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Research Paper

Modeling and Experimental Validation of a Solar Panel for Digital Twin Applications

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Abstract

As the global demand for renewable energy grows, effective management of photovoltaic (PV) systems is essential as the world's need for renewable energy increases. This paper presents the modeling and experimental validation of a 60 W monocrystalline photovoltaic module, with a focus on digital twin applications for photovoltaic system management, particularly energy generation forecasting and fault detection. The proposed model is based on the Single Diode Model (SDM), an electrical modeling approach widely adopted due to its balanced trade-off between simplicity and accuracy, and experimental validation of a 60 W monocrystalline PV module. A hybrid optimization technique that combines Powell's method and Particle Swarm Optimization (PSO) was created to estimate model parameters. Compared to standard PSO methods, which usually require 1,000 iterations, this hybrid approach achieved high accuracy in just 100 iterations. The modeling was implemented in MATLAB/Simulink and experimentally validated using data collected under two solar irradiance conditions (1000 W/m² and 500 W/m²), at 25°C and air mass AM1.5, using a flash-type solar simulator. The current-voltage (I-V) and power-voltage (P-V) curves showed remarkable precision, with R^2 values exceeding 0.998 and with MAE values of 0.2932W. Based on these results, the developed model proves to be highly suitable for digital twin-based applications, especially in scenarios that require high reliability, such as energy forecasting and real-time fault diagnosis. Furthermore, the developed experimental dataset is made publicly to support researchers who do not have access to specialized laboratory infrastructure.

Keywords: Single diode model; PSO-Powell; Photovoltaic panel modeling; Experimental validation; Digital twin; Energy forecasting; Fault detection, Simulink.

1. Introduction

The growing demand for energy and technological advances in photovoltaic cells, especially monocrystalline silicon cells, which have led to increased efficiency and reduced module costs, have consolidated solar photovoltaic energy as one of the main sources of renewable energy. It is now a critical component of the global energy matrix, accounting for 6.9% in 2024 [1]. This growth, however, has brought new operational and

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maintenance challenges for these systems, particularly the need for continuous performance monitoring, early fault detection, and tracking of module degradation over time. Issues such as partial shading, dirt accumulation, electrical connection failures, hot spot formation, and inverter inefficiencies can lead to significant reductions in energy production if not detected promptly [2].

The digital twin is a virtual representation of a physical object, process, or system, capable of simulating its behavior in real time through continuous data exchange between the physical and virtual components. In photovoltaic systems, digital twins have the potential to revolutionize operations and maintenance by enabling real-time monitoring, accurate fault diagnosis, and simulation of operational scenarios that may lead to greater operational efficiency as well as cost reduction [3-6]. The reliability and accuracy of a digital twin depend directly on the precision of the model in representing the physical system, especially in applications involving fault diagnosis and prediction [7-8].

Among the approaches for building digital twins in photovoltaic systems, the most prominent are data-driven models, physics-based models (also known as mechanistic models, such as the Single Diode Model – SDM), and hybrid models that combine both strategies to integrate interpretability with predictive flexibility [9-14]. This work adopts the physics-based modeling approach, specifically the SDM, which is widely used in photovoltaic applications due to its balance between simplicity and fidelity to the real behavior of the module. The choice of this approach aligns with the objective of developing a digital model with a high degree of fidelity and reliability, which is essential for applications such as energy generation forecasting and fault detection and diagnosis while remaining compatible with future hybrid extensions through integration with data-driven techniques.

Although many studies have already explored the modeling of photovoltaic modules based on the SDM, significant limitations still persist that may compromise the fidelity, applicability, and reliability of the generated models:

i. Modeling based solely on manufacturer data: modeling that relies exclusively on datasheet values provided by manufacturers tends to be less accurate compared to approaches based on experimental data, as it lacks I–V and P–V curves obtained under real conditions, which are essential for robust validation. This limitation affects the fidelity and applicability of the resulting models, especially in critical applications such as digital twins for fault diagnosis, where small discrepancies between the model and the physical system can lead to incorrect decisions [15-20]. However, studies such as [21-24] rely on manufacturer data, while others like [23, 25] use experimental data but focus on reference cells, such as the RTC France cell, rather than complete modules.

ii. Use of photovoltaic mini-modules: mini-modules are useful for preliminary testing and educational purposes but do not accurately reflect real-world operating conditions, as they differ in materials, encapsulation, and electrical configuration. Therefore, models derived from such devices tend to be less representative for demanding applications such as digital twins [26-27]. However, studies such as [27-28] make use of photovoltaic mini-modules.

iii. Low-accuracy parameter estimation methods: the quality of the models depends on the accuracy of the estimation of their electrical parameters, such as series resistance, shunt resistance, saturation current, ideality factor, and photocurrent [29-32]. However, some studies such as [27, 33-34] still rely on traditional methods like Newton-Raphson, linear adjustments, or genetic algorithms (GA), which can lead to considerable errors, especially under off-maximum-power-point operating conditions, while others like [31, 35-37] apply more advanced algorithms such as PSO, JAYA optimization algorithm, and the Equilibrium Optimizer (EO), but focus on reference cells like Radio Technique Compelec (RTC) France cell rather than on actual modules.

iv. Use of experimental data obtained under inadequate artificial lighting: the electrical response of photovoltaic cells varies significantly depending on the lighting conditions or light source. For this reason, experimental data from modules should be obtained under Standard Test Conditions (STC), using certified solar simulators that comply with technical standards to ensure the reliability of the data [38]. This ensures that the modeled performance accurately reflects real-world operating conditions [39]. However, studies such as [28] use artificial lighting that does not accurately replicate the spectrum and intensity of natural sunlight.

In contrast to the above studies, this paper provides the following contributions:

- Modeling and validation of a 60 W monocrystalline photovoltaic module based on experimental data.
- Validation of the model using data obtained from a flash-type solar simulator under STC.
- Estimation of electrical parameters using a hybrid approach combining PSO and Powell methods, enabling efficient global search with local refinement. This combination results in more realistic parameters and models that closely match the experimental characteristic curves, which are essential for critical applications such as digital twins for fault diagnosis.
- Provision of a validated digital model for integration into digital twins aimed at energy estimation and fault detection.
- Publication of an experimental dataset including measurements of voltage, current, temperature, and solar irradiance, to support researchers without access to laboratory infrastructure in modeling solar modules and developing digital twin applications.

2. Mathematical Modeling of the Module

2.1. Single-Diode Model (SDM)

The electrical model used in this work is based on the SDM, which is widely adopted in the literature for offering a good balance between accuracy and computational simplicity. This model represents the photovoltaic module as a photocurrent source (Iph) connected in parallel with an ideal diode, along with a series resistance (Rs) and a parallel (shunt) resistance (Rsh). The photocurrent (Iph) acts as the primary source of electrical current, while the ideal diode simulates the PN junction under different operating conditions. The series resistance accounts for internal ohmic losses, whereas the parallel resistance models leakage currents. The SDM has five main parameters that must be accurately estimated: photocurrent (Iph), diode saturation current (I0), series resistance (Rs), shunt resistance (Rsh), and diode ideality factor (n) [40-41]. The choice of this model is supported by recent studies [14, 42-47] that discuss analytical and metaheuristic methods applied to the SDM, highlighting its practical relevance, simplicity, and reliability. When properly parameterized, the SDM provides results comparable to those of more complex models while maintaining high accuracy. For these reasons, the SDM was adopted in this work, particularly due to its clear and streamlined structure, which facilitates integration with hybrid optimization methodologies and digital twin frameworks. Figure 1 shows the electrical circuit corresponding to the SDM.

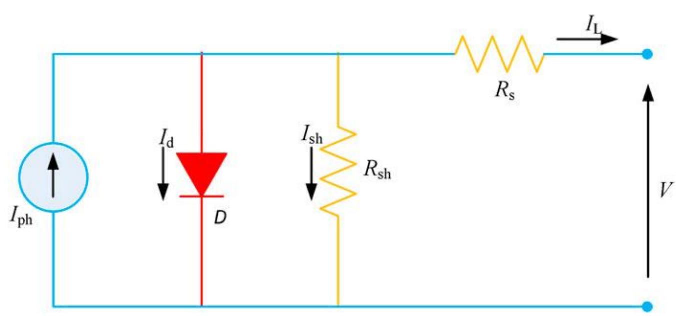

Figure 1. Equivalent electrical circuit of the SDM [48].

From the circuit, using Kirchhoff's laws, the single-diode model yields the following equations 1-7:

The $I_L = I_{ph} - I_d - I_{sh}$ (1)

$$I_d = I_0\left[exp\left(\frac{q(V+I_L.R_S)}{nN_SkT}\right) - 1\right] \quad (2)$$

$$I_{sh} = \frac{V+I_L.R_S}{R_{sh}} \quad (3)$$

$$I_{ph} = [I_{sc} + k_i(T - 298)]\frac{G}{1000} \quad (4)$$

$$I_0 = I_{rs}\left(\frac{T}{T_n}\right)^3 .\exp\left[\frac{qE_{g0}}{nk}\left(\frac{1}{T_n} - \frac{1}{T}\right)\right] \quad (5)$$

$$I_{rs} = \frac{I_{SC}}{\exp\left(\frac{qV_{OC}}{nN_SkT}\right) - 1} \quad (6)$$

$$I_L = I_{ph} - I_0\left[exp\left(\frac{q(V+I_L.R_S)}{nN_SkT}\right) - 1\right] - \frac{V+I_L.R_S}{R_{sh}} \quad (7)$$

Where:

I_L: Output current of the cell/panel
V: Output voltage of the panel
I_{ph}: Photogenerated current
I_d: Diode current
I_{sh}: Shunt (leakage) current
I_0: Diode saturation current
I_{rs}: Reference saturation current
I_{sc}: Short-circuit current
V_{oc}: Open-circuit voltage
R_s: Series resistance
R_{sh}: Shunt (parallel) resistance
N_s: Number of cells in series
k: Boltzmann constant (1.38×10^{-23} J/K)
q: Electron charge (1.6×10^{-19} C)
T: Cell temperature (K)
T_n: Nominal temperature (298 K)
G: Solar irradiance (W/m^2)
k_i: Temperature coefficient of short-circuit current
E_{g0} Bandgap energy of the semiconductor at 0 K
n: Diode ideality factor

2.2. Hybrid Particle Swarm Optimization (PSO) + Powell algorithm for parameter estimation

The parameter estimation was carried out using a hybrid algorithm that combines PSO with Powell's local refinement technique, aiming to enhance the estimation process. PSO is an algorithm inspired by social behavior patterns observed in nature, widely recognized for its efficiency in searching for optimal or near-optimal solutions [37, 43, 49-50]. This method iteratively updates the position of the particles within a predefined search space in order to minimize an objective function [51-53], in this study, the error between the simulated I–V curve and the experimental data obtained from the photovoltaic module was minimized. The objective function used is shown in Equation 8.

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(I_{simulado}(V_i) - I_{experimental}(V_i)\right)^2} \qquad (8)$$

To enhance the robustness of the results and avoid stagnation in local minima, PSO was complemented with the Powell method, which acts as a local refinement technique for the solutions obtained. This two-stage approach is particularly well-suited for dealing with the highly nonlinear nature of the single-diode model, enabling more efficient exploration of the search space and more accurate adjustment of the estimated parameters [54-55].

2.3 PSO-Powell hybrid algorithm flowchart

Figure 2 shows the workflow of the hybrid optimization process for estimating photovoltaic (PV) model parameters using Particle Swarm Optimization (PSO). By updating particle positions and velocities, the algorithm iteratively minimizes the root mean square error (RMSE) between simulated and measured PV characteristics. Following convergence, a local Powell-based refinement is used to increase accuracy, and key PV parameters (Isc, Voc, and Pmax) are used for validation.

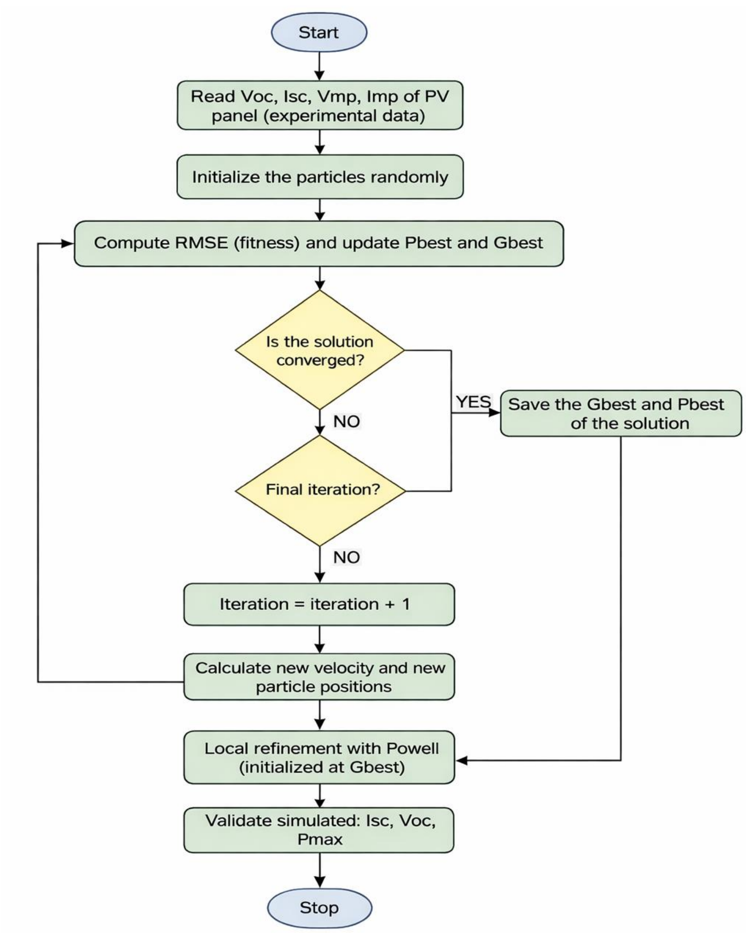

Figure 2. Implemented PSO-Powell hybrid algorithm flowchart.

3. Materials and Methods

The experimental tests were carried out using a flash-type solar simulator at the Institute of Energy and Environment of the University of São Paulo (IEE-USP). This equipment reproduces the Standard Test Conditions (STC) as shown in Figure 3. Lower and upper bounds were defined to guide the search within physically plausible regions, avoiding unrealistic or divergent solutions. These bounds were established based on the electrical characteristics of the photovoltaic module used Table I and recommendations from the literature [56-60].

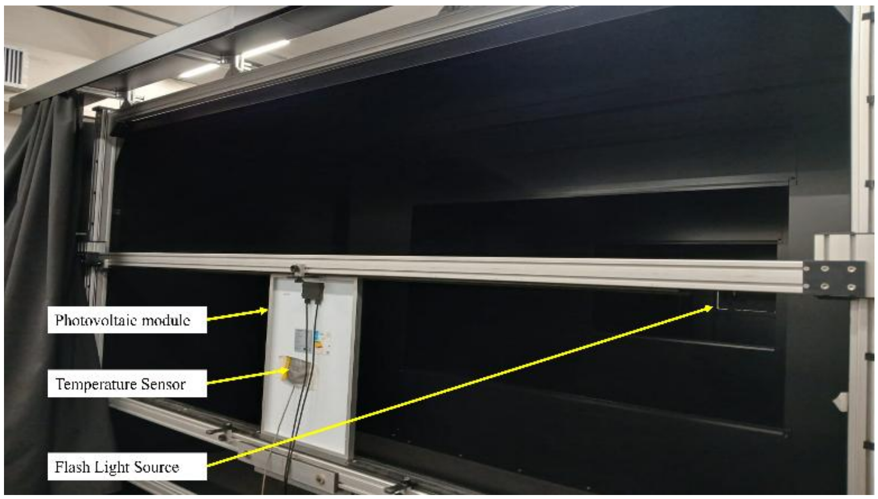

Figure 3. Flash-Type Solar Simulator at IEE-USP.

Table 1. Technical specifications of the photovoltaic module used

Parameter	Value
Nominal power (Pmax)	60 W
Voltage at maximum power point (Vmp)	18.62 V
Current at maximum power point (Imp)	3.20 A
Open-circuit voltage (Voc)	21.7 V
Short-circuit current (Isc)	3.56 A
Efficiency	17.89%
Maximum system voltage	600 V
Maximum fuse current	5 A
Power temperature coefficient	-0.51%/K
Voltage temperature coefficient	-0.39%/K
Current temperature coefficient	+0.08%/K
Number of cells	32 (monocrystalline silicon)
Technology	PERC
Dimensions (L × W × H)	742 × 452 × 25 mm
Total module area	0.335 m²
Weight	2.4 kg
Protective enclosure IP code	IP65

The photogenerated current I_{ph} was set between $0.9.I_{sc}$ and $3.1.I_{sc}$, covering both shading losses and deviations from the ideal short-circuit current. The saturation current I_0, typically ranging from 10^{-12} to 10^{-6} in silicon cells, was limited to this interval. The diode ideality factor $\alpha = n.N_s$ was constrained between 1.0 and 1.7, typical values for monocrystalline modules. The use of PERC technology in the tested module, known for its passivation techniques that reduce recombination and enhance efficiency, justifies not considering $n = 2$. The modeling of the photovoltaic module was carried out using MATLAB/Simulink, employing blocks that represent the equations of the single-diode model described in Section 2.
The series resistance R_s was bounded between 0.01 and $0.5\ \Omega$, while the shunt resistance R_{sh} was set between 100 and $800\ \Omega$ representing ohmic and leakage losses, respectively. These constraints improve the robustness of the optimization process, preventing physically unfeasible local minima and ensuring coherence of the estimated parameters. Table 2 presents the defined lower and upper bounds for each parameter.

Table 2. Configuration of the Lower and Upper Bounds of the Optimized Parameters

Parameter	Lower Bound	Upper Bound
I_{ph}	0.9 *Isc*	3.1 *Isc*
I_0	1×10^{-12}	1×10^{-6}
n	1.0	1.7
R_s	0.01	0.5
R_{sh}	100	800

3.1. PSO Configuration

For the PSO algorithm configuration, a maximum of 500 iterations was initially set. However, experimental results showed that convergence was consistently achieved well before this limit. At 100 iterations, the root mean square error (RMSE) was already below 0.0983, indicating that the PSO effectively explored the search space and approached the global minimum. Given this satisfactory early convergence and the subsequent application of Powell's method for local refinement, the number of PSO iterations was reduced to 100. This configuration enabled Powell's method to accurately locate the absolute minimum within the converged region, ensuring stable and precise parameter estimation while significantly reducing the overall computational cost. The initial population consisted of 50 particles, uniformly distributed within the predefined bounds of the five parameters to be estimated. The stopping criterion was defined as swarm convergence or reaching the maximum number of iterations, whichever occurred first. Table 3 summarizes the final PSO configuration adopted for the parameter estimation of the photovoltaic model.

Table 3. PSO Configuration

Category	Details
Algorithm	PSO
Objective	RMSE minimization
Number of parameters	5
Initial population	50 particles
Maximum iterations	100
Stopping criterion	Maximum iterations reached
Initialization	Random (uniform within bounds)

3.2. Powell Configuration

After the global search performed by PSO, the Powell method was employed for local refinement of the parameters, aiming to improve the accuracy of the estimates by using the best global solution as the starting point. Table 4 presents the configuration used for the Powell method.

Table 4. Configuration of the Powell Method for Local Refinement

Category	Details
Algorithm	Powell (derivative-free local optimization)
Objective	Refine the parameters obtained by PSO
Initial guess	Best global solution from PSO
Optimization method	"Powell" via scipy.optimize
Parameter bounds	Same as those defined in the PSO
Maximum number of iterations	100
Stopping criterion	Maximum iterations reached

4. Results and Discussion

The following presents the results obtained from the model validation experiments, followed by a discussion on the accuracy, robustness, and applicability of both the proposed method and the resulting digital model of the photovoltaic module.

4.1 Estimated Parameters

The parameters estimated using PSO and PSO enhanced with Powell are presented in Table 5. Figure 5 visually highlights the superior accuracy of the hybrid approach (PSO + Powell) in replicating the experimental I–V curve, while Table V displays the corresponding numerical values obtained by each method. Given the noticeable deviation of the PSO only curve from the experimental data, the discussion will focus solely on the comparison between the experimental results and the curve obtained using the hybrid estimation approach. This decision is supported by the fact that the PSO only model fails to accurately capture the knee and tail regions of the I–V characteristic, which are critical for evaluating model fidelity.

Table 5 Comparison of the Estimated Parameters (SDM) using PSO and PSO + Powell

Parameter	Unit	Value (PSO)	Value (PSO+Powell)
I_{ph}	A	3.4568	3.4275
I_0	A	1.0000e-10	3.2272e-10
n	–	1.1179	1.1577
R_s	Ω	0.50309	0.24018
R_{sh}	Ω	390.6199	406.3782

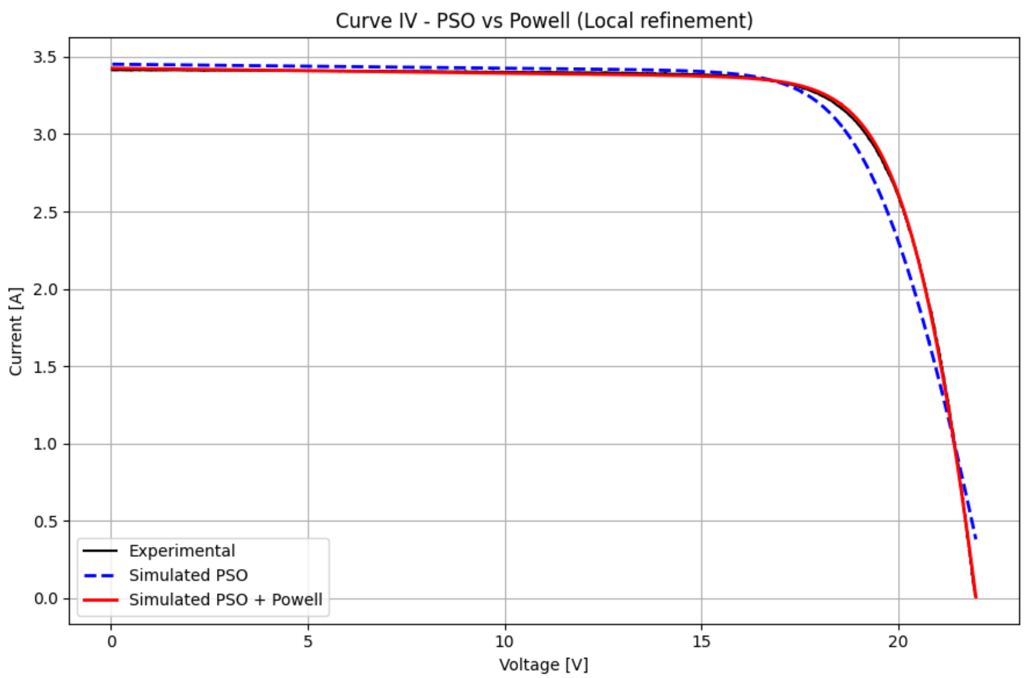

Figure 5. Comparison between the experimental I–V curve and the curves generated by PSO and PSO + Powell.

4.2 Experimental vs Simulated Curves (I-V and P-V)

After determining the model parameters, it is essential to validate the accuracy of the proposed approach. To this end, the characteristic current-voltage (I–V) and power-voltage (P–V) curves generated by the simulated model, using the estimated parameters, are compared with experimental measurements. This visual comparison enables assessment of the model's fidelity in replicating the real behavior of the photovoltaic module under different operating conditions. The corresponding curves are presented in the figures below.

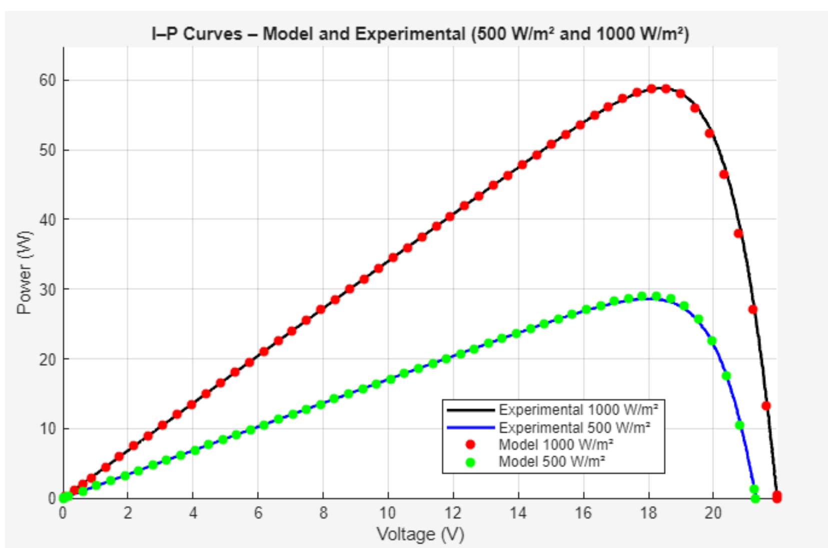

Figure 6. I–V Curve, Model vs Experimental (500 W/m² and 1000 W/m²)

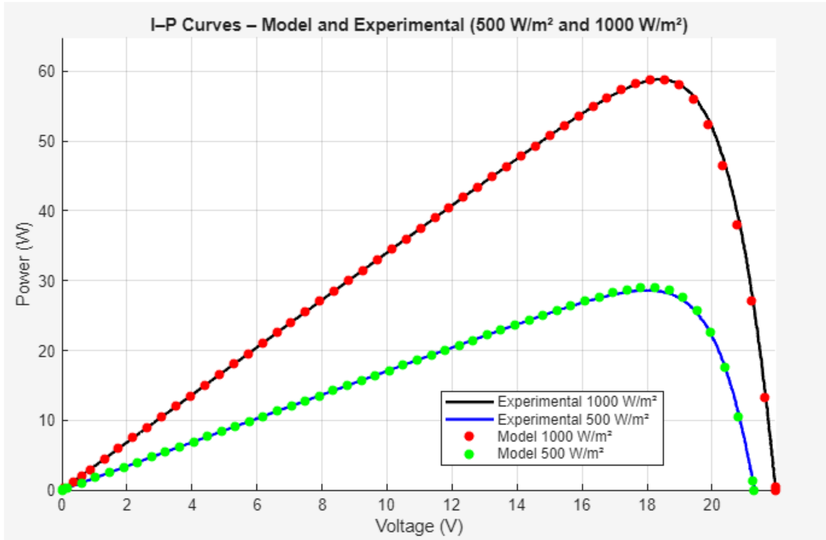

Figure 7. P–V Curve, Model vs Experimental (500 W/m² and 1000 W/m²)

4.3 Error Metrics

To evaluate the performance of the obtained model, five widely recognized statistical metrics were employed: Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Coefficient of Determination (R^2), and Mean Absolute Percentage Error (MAPE). These indicators quantify the discrepancy between the model's predictions, based on the extracted parametersand the experimental data collected in real time from the photovoltaic panel. RMSE, MSE, and MAE evaluate the magnitude of the prediction errors. RMSE and MSE penalize larger deviations more heavily due to squaring, while MAE offers a more robust measure against outliers. In all three cases, lower values indicate better model performance, with zero representing a perfect fit. R^2 measures the proportion of variance in the experimental data explained by the model, ranging from 0 to 1, with values closer to 1 indicating a better fit. Negative R^2 values suggest that the model underperforms compared to a naive prediction based on the mean. MAPE, expressed as a percentage, enables an intuitive understanding of the average prediction error relative to the actual values, making it particularly useful for cross-comparison across datasets of different scales. In the context of the Single Diode Model (SDM), RMSE and MAPE are especially relevant, as they directly reflect the model's ability to replicate the electrical behavior of the photovoltaic module under varying conditions. Table 6 summarizes the results obtained for all performance metrics, supporting the effectiveness of the proposed estimation methodology [9], 61-64]. Table VI presents the values obtained for these metrics.

Table 6 Performance metrics (MAE, MSE, RMSE, R^2, and MAPE)

Metrics	I–V		I–P	
	1000 W/m²	**500 W/m²**	**1000 W/m²**	**500 W/m²**
MAE (A/W)	**0.0156**	**0.0061**	**0.2932**	**0.1021**
MSE (A^2/W^2)	0.0011	0.0001	0.4935	0.0327
RMSE (A/W)	0.0333	0.0094	0.7025	0.1809
R^2	**0.9983**	**0.9993**	**0.9985**	**0.9996**
MAPE (%)	1.36	0.90	1.39	0.93

4.4 Discussion of the Results

The results indicate a strong correlation between the simulated data and the experimental data. For the I–V curves, the RMSE values are very low, 0.0094 A and 0.0092 A for 1000 W/m² and 500 W/m², respectively, highlighting the model's effectiveness in accurately representing the real behavior of electric current as a function of voltage. Although the RMSE values for the I–P curves are higher (0.4430 W and 0.1443 W), this is expected due to the nature of electric power, which is the product of current and voltage. Small variations in either quantity are amplified when calculating power, especially near the maximum power point. Furthermore, the high R^2 values (all above 0.998) reinforce the quality of the fit, indicating that the model is capable of explaining more than 99.8 % of the variability in the experimental data. The Mean Absolute Percentage Error (MAPE) also remained below 1.5 % in all cases, which is acceptable and desirable for applications that require high reliability, such as generation forecasting and fault detection in photovoltaic systems. Despite small discrepancies observed, particularly in the power curves, the errors remain within acceptable ranges for simulation, energy estimation, and future applications in digital twins. An important advantage of the hybrid approach adopted in this study is also highlighted in terms of computational efficiency. It was possible to achieve high levels of accuracy with only 100 PSO iterations, followed by refinement using the Powell method. In contrast, studies such as [65-68] which rely exclusively on PSO, require up to 1000 iterations to achieve convergence and satisfactory results in the parameter estimation of the single diode model. This significant difference underscores the potential of the hybrid strategy not only to improve model accuracy but also to substantially reduce computational cost. Figure 6 illustrates the comparison between the simulated I-V curves (PSO and Powell) and the experimental curve, reinforcing the performance of the proposed methodology.

4.5 Relevance of the Model for Digital Twin Applications

Although this work does not yet implement a full Digital Twin (DT) architecture, it establishes a solid foundation by delivering a validated and parameterized digital representation of a photovoltaic (PV) module, derived from experimental data. This model accurately replicates the electrical behavior of the real device, making it highly suitable for integration into future DT applications.

A digital twin is a dynamic virtual counterpart of a physical system, continuously synchronized via sensor data. This integration enables real-time monitoring, control, diagnostics, and performance optimization. In this context, the proposed PV model can be incorporated into DT platforms to support key tasks such as operation, energy management, and predictive maintenance.

Beyond its value for offline analysis, the model developed herein serves as a critical building block for advancing digital twin technologies in solar energy. It contributes to greater efficiency, reliability, and intelligence in the management of PV systems, especially in remote or underserved regions, where technical support is limited and operational continuity is essential.

5. Conclusion

This study presented the modeling and experimental validation of a 60 W monocrystalline photovoltaic (PV) module, using the Single-Diode Model (SDM) as the mathematical foundation. The model parameters were extracted through a hybrid optimization approach that combines Particle Swarm Optimization (PSO) with the Powell method. Experimental tests were conducted under two irradiance levels (1000 W/m² and 500 W/m²) using a flash-type solar simulator under standard test conditions (25 °C and AM1.5). The resulting model reproduced the experimental I–V and P–V curves with high fidelity, achieving low error metrics (such as MAE and RMSE) and coefficients of determination (R^2) above 0.998, demonstrating excellent accuracy in representing the module's electrical behavior. A key highlight is that this high level of performance was achieved with only 100 PSO iterations, significantly fewer than the 1000 iterations commonly required by pure PSO approaches, demonstrating the computational efficiency of the proposed hybrid method. The obtained solution provides a robust foundation for the development of digital twins for photovoltaic systems. While the complete digital twin architecture was not implemented in this study, the parametrized model is fully applicable for tasks such as energy forecasting, simulation under varying environmental conditions, and real-time fault detection by comparing simulated versus measured behavior. The model's structure is also compatible with hybrid approaches that integrate physical and data-driven techniques, expanding its application potential. Additionally, the experimental dataset, including voltage, current, irradiance, and temperature measurements, will be made publicly available on GitHub and Kaggle to support researchers who lack access to specialized laboratory infrastructure. Future work will focus on extending the model to capture dynamic phenomena, such as transient responses and partial shading effects. Moreover, the model will be integrated into a full real-time digital twin architecture, connected via Internet of Things (IoT) protocols, enabling continuous monitoring, predictive maintenance, and intelligent control of PV systems. This evolution paves the way for more efficient, autonomous, and resilient solar energy systems. This work contributes to the advancement of the field of digital twins for solar energy, offering a robust and efficient modeling approach ready for real-world deployment.

Data Availability Statement: The datasets generated and analyzed during the current study will be publicly available in the GitHub repository: https://github.com/Ufuene/Digital-Twin-for-Photovoltaic-Systems .

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