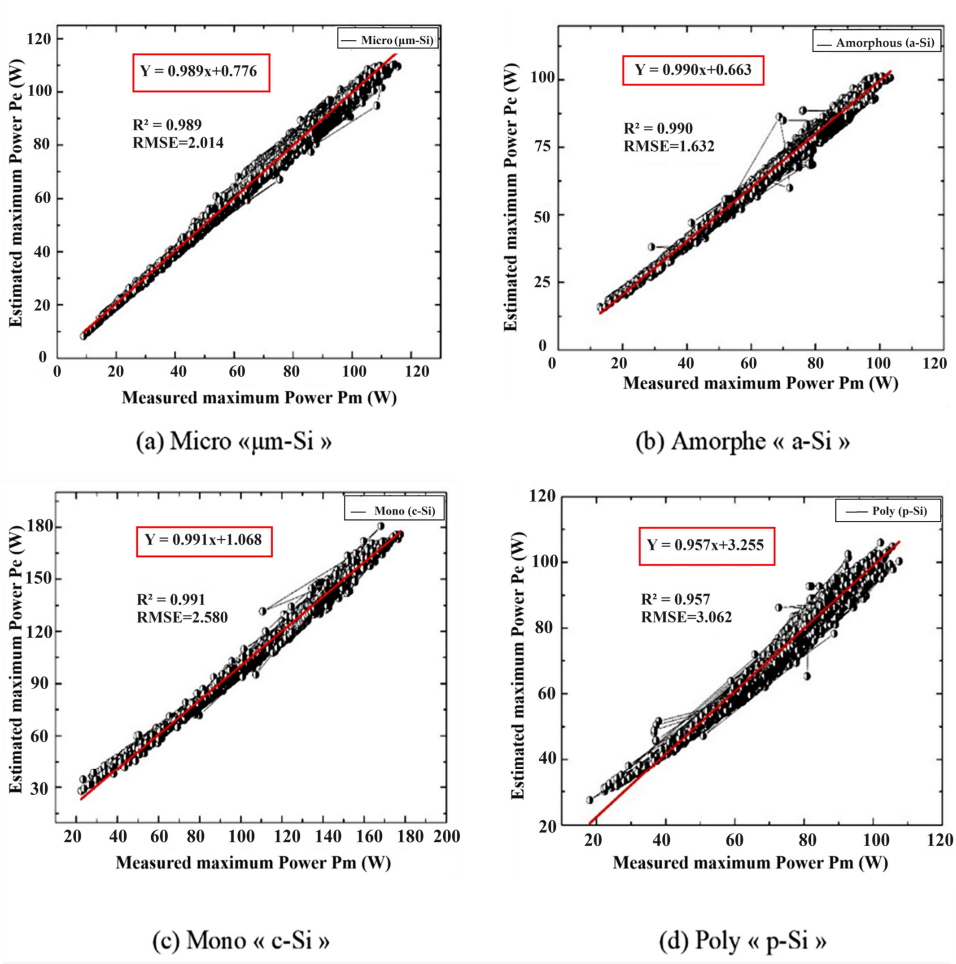


Figure 10. Estimated maximum power data (Pe) based on the maximum measured power (Pm) using the third method.

Table 6. Fitting equations were obtained for the four PV module types using the third method.

	Pm = f(Gm, Tm)	**R^2**	**RMSE**
Micro [µm-Si]	Pm = 0.1498 + 0.101 × Gm − 0.05334 × Ta	0.989	2.014
Amorphous [a-Si]	Pm = 4.186 + 0.08909 × Gm − 0.03407 × Ta	0.990	1.632
Mono [c-Si]	Pm = 24.9 + 0.146 × Gm − 0.5649 × Ta	0.991	2.580
Poly [p-Si]	Pm = 17.78 + 0.0813 × Gm − 0.08587 × Ta	0.957	3.062

Table 7. Comparison of the three proposed power estimation methods.

	First Method	**Second Method**	**Third Method**
Required parameters	• Measured power (Pm) • Measured Irradiation (Gm)	• Measured power (Pm) • Measured Irradiation (Gm) • PV Module Temperature (Tm)	• Measured power (Pm) • Measured Irradiation (Gm) • Ambient Temperature (Ta)
R^2	0.95–0.99	0.955–0.991	0.957–0.991
RMSE	1.63–3.8	1.620–3.039	1.632–3.062
Ease of use	Very easy	Easy	Easy
Accuracy	Medium	High	High
Computational complexity	No complexity	Medium complexity	Medium complexity
Required data	More than 1000	More than 10,000	More than 10,000

To provide a more comprehensive understanding of the relevance of different module types in various climates, we have expanded our discussion on the characteristics and advantages of each type. Monocrystalline silicon modules, known for their high efficiency, are particularly well-suited for regions with high solar irradiance, such as those closer to the equator. Polycrystalline silicon modules, while slightly less efficient than their monocrystalline counterparts, offer a good balance between performance and cost. Amorphous silicon modules excel in low-irradiance conditions, making them suitable for regions with frequent cloud cover or shading. Micromorphous silicon modules are known for their flexibility and potential for large-scale production, making them attractive options for various applications, especially in regions with limited space or unconventional installation requirements. The inclusion of these four distinct module types in our study allows us to evaluate their performance across a wide range of climatic conditions, providing valuable insights for researchers and practitioners seeking to optimize photovoltaic system design and deployment in different geographic locations.

Regarding the interpretation of RMSE and R^2 metrics, while these coefficients are commonly used in regression, there are no universal thresholds for judging the quality of a model in the specific field of photovoltaic power estimation. In our study, we chose to evaluate the performance of our models by comparing them to experimental data. Figures 8 and 10, which represent the relationship between estimated power and measured power, show a strong linear correlation. This observation suggests that our model is capable of capturing the main trends in photovoltaic energy prediction.

The methodology employed in this study offers a significant advantage in terms of generalizability. By relying solely on the parameters provided in the module manufacturer's datasheet, the proposed model eliminates the need for intricate physical measurements within the cells themselves. This approach enables the application of our technique to a wide range of photovoltaic module types. The versatility of our method is further demonstrated by the inclusion of four distinct cell types in this current study. Despite the diversity of these modules, the proposed technique remained consistent across all, highlighting its applicability to various photovoltaic technologies without requiring significant modifications.

6.4. Industrial Implementation and Practical Applications

The industrial implementation of our proposed prediction methods offers significant practical advantages for various scales of photovoltaic installations. The approach's strength lies in its scalability and cost-effectiveness, requiring minimal additional instrumentation for implementation. For large-scale applications, these methods can be readily integrated into existing SCADA systems, with implementation costs typically less than 0.1% of total plant cost. The first method, using only irradiance measurements, is particularly suitable for developing regions with limited monitoring capabilities, while the second and third methods can be integrated with existing thermal monitoring systems or weather station data for enhanced accuracy. The computational efficiency enables real-time power prediction with response times under one second, facilitating better grid integration and power management. These methods support predictive maintenance strategies by establishing clear performance baselines and detecting degradation trends early. Implementation requires minimal training for technical staff and can typically be completed within one week. The approach has demonstrated robust performance in pilot projects, making it suitable for industrial applications where both performance and cost-effectiveness are crucial considerations. Future applications could include integration with smart grid management systems, automated performance monitoring, and optimization of energy storage systems.

The economic benefits of our proposed prediction methods are compelling due to their cost-effective implementation and operational advantages. With an implementation cost of less than 0.1% of total plant cost, these methods provide significant returns through improved system efficiency and reduced maintenance costs. For a typical 1 MW solar plant, the approach can increase annual energy yield by 2–3% through optimized operation, potentially generating additional revenue of USD 5000–7500 annually (at USD 0.10/kWh). The minimal instrumentation requirements, particularly in the first method, which uses only irradiance measurements, make it especially attractive for developing regions where cost constraints are significant. Further economic advantages include reduced downtime through early fault detection and lower grid integration penalties through improved prediction accuracy.

7. Conclusions

Of the various natural energy resources, solar energy is one that currently presents the most significant investment. This study has advanced the field of photovoltaic power prediction by developing and validating three distinct methods for estimating maximum power output across different PV technologies. Through extensive experimental analysis conducted over a one-year period, we have demonstrated that reliable power predictions can be achieved using readily available environmental parameters. The methodologies developed here have shown exceptional accuracy, with R^2 values consistently ranging from 0.95 to 0.99 and RMSE values between 1.6 W and 3.8 W across all module types tested.

Our comprehensive analysis of four PV technologies, amorphous silicon, monocrystalline silicon, micromorphous silicon, and polycrystalline silicon, has revealed distinct performance characteristics under varying environmental conditions. The first method, based solely on irradiance measurements, provides a quick and reliable estimation tool with minimal computational requirements. The second and third methods, incorporating module temperature and ambient temperature, respectively, offer enhanced prediction accuracy by accounting for thermal effects on PV performance. These methods' success across different module types demonstrates their versatility and broad applicability.

The significance of this research extends beyond its methodological contributions. By establishing reliable prediction methods that require only basic environmental parameters, this work addresses a critical need in developing regions where sophisticated monitoring equipment may be unavailable. The simplicity and accuracy of these methods make them particularly valuable for regions with abundant solar resources but limited technical infrastructure. Furthermore, the comparative analysis of different PV technologies provides

essential insights for system designers and investors, enabling more informed decisions in technology selection based on local environmental conditions.

Looking ahead, future research directions should explore the integration of additional environmental parameters and the effects of long-term module degradation on prediction accuracy. The methodologies developed here provide a foundation for real-time prediction capabilities and could be extended to emerging PV technologies. As the global transition to renewable energy continues, these prediction methods offer valuable tools for optimizing photovoltaic system performance and enhancing the reliability of solar power generation.

This work significantly contributes to the advancement of photovoltaic energy deployment by providing practical, reliable methods for power prediction that can be readily implemented across various technological and geographical contexts. The findings support better system design, more accurate performance forecasting, and, ultimately, more efficient utilization of solar energy resources.

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