

Article

Rapid, Precise Parameter Optimization and Performance Prediction for Multi-Diode Photovoltaic Model Using Puma Optimizer

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Abstract: Photovoltaic (PV) technology is essential for achieving net-zero emissions by 2050. PV system efficiency is highly sensitive to irradiance, temperature, and shading. However, accurate parameter identification is critical for modeling, as PV models often exhibit multi-modal and strongly coupled characteristics. In addition, commercial datasheets typically lack sufficient parameter information, making precise parameter extraction difficult and limiting the accuracy of maximum power point predictions. To address these challenges, this research employs a novel metaheuristic algorithm called Puma Optimizer (PO) to optimize the parameters of multiple PV models. The PO's performance is benchmarked against four advanced metaheuristic algorithms using convergence curves, error bars, and boxplots to evaluate its robustness. Results show that PO demonstrates strong adaptability and reliable performance in PV parameter optimization. Lastly, the research analyzes parameter sensitivity to help reduce computational resource usage. Visual analysis confirms that the PO parameter optimization approach provides an effective and practical solution for enhanced energy management and stable grid integration as solar adoption continues to expand.

Keywords: photovoltaic system; puma optimizer; multi-diode model; parameter optimization; maximum power point; parameter sensitivity



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1. Introduction

The exacerbation of global warming not only leads to rising sea levels but triggers an increase in the frequency and intensity of climate disasters. In order to curb the accelerating rate of global warming, the 26th United Nations Climate Change conference (COP26) urged nationals to decrease the greenhouse gas emissions by 2030 and achieve net-zero emissions by 2050, with the aim of limiting the rise in global temperature to 1.5 °C [1]. Carbon dioxide is the key factor of greenhouse gases. It is mainly produced by burning fossil fuels and as a byproduct waste gas of industrial processes. So as to reduce dependency on fossil fuels, the energy transition towards sustainable energy sources has become a vital concern for all countries.

Photovoltaic (PV) cells are a key technology for the energy transition due to their ability to convert solar energy into usable electricity without producing any greenhouse gases as a byproduct. PV cells are made up of semiconductor materials, divided into P-type and N-type. As light strikes the surface of the cell, the separation of electrons and holes at the P–N junction creates a potential difference, which can generate an electrical current. Besides the widely commercial manufacture first generation solar cells, many advanced types of photovoltaics have been developed, such as thin film [2], organic [3], quantum dot [4], perovskite [5] and others. The performance of PV cells is affected by light intensity,

operating temperature, humidity, and various other parameters [6]. In addition, the power performance of PV cells exhibits multidimensional and nonlinear characteristics, making it difficult to comprehensively represent PV system behavior, thus affecting the accuracy of maximum power point (MPP) prediction [7]. The MPP refers to the point at which the PV cell achieves optimal power output, with the system power changing accordingly based on the electrical load. Due to the insufficient parameter information provided by most mainstream PV product datasheets, accurate modeling techniques are essential for enhancing power dispatch in energy management systems.

PV cells are often used with equivalent circuits to describe their electrical behavior. The commonly constructed models include single diode model (SDM) [8], double diode model (DDM) [9,10] and triple diode model (TDM) [11] which differ in the number of diode branches. These models can effectively represent the current–voltage (I–V) curve of the PV cells. As the number of diodes added in the PV model increases, the computational cost also increases. So, it is crucial to balance the computational cost and accuracy. To build an accurate PV model, parameter optimization can effectively solve this problem. Fine-tuning parameters such as diode saturation current, series and shunt resistance, and photocurrent, etc., make it possible to achieve the desired commercial PV performance and characteristic behavior. An effective optimization approach can ensure the PV system maintains operation under various conditions, including different irradiance, user loading, and ambient environment.

There are lots of parameter extraction techniques. Current approaches can mainly be categorized into traditional optimization methods [12] and metaheuristic optimization methods [13–16]. The main traditional methods commonly rely on gradient-based techniques such as the Newton–Raphson [17–19], Gauss–Seidel [20] or Levenberg–Marquardt algorithm [20,21]. These methods provide better solutions with less computation time, but they are highly sensitive to the system’s initial conditions provided by the manufacturer and may converge to local optima. So, the lack of product information will cause the model to have large errors due to nonlinearity and strong parameter coupling. In order to address the above problem, many researchers focused on metaheuristic approaches for parameter estimation. Among current models, SDM and DDM are commonly used models [22–24], and DDM is the most popular due to the balance between model precision and calculation time. Comprehensive studies have been published on parameter identification for PV cells using various metaheuristic algorithms, including artificial hummingbird algorithm (AHA) [25], particle swarm optimization (PSO) [26], ant lion optimizer (ALO) [27], Harris hawk Optimizer (HHO) [28], honey badger algorithm (HBA) [28] and virtual-particle adaptive bald eagle search optimization algorithm (VABES) [29], among others. In addition to cell-level modeling, considerable efforts have also been made in parameter extraction for PV modules. Notable algorithms applied at the module level include the enhanced slime mould algorithm (ESMA) [30], coyote optimization algorithm (COA) [31], transient search optimization (TSO) [31] and gorilla troops optimizer (GTO) [31], northern goshawk optimization algorithm [32], enhanced material generation optimization (IMGGO) algorithm [33], hybrid brown-bear [34], rime-ice growth optimizer [35] and enhanced artificial rabbits algorithm [36]. The detailed metaheuristic method in recent years is collated in Table 1.

Table 1. Metaheuristic optimization method research in recent years.

Year	Algorithm	Modeling	Objective Function	Reference
2025	OBEDO	SDM, DDM, TDM	RMSE	[37]
2025	I_SCHO	SDM, DDM, TDM	RMSE	[38]
2025	WSO	SDM, DDM, PV module	RMSE	[39]

Table 1. *Cont.*

Year	Algorithm	Modeling	Objective Function	Reference
2024	GPSO	SDM	RMSE	[40]
2024	MSHOA	SDM, DDM, TDM	RMSE	[41]
2024	ICOA	SDM, DDM, PV module	RMSE	[42]
2024	DIWJAYA	SDM, DDM, PMM	RMSE	[43]
2024	MS-TSA	SDM, DDM, PVM	RMSE	[44]
2024	IKOA	SDM, DDM, TDM	RMSE	[45]

The continuous development and refinement of optimization algorithms for PV parameter identification are primarily driven by the no free lunch (NFL) theorem [46]. The NFL theorem posits that no single optimization algorithm can outperform all others across all types of problems; rather, an algorithm's effectiveness is inherently problem-dependent. Consequently, the search strategies embedded within a particular algorithm may perform well for certain classes of problems but poorly for others. Against this background, PV parameter extraction optimization implies the necessity of selecting or designing optimization algorithms specifically suited to the unique characteristics of PV modeling problems. Puma optimizer is an advantageous algorithm which has varied search mechanisms with fast convergence for solving many optimization problems, such as in nonparametric modeling of ship dynamics [47], power systems [48], efficient distributed generation planning [49], and efficient distributed generation planning in electrical distribution network [50], etc.

1.1. Contribution

In order to accurately characterize the behavior of the commercial photovoltaics system, this research employed a novel metaheuristic algorithm known as puma optimizer (PO) to optimize the parameters of multiple PV models, and comprehensively compared it with four advanced metaheuristic algorithms: whale optimization algorithm (WOA), honey badger algorithm (HBA), Harris Hawks optimization (HHO) and JAYA algorithm, along with other benchmark references.

This comparative evaluation was conducted to assess the robustness, performance, and stability of PO across different PV modeling scenarios. Each algorithm's effectiveness was analyzed based on convergence curves, error bars and boxplots to evaluate algorithms' advantages and limitations. In addition, the PO-based method was applied to predict the performance and the maximum power point of the PV systems under various temperature conditions. Finally, the research integrated the performance variables into a visual analysis using a radar chart and further discussed the sensitivity of each parameter in the PV models. The research flowchart is shown in Figure 1.

1.2. Research Framework

The research steps and flowchart are shown below.

1. Collect experimental data from photovoltaic cells and modules.
2. Develop multi-diode models to represent the behavior of photovoltaic cells and modules.
3. Construct Puma Optimizer algorithm and the objective function.
4. Comprehensively compare the search performance of the system with calculated results.
5. Predict the performance and maximum power point of several photovoltaic systems under various temperature conditions.
6. Integrate the algorithm performance variables into a visual analysis using radar charts.
7. Use a one-factor-at-a-time approach to analyze the sensitivity of system parameters.

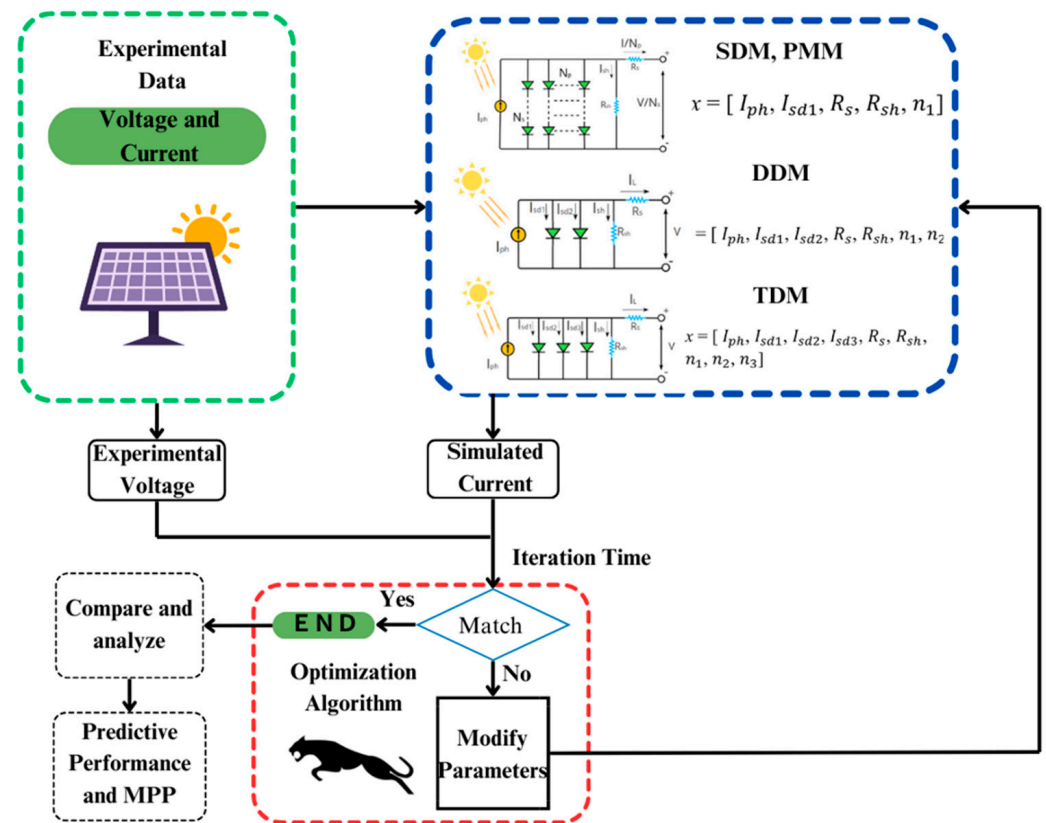


Figure 1. The research flowchart.

2. Methodology

2.1. Photovoltaics Modeling

To efficiently characterize the behavior of PV models, it is necessary to establish an appropriate mathematical model. For all intents and purposes, PV systems can be considered to be fundamentally similar to photodiodes. In this study, four PV circuit models are explored in depth: SDM, DDM, TDM, and PMM. The following section will elaborate on the mathematical description of these models and introduce the uncertainty parameters used for parameter identification.

2.1.1. Single Diode Model

SDM is the simplest model, and it considers the effects of negative impurities, defects and leakage current that might exist in the PV system. The terminal current I_L is shown in Equation (1), where I_{ph} is the photocurrent source; R_s is the series resistor; and R_{sh} is the shunt resistor [51].

$$I_L = I_{ph} - I_D - I_{sh} \quad (1)$$

$$I_D = I_{sd1} \left[\exp \left(\frac{q(V_L + I_L R_s)}{n_1 k T} \right) - 1 \right] \quad (2)$$

$$I_{sh} = \frac{V_L + I_L R_s}{R_{sh}} \quad (3)$$

Equation (2) shows the calculation for the diode current I_D according to the Shockley diode equation, where I_{sd1} is the reverse saturation current of the diode; V_L is the terminal voltage; n_1 is the ideality factor of the diode (of which the ideality factor of silicon PV cells is between 1 and 2); k is the Boltzmann constant (1.6×10^{-23} J/K); q is the electron charge (1.608×10^{-19} C); and T is the absolute temperature of the battery in Kelvin. Equation (3) presents the calculation for the current of the shunt resistor I_{sh} ; R_{sh} is the parallel resistance

which represents the leakage current generated in the PV cell, and the SDM parameters are $[I_{ph}, I_{sd1}, R_s, R_{sh}, n_1]$. The equivalent circuit diagram of the SDM is shown in Figure 2.

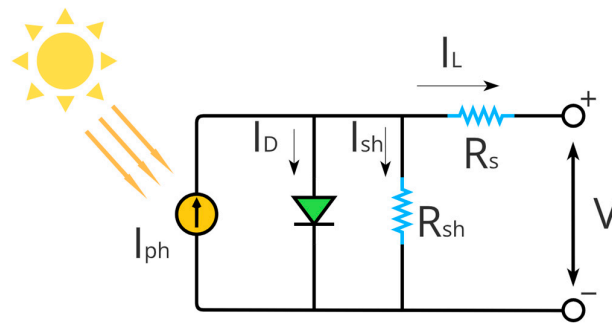


Figure 2. The SDM equivalent circuit.

2.1.2. Double Diode Model

As compared to SDM, DDM includes an additional parallel diode to account for combination current loss, which becomes increasingly significant under low irradiance conditions. While being more complex than SDM, DDM provides greater accuracy. The calculation of the DDM terminal current is shown in Equation (4) [52].

$$I_L = I_{ph} - I_{D1} - I_{D2} - I_{sh} \quad (4)$$

The calculation for I_{sh} was previously shown in Equation (3), while the calculations of I_{D1} and I_{D2} are expressed in Equations (5) and (6) below.

$$I_{D1} = I_{sd1} \left[\exp \left(\frac{q(V_L + I_L R_s)}{n_1 k T} \right) - 1 \right] \quad (5)$$

$$I_{D2} = I_{sd2} \left[\exp \left(\frac{q(V_L + I_L R_s)}{n_2 k T} \right) - 1 \right] \quad (6)$$

In Equations (5) and (6) above, I_{sd1} and I_{sd2} represent the reverse saturation current generated by the diffusion and recombination phenomena, respectively; n_1 and n_2 are the diffusion and recombination ideality factors of the diode, respectively; I_{sh} was previously calculated in Equation (3); and the parameters to be identified in the DDM are $[I_{ph}, I_{sd1}, I_{sd2}, R_s, R_{sh}, n_1, n_2]$. The equivalent circuit diagram is shown in Figure 3.

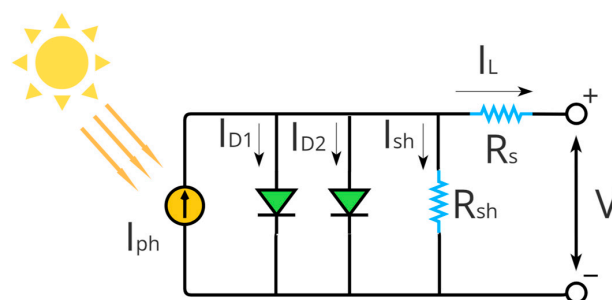


Figure 3. The DDM equivalent circuit.

2.1.3. Triple Diode Model

Building upon the previous model, TDM further accounts for leakage current generated by recombination at grain and surface boundaries, and thus offers a more accurate representation of the losses caused by potential defects and non-ideal conditions in PV cells. The equivalent circuit diagram of the TDM is shown in Figure 4, and the calculation for the terminal voltage I_L is shown in Equation (7) below [53].

$$I_L = I_{ph} - I_{D1} - I_{D2} - I_{D3} - I_{sh} \quad (7)$$

The calculation for I_{sh} was previously shown in Equation (3), while the calculations for I_{D1} , I_{D2} and I_{D3} are expressed below in Equations (8), (9) and (10), respectively.

$$I_{D1} = I_{sd1} \left[\exp \left(\frac{q(V_L + I_L R_S)}{n_1 k T} \right) - 1 \right] \quad (8)$$

$$I_{D2} = I_{sd2} \left[\exp \left(\frac{q(V_L + I_L R_S)}{n_2 k T} \right) - 1 \right] \quad (9)$$

$$I_{D3} = I_{sd3} \left[\exp \left(\frac{q(V_L + I_L R_S)}{n_3 k T} \right) - 1 \right] \quad (10)$$

In the equations above, I_{sd3} represents the reverse saturation current generated by the grain boundary effect; n_3 is the ideality factor of the third diode; and the parameters to be identified in the TDM are $[I_{ph}, I_{sd1}, I_{sd2}, I_{sd3}, R_s, R_{sh}, n_1, n_2, n_3]$.

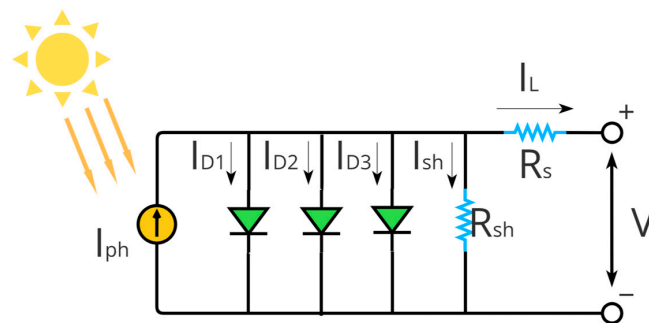


Figure 4. The TDM equivalent circuit.

2.1.4. Photovoltaic Module Model

PMM extends the single diode model to represent the behavior of interconnected PV cells within a module. As shown in Figure 5, the model incorporates series (N_s) and parallel (N_p) cell configurations to account for practical module construction. The output current is divided by the number of parallel-connected cells N_p and the terminal voltage is normalized by the number of series connected cells N_s [54].

$$I_L = N_p (I_{ph} - I_D - I_{sh}) \quad (11)$$

$$I_D = I_{sd1} \left[\exp \left(\frac{q(V_L/N_s + I_L R_S/N_p)}{n_1 k T} \right) - 1 \right] \quad (12)$$

$$I_{sh} = \frac{V_L/N_s + I_L R_S/N_p}{R_{sh}} \quad (13)$$

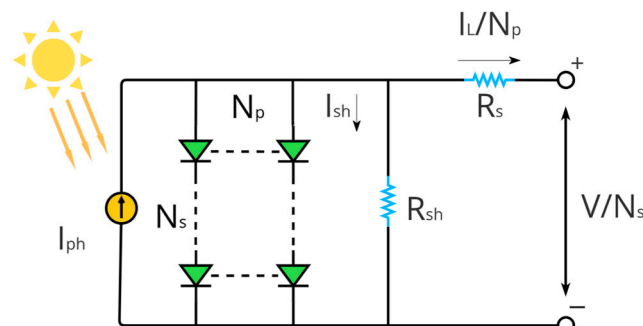


Figure 5. The PMM equivalent circuit.

2.2. Puma Optimizer

Puma Optimizer (PO) was proposed by Abdollahzadeh et al. and is a swarm intelligence (SI) algorithm inspired by the behavior and hunting habits of pumas [55]. The algorithm features a powerful search mechanism that maintains a balance between exploration and exploitation. The PO is capable of executing phase transitions during the optimization process and can dynamically switch between different search phases. This section is going to introduce the mathematical model of the algorithm.

2.2.1. Initialization

First of all, pumas are randomly initialized within the search area.

$$A = \begin{bmatrix} x_1 \\ x_2 \\ \dots \\ x_n \end{bmatrix} = \begin{bmatrix} x_{11} & x_{12} & x_{13} & \dots & x_{1D} \\ x_{21} & x_{22} & x_{23} & \dots & x_{2D} \\ \dots & \dots & \dots & \dots & \dots \\ x_{n1} & x_{n2} & x_{n3} & \dots & x_{nD} \end{bmatrix} \quad (14)$$

In Equation (14), A represents the total population of pumas; X_i represents the position of the i th puma; n represents the number of pumas; and D represents the dimension of the problem.

$$x_i = LB_i + r_1 * (UB_i - LB_i) \quad (15)$$

In Equation (15), the pumas' positions are generated between the upper bound (UB) and lower bound (LB), where r_1 represents a random number between $[0, 1]$ and x_i represents the position of the i th puma.

2.2.2. Inexperienced Phase

In the initial phase of the algorithm, pumas are still inexperienced. Accordingly, in the first three iterations of PO, both exploration and exploitation phases are executed simultaneously. n represents number of pumas in a group. The original puma population A will generate two new populations in each iteration, with the new populations represented as A_{explore} and A_{exploit} . The population set comprising the three groups is expressed as $A_{\text{pop}} = [A \ A_{\text{explore}} \ A_{\text{exploit}}]$. The set A_{pop} is then evaluated and sorted by fitness, retaining the top-performing pumas at the end of each iteration to ensure optimal evolutionary direction. After the first three iterations, functions $f1$ and $f2$ are calculated to assess the performance of the exploration and exploitation phases, with the corresponding scores represented as $Score_{\text{Explore}}$ and $Score_{\text{Exploit}}$, respectively. These scores then serve as indicators to determine the search phase to be implemented during the experienced phase. The algorithm executes the steps as follows:

Equations (16)–(19): Calculation of $f1$ and $f2$.

Equations (20)–(25): Calculation of the variable Seq found in $f1$ and $f2$.

Equations (26) and (27): Calculation of the final scores of the exploration and exploitation phases, namely $Score_{\text{Explore}}$ and $Score_{\text{Exploit}}$.

$$f1_{\text{Explore}} = PF_1 \cdot \left(\frac{Seq_{\text{Cost Explore}}^1}{Seq_{\text{Time}}} \right) \quad (16)$$

$$f1_{\text{Exploit}} = PF_1 \cdot \left(\frac{Seq_{\text{Cost Exploit}}^1}{Seq_{\text{Time}}} \right) \quad (17)$$

$$f2_{\text{Explore}} = PF_2 \cdot \left(\frac{Seq_{\text{Cost Explore}}^1 + Seq_{\text{Cost Explore}}^2 + Seq_{\text{Cost Explore}}^3}{Seq_{\text{Time}}^1 + Seq_{\text{Time}}^2 + Seq_{\text{Time}}^3} \right) \quad (18)$$

$$f2_{Exploit} = PF_2 \cdot \left(\frac{Seq_{Cost\ Exploit}^1 + Seq_{Cost\ Exploit}^2 + Seq_{Cost\ Exploit}^3}{Seq_{Time}^1 + Seq_{Time}^2 + Seq_{Time}^3} \right) \quad (19)$$

In Equations (16)–(19), $f1_{Explore}$ and $f2_{Explore}$ represent the calculations of $f1$ and $f2$ for the exploration search, $f2_{Exploit}$ and $f1_{Exploit}$ represent the calculations of $f1$ and $f2$ for the exploitation search. The variables $Seq_{Cost\ Explore}^t$ and $Seq_{Cost\ Exploit}^t$ represent the calculation results of Seq during the exploration and exploitation search at the t^{th} iteration. In Equations (20)–(25), Seq_{Time}^t represents the number of times each phase was chosen. Because both searches are selected in every iteration during the inexperienced phase, the value of Seq_{Time}^t will be 1. Lastly, PF_1 and PF_2 represent the priority factors of $f1$ and $f2$ which are used to determine the relative priority between the two functions. The initial values of PF_1 and PF_2 are set to 0.5.

$$Seq_{Cost\ Explore}^1 = |Cost_{Best}^{Initial} - Cost_{Explore}^1| \quad (20)$$

$$Seq_{Cost\ Explore}^2 = |Cost_{Explore}^2 - Cost_{Explore}^1| \quad (21)$$

$$Seq_{Cost\ Explore}^3 = |Cost_{Explore}^3 - Cost_{Explore}^2| \quad (22)$$

$$Seq_{Cost\ Exploit}^1 = |Cost_{Best}^{Initial} - Cost_{Exploit}^1| \quad (23)$$

$$Seq_{Cost\ Exploit}^2 = |Cost_{Exploit}^2 - Cost_{Exploit}^1| \quad (24)$$

$$Seq_{Cost\ Exploit}^3 = |Cost_{Exploit}^3 - Cost_{Exploit}^2| \quad (25)$$

In Equations (20)–(25) above, $Cost_{Best}^{Initial}$ represents the best fitness value in the previous population, while $Cost_{Explore}^t$ and $Cost_{Exploit}^t$ represent the best fitness values in the puma populations $A_{Explore}$ and $A_{Exploit}$ generated in the exploration and exploitation phases at the t^{th} iteration, respectively. $f1$ and $f2$ represent the mean differences in the best fitness values across the different phases and iterations.

$$Score_{Explore} = (PF_1 \cdot f1_{Explore}) + (PF_2 \cdot f2_{Explore}) \quad (26)$$

$$Score_{Exploit} = (PF_1 \cdot f1_{Exploit}) + (PF_2 \cdot f2_{Exploit}) \quad (27)$$

In Equations (26) and (27) above, PF_1 and PF_2 are constants set to 0.5. $f1_{Explore}$, $f2_{Explore}$, $f1_{Exploit}$ and $f2_{Exploit}$ represent the values obtained from the exploration and exploitation calculations. If $Score_{Explore}$ is greater than $Score_{Exploit}$, the phase selected in the following experienced phase will be exploration. Conversely, if $Score_{Exploit}$ is greater than $Score_{Explore}$, the phase will instead be exploitation.

2.2.3. Experienced Phase

After completing the first three iterations during the inexperienced phase, the puma will choose one search mechanism to execute based on the accrued experience. Thereafter, it will continue to change search strategy between iterations. The algorithm will select explore or exploitation according to values $f1$, $f2$ and $f3$. These functions serve to integrate the established effectiveness of exploration and exploitation operations, ensuring that the most advantageous phase will be chosen for successive iterations. The calculation methods for $f1$, $f2$ and $f3$ for this phase are elaborated below. These methods allow the algorithm to effectively evaluate and transition between search mechanisms, thereby enhancing its global and local search capabilities.

The calculation method for f_1 is shown in Equations (28) and (29) below.

$$f_{1t}^{exploit} = PF_1 \cdot \left| \frac{Cost_{old}^{exploit} - Cost_{new}^{exploit}}{T_t^{exploit}} \right| \quad (28)$$

$$f_{1t}^{explore} = PF_1 \cdot \left| \frac{Cost_{old}^{explore} - Cost_{new}^{explore}}{T_t^{explore}} \right| \quad (29)$$

$f_{1t}^{exploit}$ represents the calculation method of f_1 in the exploitation phase; $f_{1t}^{explore}$ represents the calculation method of f_1 in the exploration phase; t represents the current iteration number; PF_1 represent the priority factor for f_1 and needs to be set to a value between $[0, 1]$ at the start of the algorithm; $Cost_{old}^{exploit}$ and $Cost_{old}^{explore}$ represent the old best fitness values for the pumas in the population; $Cost_{new}^{exploit}$ and $Cost_{new}^{explore}$ represent the new best fitness values for the population after each phase is executed; while $T_t^{exploit}$ and $T_t^{explore}$ represent the number of iterations that the phases have been unselected for since they were last chosen.

The calculation method for f_2 is shown in Equations (30) and (31) below.

$$f_{2t}^{exploit} = PF_2 \cdot \left| \frac{S_1^{exploit} + S_2^{exploit} + S_3^{exploit}}{T_{t,1}^{exploit} + T_{t,2}^{exploit} + T_{t,3}^{exploit}} \right| \quad (30)$$

$$f_{2t}^{explore} = PF_2 \cdot \left| \frac{S_1^{explore} + S_2^{explore} + S_3^{explore}}{T_{t,1}^{explore} + T_{t,2}^{explore} + T_{t,3}^{explore}} \right| \quad (31)$$

$f_{2t}^{exploit}$ and $f_{2t}^{explore}$ represents the calculation method of f_2 in the exploitation and exploration phases, respectively. t represents the current iteration number, and PF_2 represents the priority factor for f_2 and needs to be set to a value between $[0, 1]$ at the start of the algorithm.

$$S_1^{exploit} = Cost_{Old,1}^{exploit} - Cost_{New,1}^{exploit} \quad (32)$$

$$S_2^{exploit} = Cost_{Old,2}^{exploit} - Cost_{New,2}^{exploit} \quad (33)$$

$$S_3^{exploit} = Cost_{Old,3}^{exploit} - Cost_{New,3}^{exploit} \quad (34)$$

$$S_1^{explore} = Cost_{Old,1}^{explore} - Cost_{New,1}^{explore} \quad (35)$$

$$S_2^{explore} = Cost_{Old,2}^{explore} - Cost_{New,2}^{explore} \quad (36)$$

$$S_3^{explore} = Cost_{Old,3}^{explore} - Cost_{New,3}^{explore} \quad (37)$$

In Equations (32)–(37), $S^{exploit}$ and $S^{explore}$ represent the cost difference between the two phases. $Cost_{Old}^{exploit}$ and $Cost_{Old}^{explore}$ represent the old best fitness values of the solution in the current exploitation and exploration phase selections. $Cost_{New}^{exploit}$ and $Cost_{New}^{explore}$ represent the new best fitness values of the solution in the current exploitation and exploration phase selections. $T_t^{explore}$ and $T_t^{exploit}$ represent the number of iterations that the exploration and exploitation phases have been unselected for since they were last chosen.

The calculation method for f_3 is shown in Equations (38) and (39) below.

$$f_{3t}^{exploit} = \begin{cases} \text{if selected, } f_{3t}^{exploit} = 0 \\ \text{otherwise, } f_{3t}^{exploit} + PF_3 \end{cases} \quad (38)$$

$$f_{3t}^{explore} = \begin{cases} \text{if selected, } f_{3t}^{explore} = 0 \\ \text{otherwise, } f_{3t}^{explore} + PF_3 \end{cases} \quad (39)$$

In Equations (38) and (39), $f_{3t}^{exploit}$ and $f_{3t}^{explore}$ represent the calculation expressions of f_3 in the exploitation and exploration phases. t represents the current iteration number and PF_3 is a constant value of 0.3 in the algorithm.

Equations (40) and (41) below show the score calculation expressions for the exploration and exploitation phases.

$$F_t^{explore} = (\alpha_t^{explore} \cdot (f_{1t}^{explore})) + (\alpha_t^{explore} \cdot (f_{2t}^{explore})) + (\delta_t^{explore} \cdot (lc \cdot f_{3t}^{explore})) \quad (40)$$

$$F_t^{exploit} = (\alpha_t^{exploit} \cdot (f_{1t}^{exploit})) + (\alpha_t^{exploit} \cdot (f_{2t}^{exploit})) + (\delta_t^{exploit} \cdot (lc \cdot f_{3t}^{exploit})) \quad (41)$$

In the above equation, $F_t^{explore}$ and $F_t^{exploit}$ represent the scores of the exploration and exploitation phase in the current iteration, while lc , α and δ are defined in Equations (42)–(45) below.

$$lc = \begin{cases} \{|Cost_{old} - Cost_{New}|\}^{exploitation} \\ \{|Cost_{old} - Cost_{New}|\}^{exploration} \end{cases}, 0 \notin lc \quad (42)$$

$$\alpha_t^{explore, exploit} = \begin{cases} \text{if } F^{exploit} > F^{explore} : \alpha^{exploit} = 0.99, \alpha^{explore} = [\alpha^{explore} - 0.01, 0.01] \\ \text{otherwise} : \alpha^{explore} = 0.99, \alpha^{exploit} = [\alpha^{exploit} - 0.01, 0.01] \end{cases} \quad (43)$$

$$\delta_t^{exploit} = 1 - \alpha_t^{exploit} \quad (44)$$

$$\delta_t^{explore} = 1 - \alpha_t^{explore} \quad (45)$$

In Equation (42), lc represents the calculation of the difference in best fitness values of the exploration and exploitation phase before and after the iteration. In Equation (43), $\alpha^{explore}$ and $\alpha^{exploit}$ respectively represent the values of α in the exploration and exploitation phase, while $F^{explore}$ and $F^{exploit}$ respectively represent the scores of the previous exploration and exploitation phases. Lastly, in Equations (44) and (45), $\delta_t^{exploit}$ and $\delta_t^{explore}$ represent the values of δ in the exploitation and exploration phases, respectively. The algorithm intelligently adjusts the weightage of f_1 and f_2 based on the scores of the exploration and exploitation phases. When the score of the exploitation phase is greater than that of the exploration phase, it indicates that the weight of exploitation is too low, and the weight of exploration will be linearly reduced through α . Conversely, if the score of the exploration is greater than that of exploitation, the opposite adjustment is implemented. By switching between different phases through the continuous score calculations for exploration and exploitation, the algorithm effectively prevents premature convergence to local optima and avoids excessive global searches which could lead to inaccurate solutions.

2.2.4. Exploration Phase

This phase imitates pumas' prey-searching behavior, where they travel to new areas or randomly approach other pumas during the exploration process. The position of the puma is updated according to Equation (46) to improve the search efficiency and expand the exploration range. If $rand_1$ is greater than 0.5, then execute Equation (46); otherwise, Equation (47) is applied.

$$Z_{i,G} = R_{Dim} \times (UB - LB) + LB \quad (46)$$

$$Z_{i,G} = X_{a,G} + G \cdot (X_{a,G} - X_{b,G}) + G \cdot \left(((X_{a,G} - X_{b,G}) - (X_{c,G} - X_{d,G})) + ((X_{c,G} - X_{d,G}) - (X_{e,G} - X_{f,G})) \right) \quad (47)$$

$$G = 2 \cdot \text{rand}_2 - 1 \quad (48)$$

In Equations (46) and (47), UB and LB represent the upper and lower search boundaries and $X_{a,G}$, $X_{b,G}$, $X_{c,G}$, $X_{d,G}$, $X_{e,G}$, $X_{f,G}$ represent the solutions of six random pumas from the population. In Equation (48), rand_2 is a random number between $[0, 1]$ and G falls between $[-1, 1]$ and can be considered as a directional factor. Equations (49)–(52) below determined the replacement strategy for deciding whether the new solution should replace the old one.

$$X_{\text{new}} = \begin{cases} Z_{i,G}, & \text{if } j = j_{\text{rand}} \text{ or } \text{rand}_3 \leq U \\ X_{a,G}, & \text{otherwise} \end{cases} \quad (49)$$

$$NC = 1 - U \quad (50)$$

$$p = \frac{NC}{N_{\text{pop}}} \quad (51)$$

$$\begin{aligned} &\text{if } \text{Cost}X_{\text{new}} < \text{Cost}X_i : X_{a,G} = X_{\text{new}} \\ &\text{Otherwise} : U = U + p \end{aligned} \quad (52)$$

In Equation (49), $Z_{i,G}$ represents the i -th puma solution generated in Equations (46) and (47); j_{rand} is a randomly generated integer in the dimensional range; rand_3 is a random number between $[0, 1]$; and U is a decreasing value between $[0, 1]$, with an initial preset value of 0.2. N_{pop} represents the total number of the puma population; and U is a value that constantly increases through the value of p , where the p is calculated in Equation (51). In Equation (52), $\text{Cost}X_{\text{new}}$ represents the fitness value of the new solution; $\text{Cost}X_i$ represents the fitness value of the original solution.

2.2.5. Exploitation Phase

As inspired by the hunting habits of the puma, the algorithm uses two different search mechanisms to obtain new solutions by ambush and sprinting strategy. The mathematical models of these mechanisms are elaborated upon in Equations (53)–(59) below.

$$\begin{aligned} \text{rand}_4 \geq 0.5 : X_{\text{new}} &= \frac{\left(\frac{\text{mean}(\text{Sol}_{\text{total}})}{N_{\text{pop}}} \right) \cdot X_1^r - (-1)^\beta \times X_i}{1 + (\alpha \cdot \text{rand}_5)} \\ &\text{otherwise :} \end{aligned} \quad (53)$$

$$\begin{aligned} \text{rand}_6 \geq L : X_{\text{new}} &= Puma_{\text{male}} + (2 \cdot \text{rand}_7) \cdot \exp(\text{rand}_{n_1}) \cdot (X_2^r - X_i) \\ \text{otherwise : } X_{\text{new}} &= (2 \times \text{rand}_8) \times \frac{(F_1 \cdot R \cdot X(i) + F_2 \cdot (1 - R) \cdot Puma_{\text{male}})}{(2 \cdot \text{rand}_9 - 1 + \text{rand}_{n_2})} - Puma_{\text{male}} \end{aligned}$$

$$X_2^r = \text{round}(1 + (N_{\text{pop}} - 1) \cdot \text{rand}_{10}) \quad (54)$$

$$R = 2 \cdot \text{rand}_{11} - 1 \quad (55)$$

$$F_1 = \text{rand}_{n_3} \cdot \exp\left(2 - \text{Iter} \cdot \left(\frac{2}{\text{MaxIter}}\right)\right) \quad (56)$$

$$F_2 = w \times (v)^2 \cdot \cos((2 \times \text{rand}_{12}) \cdot w) \quad (57)$$

$$w = \text{rand}_{n_4} \quad (58)$$

$$v = \text{rand}_{n_5} \quad (59)$$

In the Equations above, $rand$ is a random number between $[0, 1]$, and if $rand_4 \geq 0.5$, the sprinting strategy is executed; otherwise, the ambush strategy is applied. And if $rand_6 \geq L$, where L represents a constant set to 0.67, short jumps are performed; otherwise, long jumps are performed. $mean(Sol_{total})$ represents the average of all solutions in the population; N_{pop} represents the total puma population; X_1^r represents a solution randomly selected from the entire population; $Puma_{male}$ represents the best individual in the population; β is a constant randomly set to either 0 or 1; α is a constant set to 2; exp represents the exponential function, $randn_1$ and $randn_2$ represent random numbers following normal distribution; and X_2^r is a solution randomly selected according to Equation (54).

Following that, R , $F1$, and $F2$ are calculated using Equations (55)–(57), where $randn_3$ represents a random number following normal distribution; exp represents the exponential function; $Iter$ represents the current iteration number; and $MaxIter$ represents the maximum number of iterations. In Equation (56), cos represents the cosine function. In Equations (58) and (59), parameters w and v are defined as $randn_4$ and $randn_5$ which represent random numbers following normal distribution. At the end of the exploitation phase, the superior individuals are retained after comparing the fitness values of the new and old solutions. The algorithm flowchart is shown below as Figure 6.

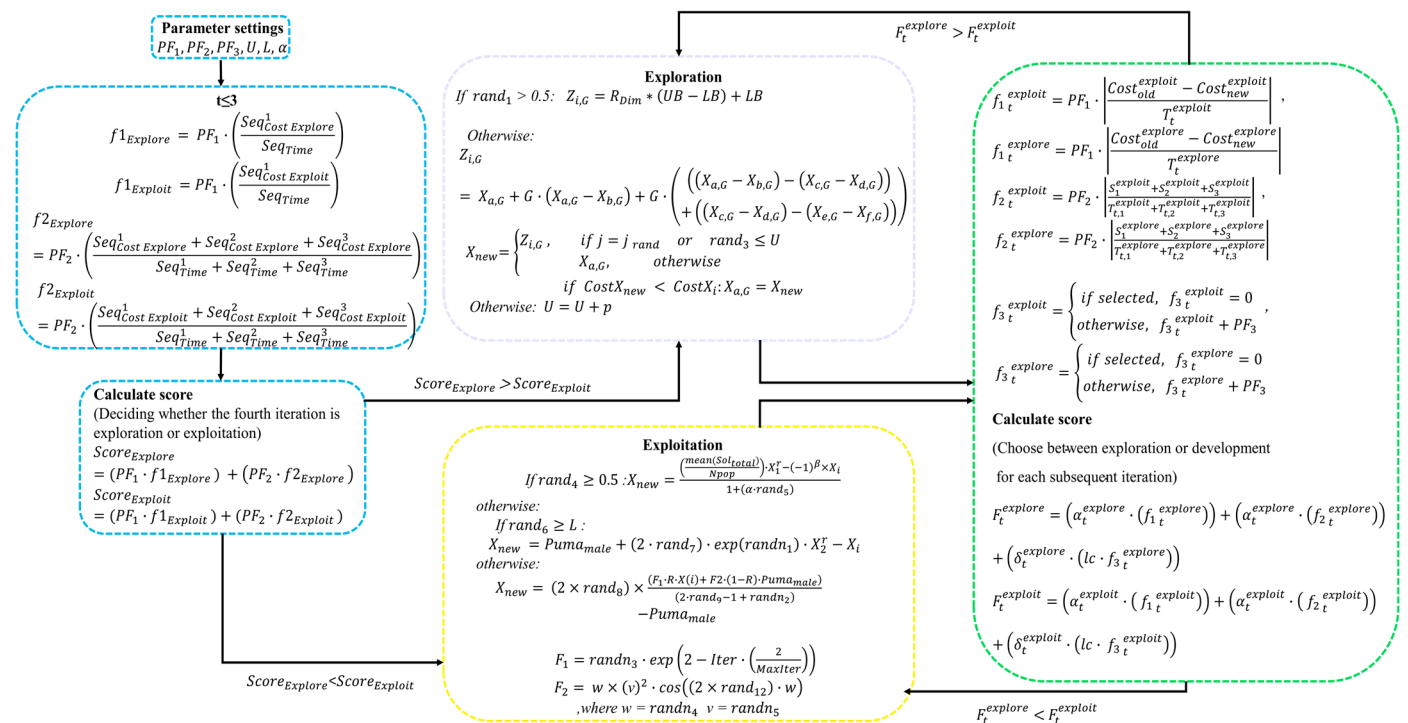


Figure 6. Flowchart of PO optimization process.

2.3. Objective Function

During the process of parameter identification, the algorithm continuously searches for model parameters within the search space until the set number of iterations is reached. The algorithm aims to obtain search optimal parameter solutions that can approach experimental data. This study uses the root mean square error (RMSE) as the objective function to calculate the error between the calculated and experimental current, which is shown in Equation (60) below.

$$RMSE = \sqrt{\frac{1}{N} \sum_{t=1}^N (I_{calculated} - I_{experimental})^2} = \sqrt{\frac{1}{N} \sum_{t=1}^N (f_{model}(V_L, I_L, x) - I_t)^2} \quad (60)$$

Here, N represents the number of data points; $I_{calculated}$ represents the value of the calculated current; $I_{experimental}$ represents the value of the experimental current; V_L and I_L represent the experimental terminal voltage and experimental terminal current, respectively; x represents the parameter array, which is defined in Table 1; and f represents the objective functions of the three models. The PV model's unscented parameters are shown in Table 2.

Table 2. The photovoltaic model parameter array.

Function	Parameter Vector
f_{SDM}	$x = [I_{ph}, I_{sd1}, R_s, R_{sh}, n_1]$
f_{DDM}	$x = [I_{ph}, I_{sd1}, I_{sd2}, R_s, R_{sh}, n_1, n_2]$
f_{TDM}	$x = [I_{ph}, I_{sd1}, I_{sd2}, I_{sd3}, R_s, R_{sh}, n_1, n_2, n_3]$
f_{PMM}	$x = [I_{ph}, I_{sd1}, R_s, R_{sh}, n_1]$

The parameter sensitivity function is calculated as shown in Equation (61). We use the one-factor-at-a-time method to determine the importance level of each parameter in the PV model.

$$STD = \sqrt{\frac{1}{N} \sum_{z=0.8}^{1.2} (RMSE_z - \overline{RMSE})^2} \quad (61)$$

In this approach, STD represents the standard deviation of the results across different values of a given parameter. N represents the number of data points. $RMSE_z$ denotes the root mean square error corresponding to each variation in the parameter. The parameter values are varied over a range from 0.8 to 1.2 times their nominal values denoted as z . $\overline{RMSE}$ is the average error across all cases.

2.4. Parameter Setting

To verify the suitability of PO for PV parameter identification and to boost further performance prediction, this study made use of a widely adopted PV dataset from the commercial R.T.C France solar cell and solar module Photowatt-PWP 201 [56]. The relevant cell and module specifications, along with the parameter search ranges, are provided in Tables 3–6.

To assess the robustness of PO algorithm, we compared four additional metaheuristic algorithms: whale optimization algorithm, honey badger algorithm, Harris Hawks optimization and JAYA Algorithm. The parameter settings for each algorithm are listed in Table 7. The research was conducted using equipment featuring an 11th Gen Intel Core i5-11320H CPU, manufactured by Intel Corporation (Santa Clara, CA, USA) and MATLAB R2022b.

Table 3. Specifications of commercial PV cell [57].

57 mm Diameter R.T.C France Solar Cell	
Operation Temperature (K)	303.15
Operation radiation (W/m^2)	1000
Maximum power (P_{mpp}) (W)	0.3101
Voltage at MPP (V_{MPP}) (V)	0.4507
Current at MPP (I_{MPP}) (A)	0.6880
Open circuit voltage (V_{OC}) (V)	0.5728
Short circuit current (ISC) (A)	0.7603

Table 4. Photovoltaic cell parameter identification range.

	Parameter	Range		Parameter	Range
1	I_{ph} (A)	[0, 1]	6	I_{sd2} (μ A)	[0.001, 1]
1	R_s (Ω)	[0, 0.5]	7	n_2	[1, 2]
2	R_{sh} (Ω)	[0, 100]	8	I_{sd3} (μ A)	[0.001, 1]
4	I_{sd1} (μ A)	[0.001, 1]	9	n_3	[1, 2]
5	n_1	[1, 2]	-	-	-

Table 5. Specifications of commercial PV module [58].

Photowatt-PWP 201 Solar Module	
Operation Temperature (K)	318.15
Operation radiation (W/m^2)	1000
Maximum power (P_{mpp}) (W)	11.54
Voltage at MPP (V_{MPP}) (V)	12.6490
Current at MPP (I_{MPP}) (A)	0.9120
Open circuit voltage (V_{OC}) (V)	16.7785
Short circuit current (I_{SC}) (A)	1.0317

Table 6. Photovoltaic module parameter identification range.

	Parameter	Range		Parameter	Range
1	I_{ph} (A)	[0, 2]	4	I_{sd1} (μ A)	[0, 50]
2	R_s (Ω)	[0, 2]	5	n_1	[1, 50]
3	R_{sh} (Ω)	[0, 2000]			

Table 7. The optimization algorithm setting.

Algorithm Setting	
Independent run time	30
Population size	30
Iteration time	1000

3. Results and Discussion

PO and the four other algorithms were applied to identify parameters of three PV models (SDM, DDM, TDM and PMM), the calculation results of which will be discussed in detail in the following section. To evaluate the calculation process and suitability of each algorithm in depth, the study will calculate the best fitness, mean fitness, and standard deviation (Std.) of the algorithms and perform statistical analysis on their performances through the methods of convergence history, error bar and boxplot.

3.1. Single Diode Model

For the SDM parameter identification, five algorithms were used to identify five undetermined parameters. Table 8 presents the comparison between the experimental current and the computed current obtained by each algorithm. Table 9 shows the values of the optimal parameters, best fitness, mean fitness and standard deviation of 30 independent operations executed by each algorithm. Figure 7 displays the mean and best convergence curves of the algorithms. The results show that PO was also significantly faster than all the other algorithms during the iterative process. The analytical methods are illustrated

in Figure 8. PO also shows a significant advantage in computational stability. Figure 9 plots the I–V and P–V curves based on PO results in comparison with the experimental values. Figure 10 shows the prediction of the characteristic curves under four temperature conditions (25, 33, 50 and 75 °C), with the MPPs at different temperatures marked by black dots.

Table 8. SDM experimental data compared against five advanced algorithms.

Experimental Data		HBA	WOA	HHO	JAYA	PO
Vt(V)	It(A)	Computed It(A)				
−0.2057	0.7640	0.7642	0.7632	0.7637	0.7629	0.7642
−0.1291	0.7620	0.7628	0.7620	0.7623	0.7618	0.7628
−0.0588	0.7605	0.7614	0.7609	0.7611	0.7607	0.7614
0.0057	0.7605	0.7602	0.7600	0.7600	0.7598	0.7602
0.0646	0.7600	0.7590	0.7591	0.7590	0.7589	0.7590
0.1185	0.7590	0.7580	0.7582	0.7581	0.7581	0.7580
0.1678	0.7570	0.7570	0.7574	0.7572	0.7573	0.7570
0.2132	0.7570	0.7560	0.7566	0.7563	0.7565	0.7560
0.2545	0.7555	0.7550	0.7557	0.7553	0.7556	0.7550
0.2924	0.7540	0.7535	0.7543	0.7540	0.7542	0.7535
0.3269	0.7505	0.7513	0.7520	0.7517	0.7519	0.7513
0.3585	0.7465	0.7473	0.7478	0.7476	0.7478	0.7473
0.3873	0.7385	0.7401	0.7404	0.7403	0.7403	0.7401
0.4137	0.7280	0.7275	0.7273	0.7275	0.7273	0.7275
0.4373	0.7065	0.7071	0.7066	0.7069	0.7065	0.7071
0.4590	0.6755	0.6755	0.6747	0.6750	0.6745	0.6755
0.4784	0.6320	0.6309	0.6301	0.6303	0.6298	0.6309
0.4960	0.5730	0.5720	0.5715	0.5714	0.5710	0.5720
0.5119	0.4990	0.4995	0.4996	0.4990	0.4990	0.4995
0.5265	0.4130	0.4134	0.4143	0.4132	0.4135	0.4134
0.5398	0.3165	0.3171	0.3187	0.3172	0.3179	0.3171
0.5521	0.2120	0.2118	0.2137	0.2121	0.2131	0.2118
0.5633	0.1035	0.1022	0.1038	0.1026	0.1036	0.1022
0.5736	−0.0100	−0.0083	−0.0079	−0.0080	−0.0073	−0.0083
0.5833	−0.1230	−0.1243	−0.1257	−0.1243	−0.1242	−0.1243
0.5900	−0.2100	−0.2065	−0.2101	−0.2070	−0.2077	−0.2065
RMSE		8.8186×10^{-4}	1.2986×10^{-3}	9.4210×10^{-4}	1.1566×10^{-3}	8.8180×10^{-4}

Table 9. The results of the SDM parameter identification.

PARAM/ ALGO	OBEDO [37]	μ AFCSO [58]	ESMA [30]	HBA	WOA	HHO	JAYA	PO
Rs (Ω)	0.0364	0.03639	0.036373	0.037	0.0349	0.0363	0.0354	0.037
R_{sh} (Ω)	53.7185	52.64088	53.724744	51.8812	65.4335	58.5555	67.1110	52.1089
I_{ph} (A)	0.7608	0.76091	0.760776	0.7608	0.7605	0.7606	0.7602	0.7608
I_{sd1} (μ A)	3.2310^{-7}	0.32168	0.323260	0.2905	0.4395	0.3476	0.4258	0.2918
n1	1.4812	1.48077	1.481095	1.4719	1.5142	1.4899	1.5109	1.4723
Best	9.8602×10^{-4}	9.8314×10^{-4}	9.860231×10^{-4}	8.8186×10^{-4}	1.2986×10^{-3}	9.4210×10^{-4}	1.1566×10^{-3}	8.8180×10^{-4}
	(5)	(4)	(6)	(2)	(8)	(3)	(7)	(1)
Mean	9.8602×10^{-4}	9.8314×10^{-4}	1.499893×10^{-3}	6.3622×10^{-3}	1.2364×10^{-2}	7.0523×10^{-3}	1.4668×10^{-3}	9.3341×10^{-4}
	(3)	(2)	(5)	(6)	(8)	(7)	(4)	(1)
Std.	4.7451×10^{-17}	2.4921×10^{-14}	4.828118×10^{-4}	1.3270×10^{-2}	1.5128×10^{-2}	8.1770×10^{-3}	1.6326×10^{-4}	8.3827×10^{-5}
	(1)	(2)	(5)	(7)	(8)	(6)	(4)	(3)

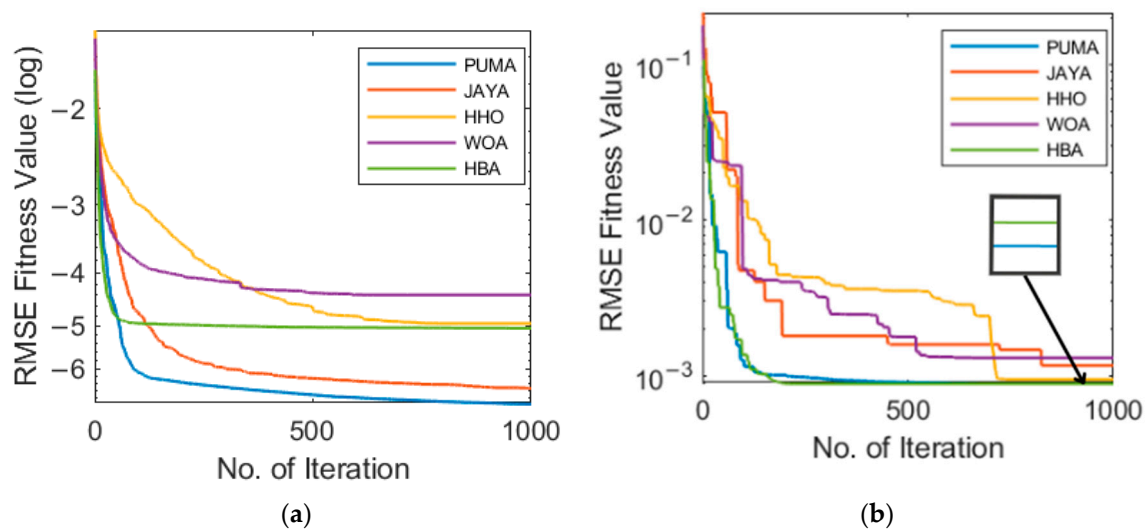


Figure 7. The (a) mean and (b) best convergence history curves for the algorithms used in the SDM parameter search.

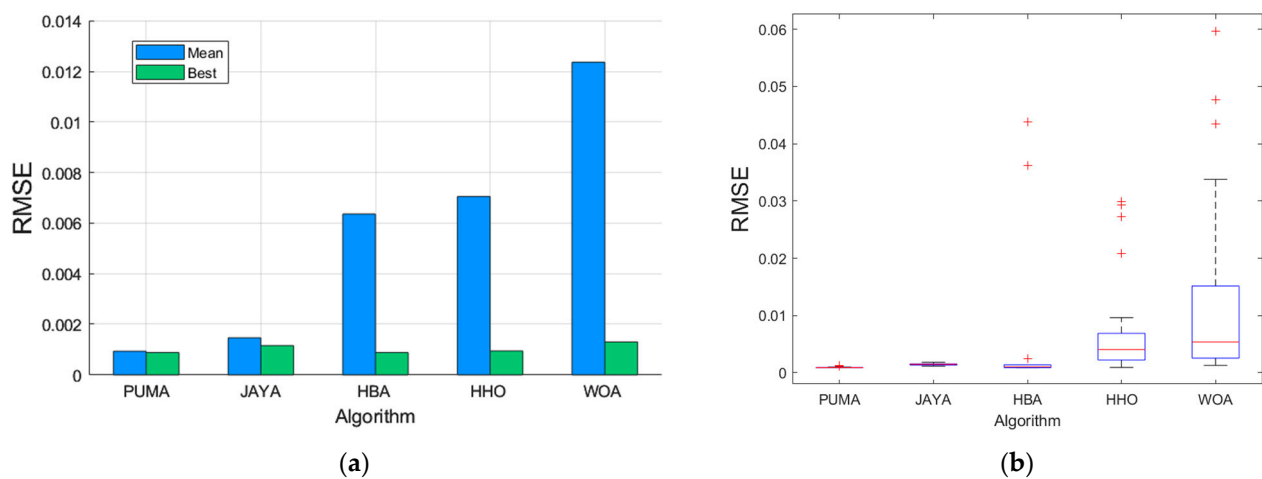


Figure 8. The (a) error bars and (b) boxplots for algorithms in SDM parameter identification results.

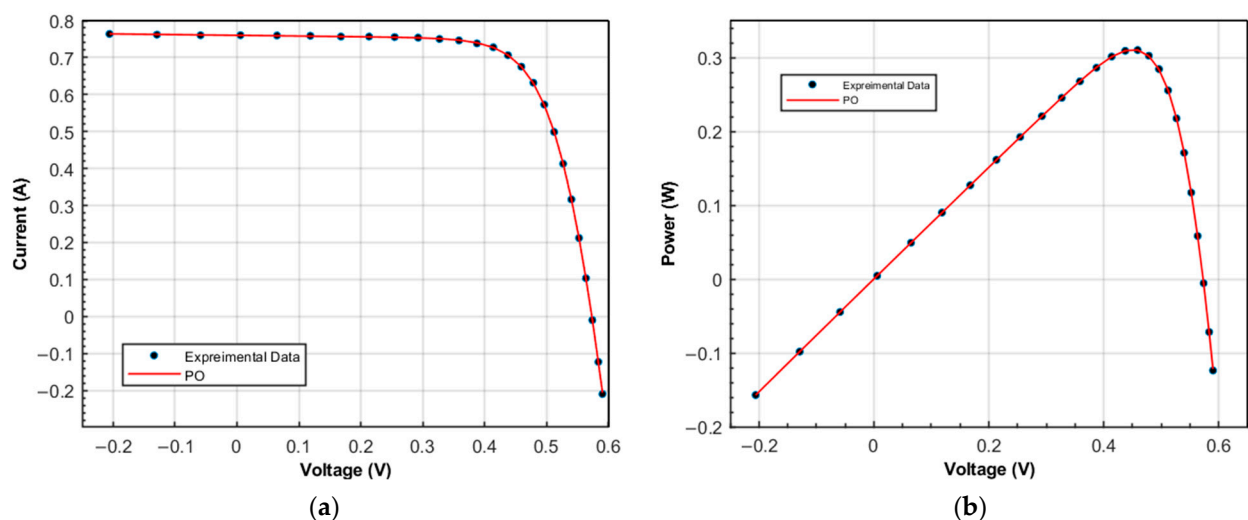


Figure 9. The SDM (a) I-V and (b) P-V curve from PO calculations compared with experimental data.

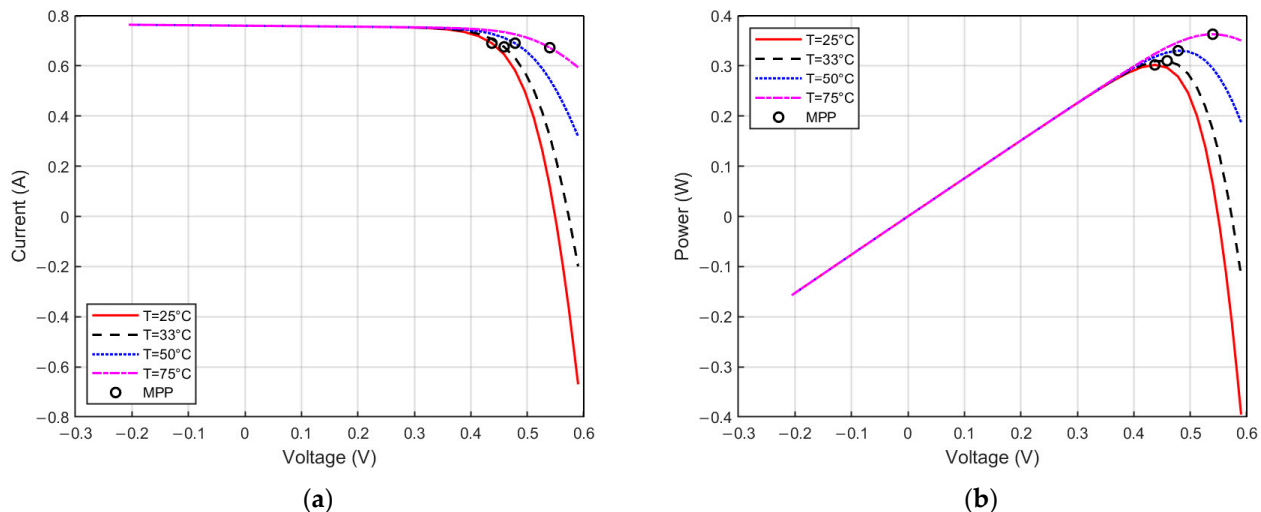


Figure 10. The prediction of SDM performance, including (a) I–V and (b) P–V curves and the maximum power point, under different temperature conditions.

3.2. Double Diode Model

For the DDM parameter identification, the algorithms were used to identify seven undetermined parameters. Table 10 shows the DDM real data compared against five algorithms. Table 11 presents the calculation results of the algorithms. Although HBA produced the best individual solution, PO achieved a better mean solution and lower standard deviation. Figure 11 shows that PO was the fastest in finding an approximate solution during the iterative process. Additionally, the error bars and box plot in Figure 12 validate the strong robustness of PO's search results. Lastly, Figure 13 plots the I–V and P–V curves of the PO values in comparison with the experimental values, while Figure 14 shows the predicted characteristic curves and MPPs under different temperature conditions.

Table 10. DDM experimental data compared against five advanced algorithms.

Experimental Data		HBA	WOA	HHO	JAYA	PO
$V_t(V)$	$I_t(A)$	Computed $I_t(A)$				
−0.2057	0.7640	0.7641	0.7662	0.7611	0.7636	0.7641
−0.1291	0.7620	0.7627	0.7645	0.7603	0.7624	0.7627
−0.0588	0.7605	0.7614	0.7630	0.7595	0.7613	0.7614
0.0057	0.7605	0.7602	0.7616	0.7588	0.7603	0.7602
0.0646	0.7600	0.7591	0.7603	0.7581	0.7594	0.7590
0.1185	0.7590	0.7581	0.7591	0.7575	0.7586	0.7580
0.1678	0.7570	0.7571	0.7579	0.7570	0.7577	0.7571
0.2132	0.7570	0.7561	0.7568	0.7563	0.7569	0.7561
0.2545	0.7555	0.7551	0.7555	0.7555	0.7560	0.7551
0.2924	0.7540	0.7536	0.7539	0.7543	0.7546	0.7536
0.3269	0.7505	0.7513	0.7513	0.7522	0.7523	0.7513
0.3585	0.7465	0.7472	0.7469	0.7483	0.7481	0.7473
0.3873	0.7385	0.7400	0.7392	0.7412	0.7406	0.7401
0.4137	0.7280	0.7273	0.7260	0.7286	0.7275	0.7274
0.4373	0.7065	0.7070	0.7051	0.7082	0.7066	0.7070
0.4590	0.6755	0.6754	0.6729	0.6765	0.6745	0.6754
0.4784	0.6320	0.6309	0.6281	0.6318	0.6297	0.6308

Table 10. Cont.

Experimental Data		HBA	WOA	HHO	JAYA	PO
$V_t(V)$	$I_t(A)$	Computed $I_t(A)$				
0.4960	0.5730	0.5721	0.5692	0.5726	0.5708	0.5719
0.5119	0.4990	0.4996	0.4971	0.4998	0.4986	0.4995
0.5265	0.4130	0.4135	0.4115	0.4132	0.4130	0.4134
0.5398	0.3165	0.3172	0.3160	0.3166	0.3172	0.3172
0.5521	0.2120	0.2118	0.2114	0.2110	0.2122	0.2119
0.5633	0.1035	0.1021	0.1025	0.1014	0.1024	0.1022
0.5736	−0.0100	−0.0084	−0.0074	−0.0086	−0.0089	−0.0083
0.5833	−0.1230	−0.1243	−0.1229	−0.1238	−0.1262	−0.1243
0.5900	−0.2100	−0.2063	−0.2049	−0.2049	−0.2100	−0.2065
RMSE		8.6505×10^{-4}	1.7562×10^{-3}	1.3853×10^{-3}	1.2703×10^{-3}	8.7497×10^{-4}

Table 11. The results of the DDM parameter identification.

PARAM/ ALGO	OBEDO [37]	μ AFCSO [58]	ESMA [30]	HBA	WOA	HHO	JAYA	PO
$R_s (\Omega)$	0.0367	2.00000	0.036685	0.0375	0.0367	0.0382	0.0353	0.0370
$R_{sh} (\Omega)$	55.3995	55.38775	55.226233	53.7479	45.2503	91.8191	64.2008	53.5530
$I_{ph} (A)$	0.7608	0.76078	0.760780	0.7608	0.7623	0.7592	0.7608	0.7608
$I_{sd1} (\mu A)$	2.31×10^{-7}	0.71140	0.645229	0.4878	0.5837	0.9081	0.4319	0.2866
$I_{sd2} (\mu A)$	7.08×10^{-7}	0.03672	0.238374	0.1255	0.0430	0.1188	0	0.2591
n_1	1.4529	0.23038	1.999999	1.7341	1.6200	1.8644	1.5122	1.9852
n_2	2.0000	1.45263	1.455321	1.4106	1.3637	1.4008	1.9608	1.4627
Best	9.8250×10^{-4} (3)	9.8250×10^{-4} (3)	9.825600×10^{-4} (5)	8.6505×10^{-4} (1)	1.7562×10^{-3} (8)	1.3853×10^{-3} (7)	1.2703×10^{-3} (6)	8.7497×10^{-4} (2)
Mean	1.0282×10^{-3} (3)	1.1718×10^{-3} (4)	1.0162100×10^{-3} (2)	5.5111×10^{-3} (6)	2.3748×10^{-2} (8)	8.3363×10^{-3} (7)	2.0297×10^{-3} (5)	9.9795×10^{-4} (1)
Std.	1.3384×10^{-4} (1)	3.6628×10^{-4} (3)	7.075800×10^{-4} (5)	1.0852×10^{-2} (7)	3.8918×10^{-2} (8)	8.2580×10^{-3} (6)	3.7328×10^{-4} (4)	1.6920×10^{-4} (2)

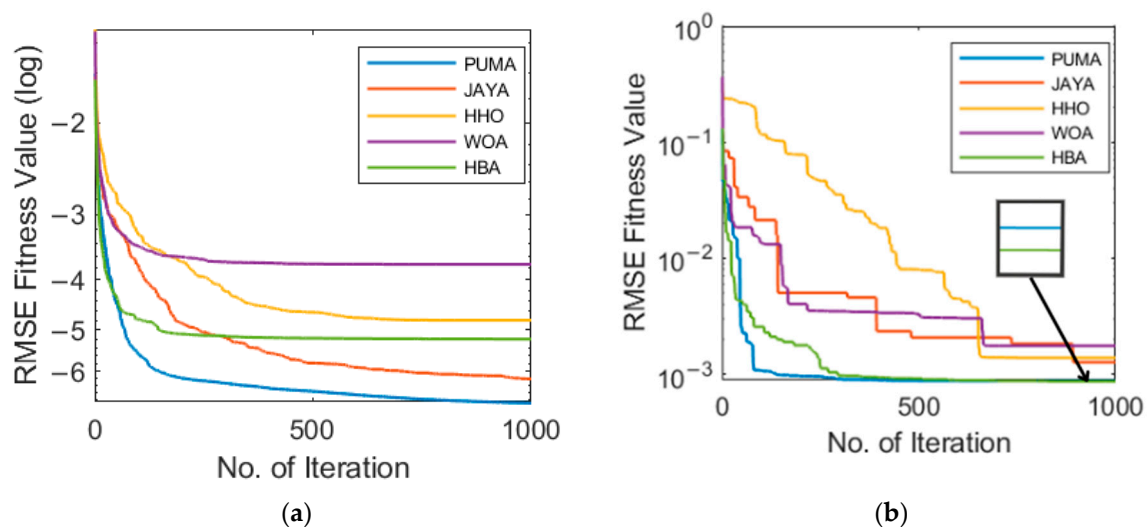


Figure 11. The (a) mean and (b) best convergence history curves for the algorithms used in the DDM parameter search.

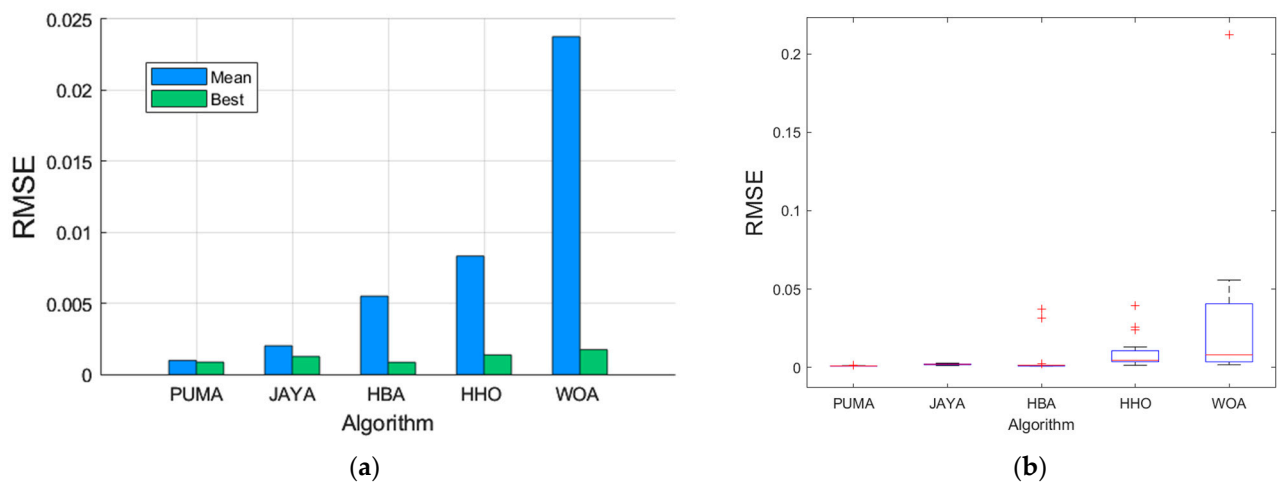


Figure 12. The (a) error bars and (b) boxplots for algorithms in DDM parameter identification results.

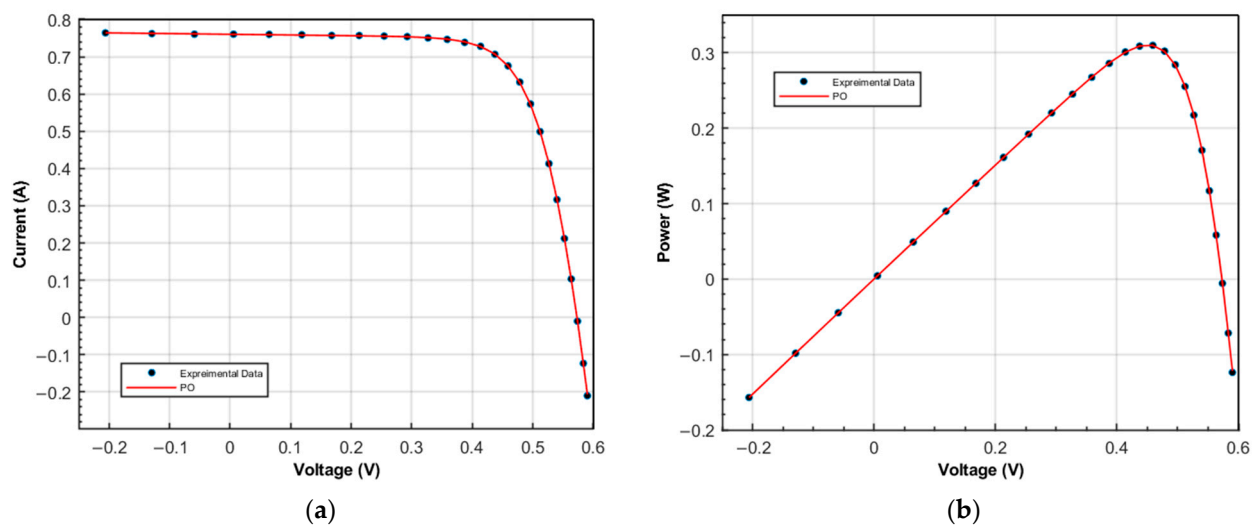


Figure 13. The DDM (a) I-V and (b) P-V curve from PO calculations compared with experimental data.

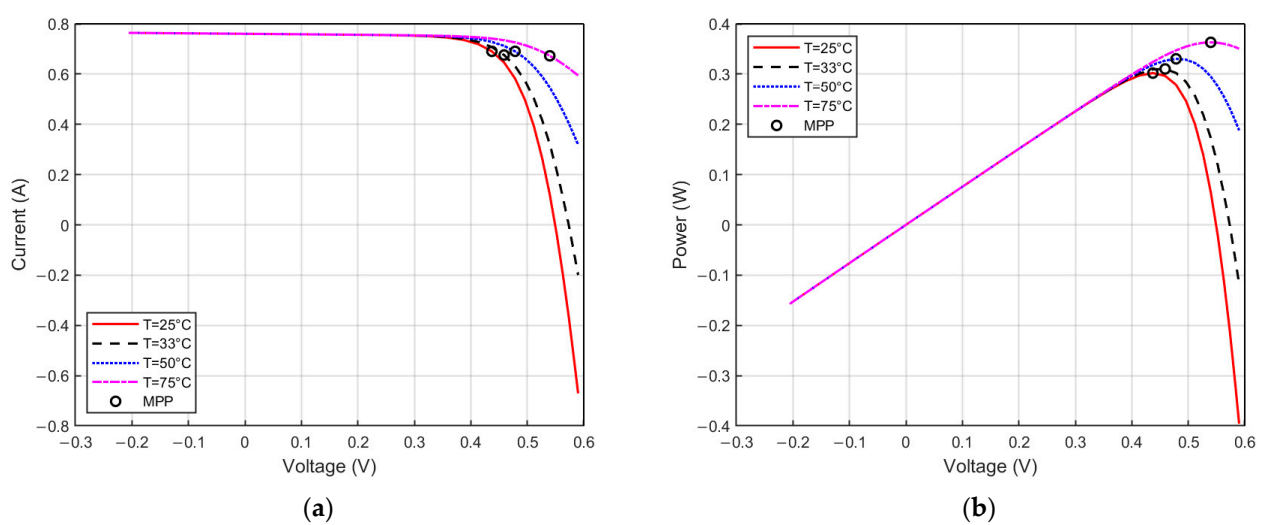


Figure 14. The prediction of DDM performance, including (a) I-V and (b) P-V curves and the maximum power point, under different temperature conditions.

3.3. Triple Diode Model

For the TDM parameter identification, the algorithms were used to identify nine undetermined parameters. Table 12 presents the comparison data between the experimental results and the algorithm calculations. Table 13 shows the values of the optimal TDM parameters, mean fitness and standard deviation determined by the five algorithms. Similar to the SDM case, although HBA achieved the best fitness, PO demonstrated better overall performance in the search strategy, as shown in Figure 15. Furthermore, the error bars and box plot in Figure 16 indicate that PO achieved significantly better results in terms of solution stability. Figure 17 plots the I–V and P–V curves of the PO values in comparison with the experimental values. Figure 18 shows PO's predicted performance of the TDM under different temperatures, along with the corresponding MPPs.

Table 12. TDM experimental data compared against five advanced algorithms.

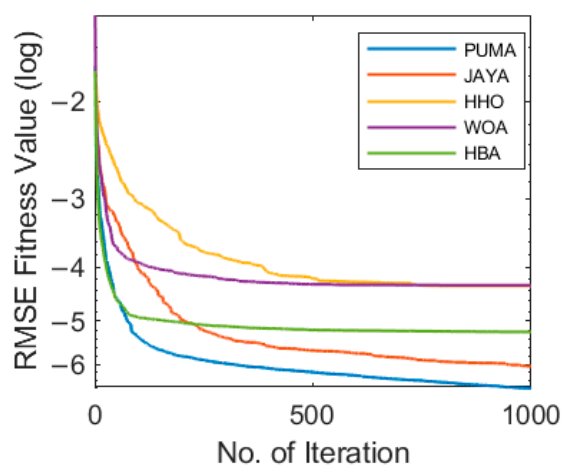
Experimental Data		HBA	WOA	HHO	JAYA	PO
Vt(V)	It(A)	Computed It(A)				
−0.2057	0.7640	0.7639	0.7617	0.7624		0.7640
−0.1291	0.7620	0.7626	0.7609	0.7614	0.7602	0.7626
−0.0588	0.7605	0.7613	0.7601	0.7606	0.7595	0.7613
0.0057	0.7605	0.7602	0.7594	0.7597	0.7589	0.7602
0.0646	0.7600	0.7591	0.7587	0.7590	0.7583	0.7591
0.1185	0.7590	0.7582	0.7581	0.7583	0.7577	0.7581
0.1678	0.7570	0.7573	0.7575	0.7576	0.7572	0.7572
0.2132	0.7570	0.7563	0.7569	0.7569	0.7566	0.7562
0.2545	0.7555	0.7552	0.7560	0.7560	0.7558	0.7551
0.2924	0.7540	0.7537	0.7547	0.7547	0.7546	0.7537
0.3269	0.7505	0.7513	0.7525	0.7524	0.7524	0.7513
0.3585	0.7465	0.7472	0.7484	0.7482	0.7483	0.7472
0.3873	0.7385	0.7399	0.7410	0.7406	0.7409	0.7400
0.4137	0.7280	0.7272	0.7281	0.7274	0.7280	0.7272
0.4373	0.7065	0.7068	0.7075	0.7065	0.7074	0.7069
0.4590	0.6755	0.6753	0.6754	0.6743	0.6755	0.6753
0.4784	0.6320	0.6309	0.6304	0.6295	0.6308	0.6309
0.4960	0.5730	0.5721	0.5708	0.5707	0.5718	0.5721
0.5119	0.4990	0.4997	0.4976	0.4987	0.4992	0.4997
0.5265	0.4130	0.4136	0.4109	0.4133	0.4129	0.4135
0.5398	0.3165	0.3172	0.3143	0.3178	0.3164	0.3172
0.5521	0.2120	0.2117	0.2091	0.2131	0.2108	0.2118
0.5633	0.1035	0.1020	0.1003	0.1035	0.1011	0.1020
0.5736	−0.0100	−0.0084	−0.0083	−0.0076	−0.0090	−0.0084
0.5833	−0.1230	−0.1243	−0.1216	−0.1248	−0.1246	−0.1243
0.5900	−0.2100	−0.2061	−0.2008	−0.2087	−0.2057	−0.2061
RMSE		8.49×10^{-4}	1.86×10^{-3}	1.29×10^{-3}	1.30×10^{-3}	8.60×10^{-4}

Table 13. The results of the TDM parameter identification.

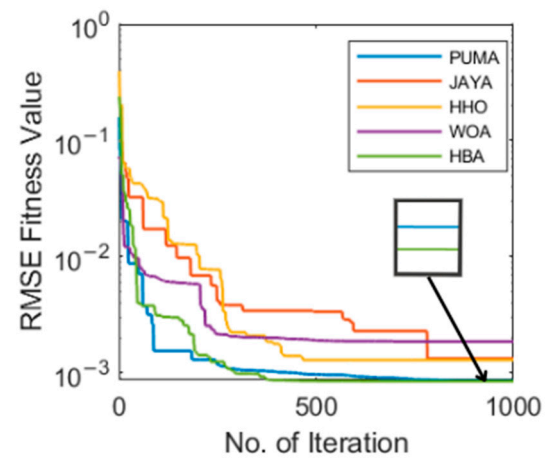
PARAM/ ALGO	OBEDO [37]	μ AFCSO [58]	HBA	WOA	HHO	JAYA	PO
R_s (Ω)	0.0367	0.03666	0.0379	0.0394	0.0351	0.0391	0.0378
R_{sh} (Ω)	55.7780	55.12808	56.8628	90.4876	78.773	100	55.1974
I_{ph} (A)	0.7608	0.76078	0.7608	0.7598	0.7601	0.7592	0.7608

Table 13. Cont.

PARAM/ ALGO	OBEDO [37]	μ AFCSO [58]	HBA	WOA	HHO	JAYA	PO
I_{sd1} (μ A)	5.88×10^{-7}	0.23805	0.6863	0.5061	0.3012	0.0010	0.0102
I_{sd2} (μ A)	2.34×10^{-7}	0.00098	0.8779	0.0434	0.0718	0.0010	0.0771
I_{sd3} (μ A)	9.79×10^{-7}	0.57956	0.1206	0.6807	0.2946	0.6901	0.6860
n_1	1.9995	1.45564	1.9774	1.7883	1.4947	1.1294	1.9999
n_2	1.4537	1.70165	0.0379	0.0394	0.0351	1.6918	1.3752
n_3	2.7316	1.97191	56.8628	90.4876	78.773	1.6042	1.7352
Best	9.8082×10^{-4} (3)	9.8295×10^{-4} (4)	8.49×10^{-4} (1)	1.86×10^{-3} (7)	1.29×10^{-3} (5)	1.30×10^{-3} (6)	8.60×10^{-4} (2)
Mean	9.9957×10^{-4} (1)	1.4196×10^{-3} (3)	5.34×10^{-3} (5)	1.35×10^{-2} (7)	1.33×10^{-2} (6)	2.40×10^{-3} (4)	1.30×10^{-3} (2)
Std.	5.1873×10^{-5} (1)	4.5925×10^{-4} (3)	1.02×10^{-2} (5)	1.26×10^{-2} (6)	1.29×10^{-2} (7)	6.78×10^{-4} (4)	4.13×10^{-4} (2)

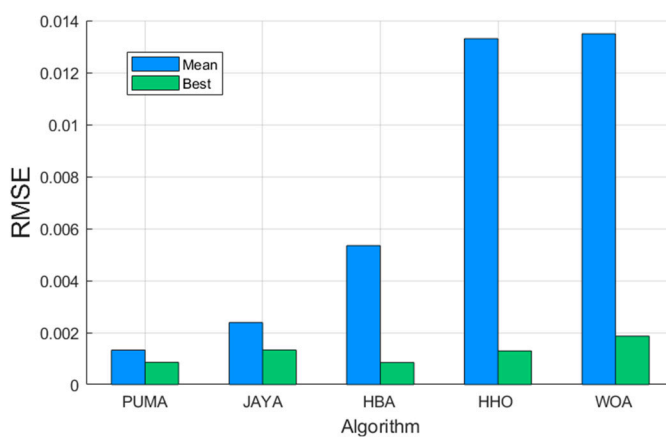


(a)

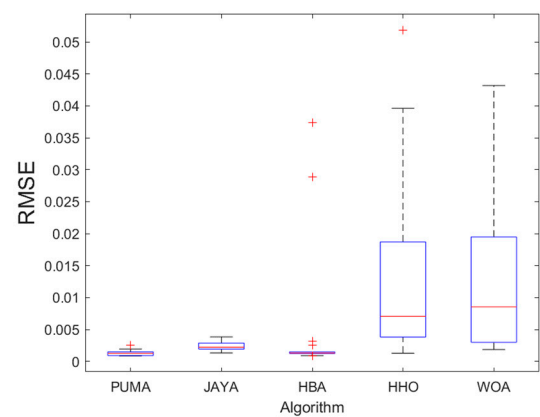


(b)

Figure 15. The (a) mean and (b) best convergence history curves for the algorithms used in the TDM parameter search.



(a)



(b)

Figure 16. The (a) error bars and (b) boxplots for algorithms in TDM parameter identification results.

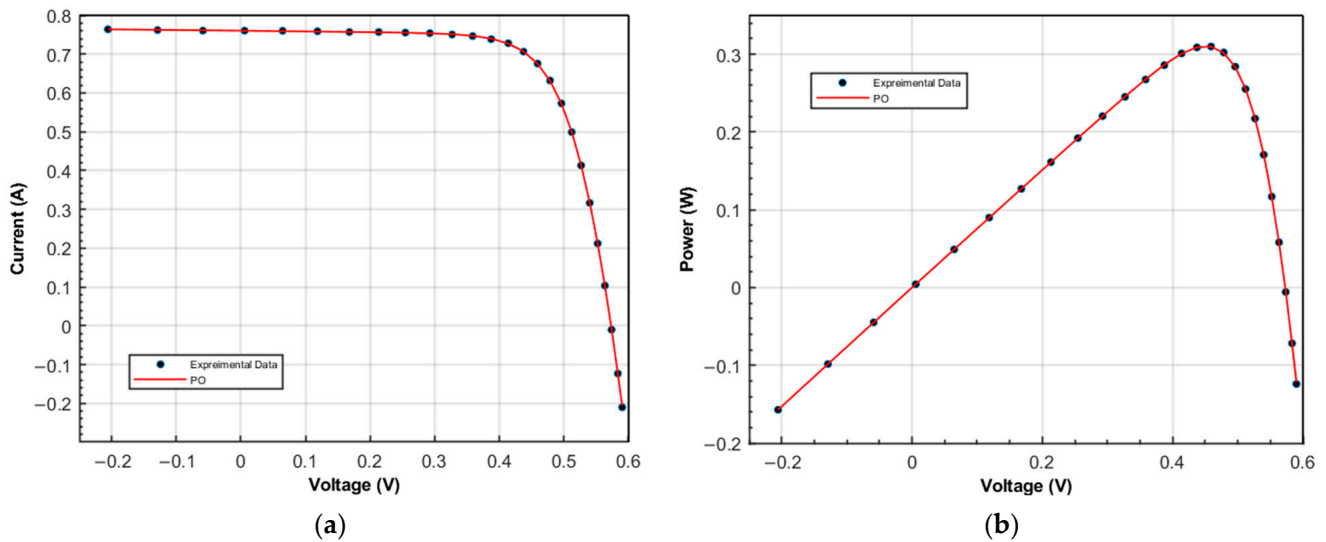


Figure 17. The TDM (a) I–V and (b) P–V curve from PO calculations compared with experimental data.

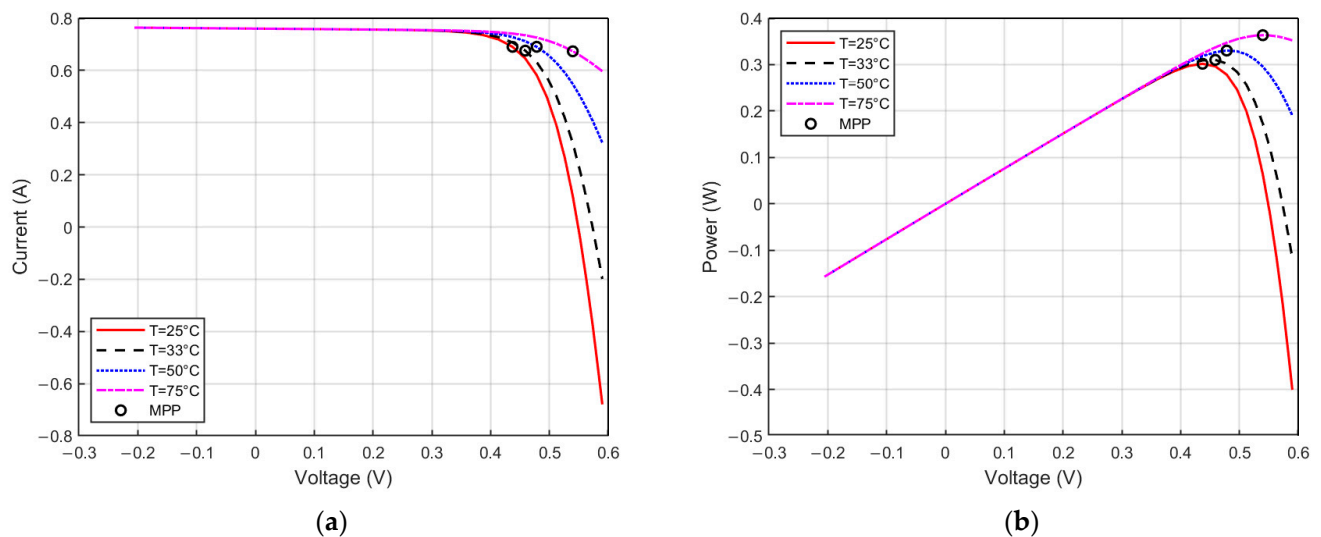


Figure 18. The prediction of TDM performance, including (a) I–V and (b) P–V curves and the maximum power point, under different temperature conditions.

3.4. Photovoltaic Module Model

For the PMM parameter identification, each algorithm was tasked with estimating five undetermined parameters. The algorithm calculation results are shown in Table 14, and the optimal parameter values, mean fitness, and standard deviation obtained by the eight algorithms are summarized in Table 15. Although PO exhibited slightly lower best fitness compared to HBA, it achieved superior overall performance in terms of search consistency and convergence behavior, as illustrated in Figure 19. This is further supported by the statistical analyses shown in Figure 20, where the error bars and box plots indicate that PO produced more stable and intent solutions across multiple runs. Figure 21 presents the I–V and P–V characteristic curves based on the PO-identified parameters, compared with the experimental data. Figure 22 illustrates the predicted performance of the PMM under different temperature scenarios, with PO accurately tracking the corresponding MPP in each case.

3.5. Data Visualization Analysis

To facilitate the visualization of each algorithm's performance, a five-variable radar chart was constructed for multivariate analysis. The considered variables include mean solution (Mean), maximum solution (Max), minimum solution (Min), standard deviation (Std.) and computation time (Time). The performance ranking is determined based on the principle that algorithms with better performance receive higher scores. The results are presented in Figures 23–26, indicating that puma optimizer exhibits the largest enclosed area, demonstrating superior overall performance.

Table 14. PMM experimental data compared against five advanced algorithms.

Experimental Data		HBA	WOA	HHO	JAYA	PO
Vt(V)	It(A)	Computed It(A)				
−1.9426	1.0345	1.0327	1.0365	1.0272	1.0283	1.0310
0.1248	1.0315	1.0302	1.0329	1.0270	1.0281	1.0291
1.8093	1.0300	1.0282	1.0300	1.0268	1.0279	1.0275
3.3511	1.0260	1.0263	1.0273	1.0266	1.0277	1.0260
4.7622	1.0220	1.0244	1.0247	1.0261	1.0273	1.0245
6.0538	1.0180	1.0223	1.0221	1.0252	1.0265	1.0227
7.2364	1.0155	1.0198	1.0191	1.0234	1.0248	1.0204
8.3189	1.0140	1.0161	1.0152	1.0200	1.0216	1.0168
9.3097	1.0100	1.0102	1.0093	1.0136	1.0156	1.0108
10.2163	1.0035	1.0003	0.9996	1.0027	1.0050	1.0007
11.0449	0.9880	0.9843	0.9839	0.9850	0.9878	0.9842
11.8018	0.9630	0.9594	0.9592	0.9580	0.9613	0.9588
12.4929	0.9255	0.9228	0.9225	0.9195	0.9232	0.9218
13.1231	0.8725	0.8727	0.8717	0.8680	0.8718	0.8713
13.6983	0.8075	0.8075	0.8049	0.8024	0.8059	0.8060
14.2221	0.7265	0.7285	0.7239	0.7240	0.7270	0.7272
14.6995	0.6345	0.6372	0.6305	0.6343	0.6365	0.6363
15.1346	0.5345	0.5362	0.5274	0.5354	0.5366	0.5359
15.5311	0.4275	0.4294	0.4195	0.4306	0.4308	0.4296
15.8929	0.3185	0.3186	0.3087	0.3216	0.3208	0.3193
16.2229	0.2085	0.2071	0.1987	0.2112	0.2097	0.2082
16.5241	0.1010	0.0960	0.0903	0.1003	0.0982	0.0971
16.7987	−0.0080	−0.0083	−0.0092	−0.0055	−0.0078	−0.0076
17.0499	−0.1110	−0.1107	−0.1058	−0.1101	−0.1123	−0.1105
17.2793	−0.2090	−0.2087	−0.1969	−0.2113	−0.2132	−0.2093
17.4885	−0.3030	−0.2999	−0.2801	−0.3068	−0.3082	−0.3016
RMSE		2.388×10^{-3}	6.240×10^{-3}	4.007×10^{-3}	3.944×10^{-3}	2.514×10^{-3}

Table 15. The results of the PMM model parameter identification.

PARAM/ ALGO	OBEDO [37]	μ AFCSO [58]	ESMA [30]	HBA	WOA	HHO	JAYA	PO
R_s (Ω)	1.2013	0.03337	1.201129	0.03367	0.03698	0.02984	0.03079	0.0327
R_{sh} (Ω)	981.98	27.27673	983.44499	23.0581	16.0008	389.6039	360.344	30.0367
I_{ph} (A)	1.0305	1.03051	1.03051	1.0319	1.0355	1.0271	1.02823	1.03035
I_{sd1} (μ A)	3.48	3.48211	3.48703	3.1442	1.6401	10.0554	7.80723	4.24014
n_I	48.6428	1.35118	48.642708	1.3410	1.2759	1.4749	1.44282	1.37310
Best	2.4251×10^{-3} (1)	2.4251×10^{-3} (1)	2.425077×10^{-3} (4)	2.388×10^{-3} (3)	6.240×10^{-3} (8)	4.007×10^{-3} (7)	3.944×10^{-3} (6)	2.514×10^{-3} (5)
Mean	2.4251×10^{-3} (1)	2.5081×10^{-3} (2)	$1.19929932 \times 10^{-1}$ (7)	0.10694 (6)	0.13499 (8)	3.032×10^{-2} (4)	3.386×10^{-2} (5)	3.685×10^{-3} (3)
Std.	5.7466×10^{-17} (1)	1.3064×10^{-4} (2)	$1.35626152 \times 10^{-1}$ (8)	0.11847 (7)	0.10889 (6)	5.066×10^{-2} (5)	7.332×10^{-2} (4)	1.302×10^{-3} (3)

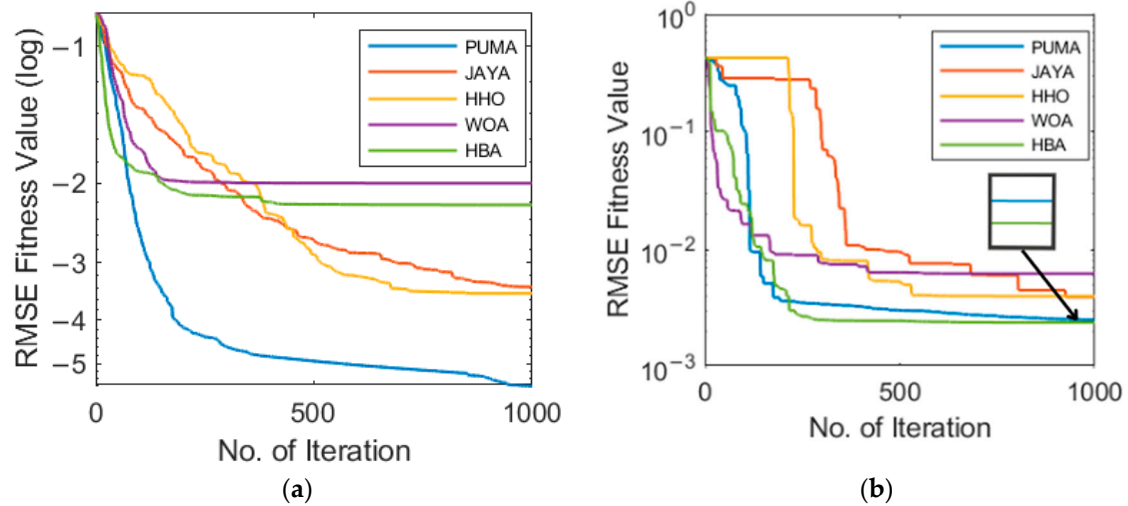


Figure 19. The (a) mean and (b) best convergence history curves for the algorithms used in the PMM parameter search.

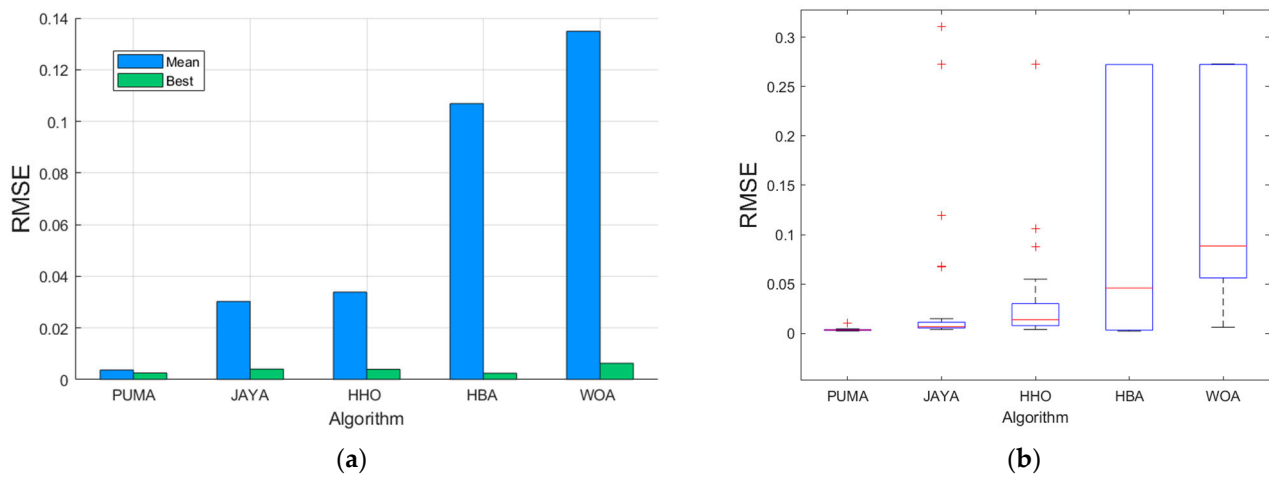


Figure 20. The (a) error bars and (b) boxplots for algorithms in PMM parameter identification results.

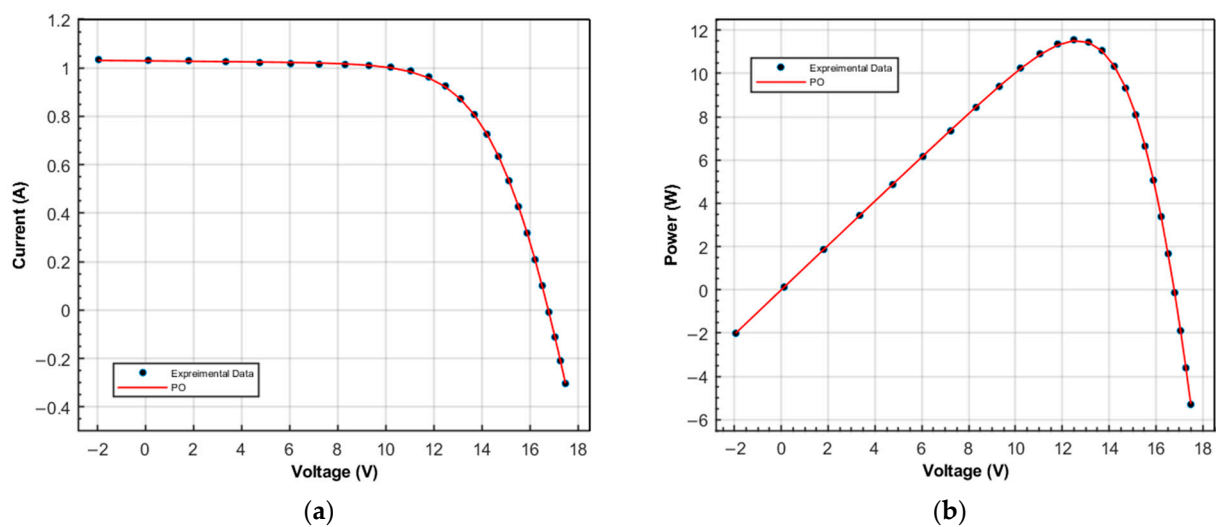


Figure 21. The PMM model (a) I–V and (b) P–V curve from PO calculations compared with experimental data.

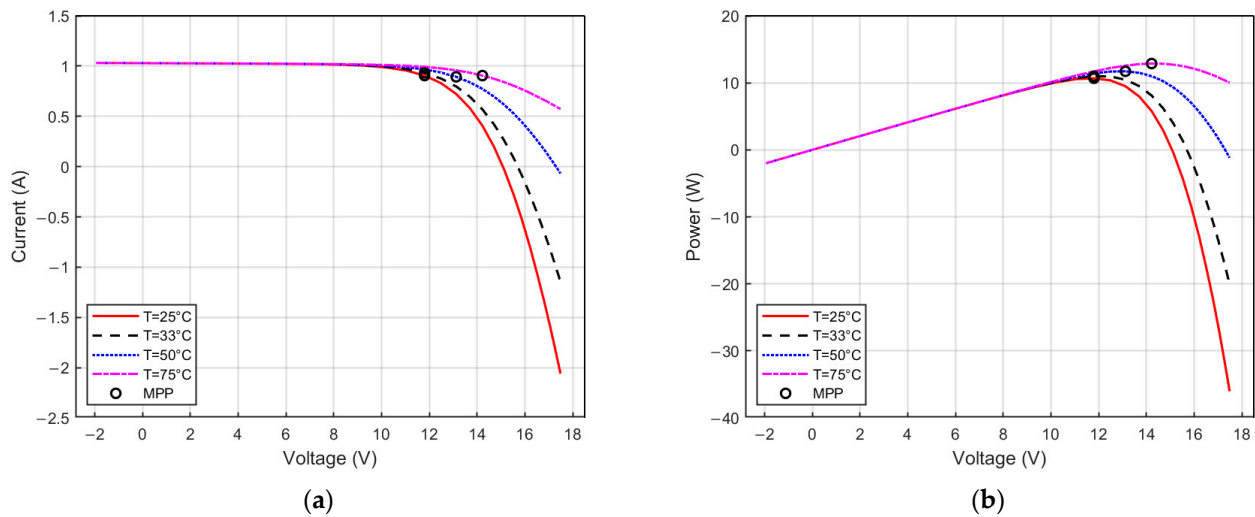


Figure 22. The prediction of PMM performance, including (a) I–V and (b) P–V curves and the maximum power point, under different temperature conditions.

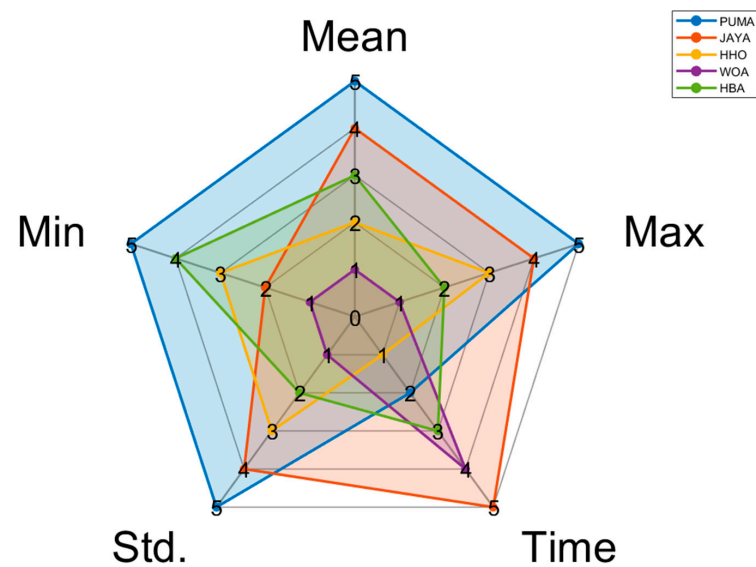


Figure 23. The radar chart of algorithm performance based on the SDM.

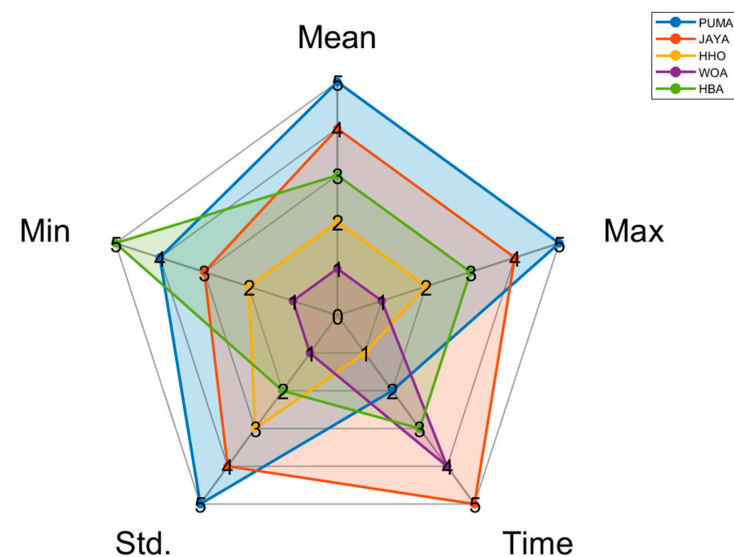


Figure 24. The radar chart of algorithm performance based on the DDM.

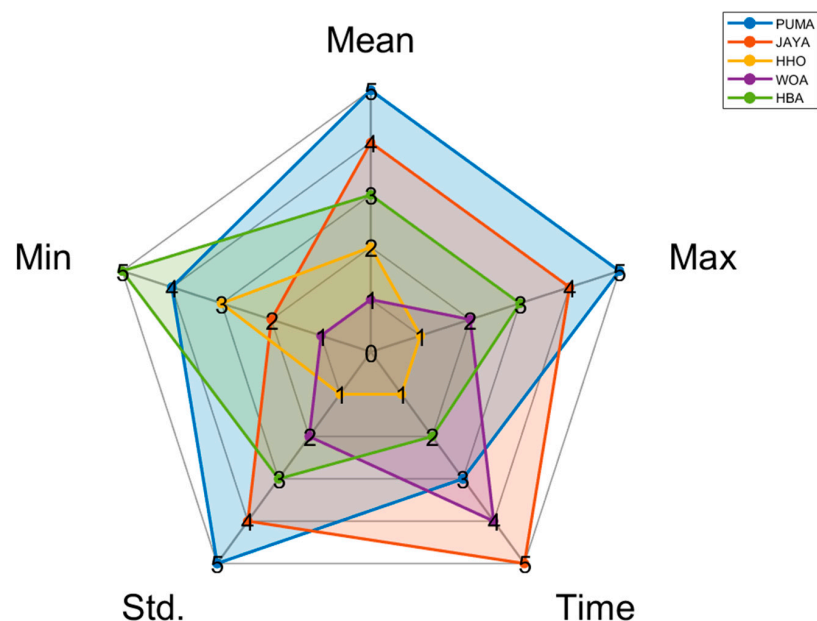


Figure 25. The radar chart of algorithm performance based on the TDM.

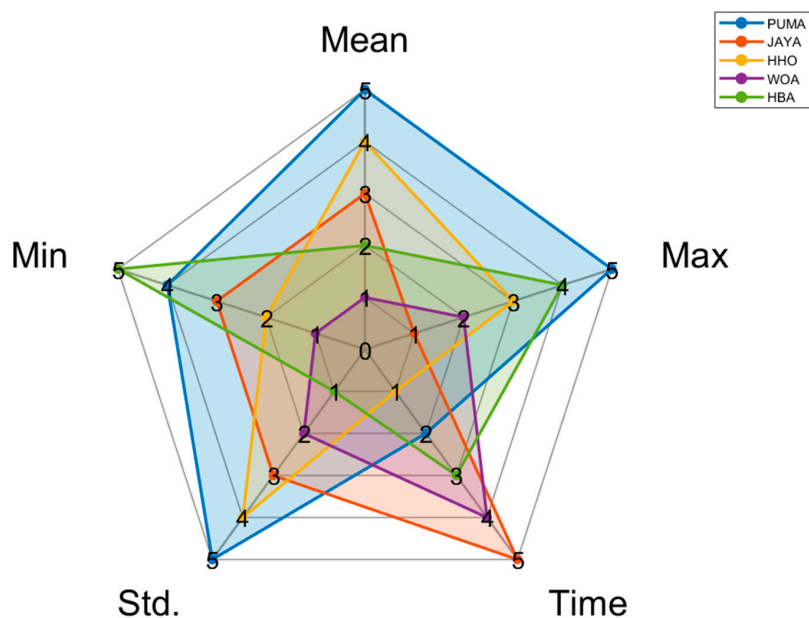


Figure 26. The radar chart of algorithm performance based on the PMM model.

3.6. System Parameter Sensitivity

The parameter sensitivity analysis reveals the significant impact of individual parameters on the mathematical model. It can also lead to increased computational cost, especially when CPU resources are limited. Our study adopts one-factor-at-a-time method, in which each parameter is adjusted from 0.8 to 1.2 times its nominal boundary. Figures 27–30 present the sensitivity results for four photovoltaic models. A larger standard deviation (STD) indicates that the parameter has a greater influence on the model's behavior.

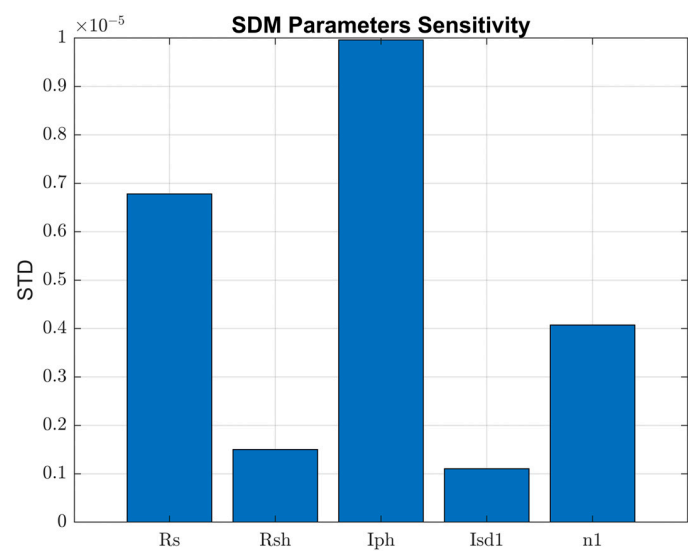


Figure 27. The parameter sensitivity of SDM.

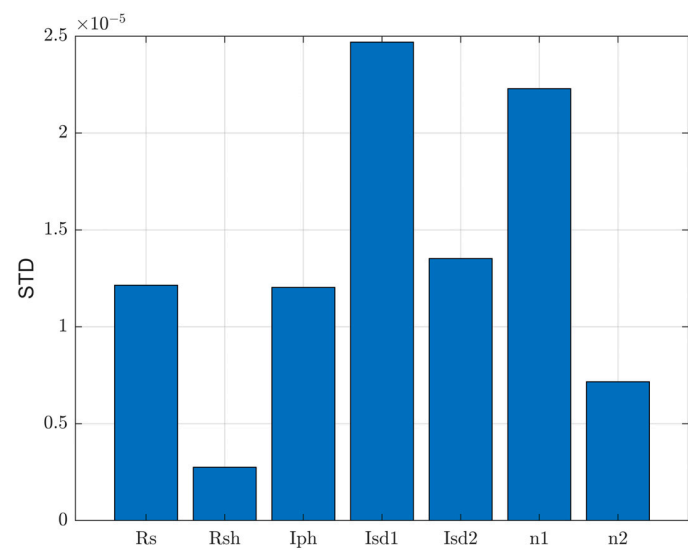


Figure 28. The parameter sensitivity of DDM.

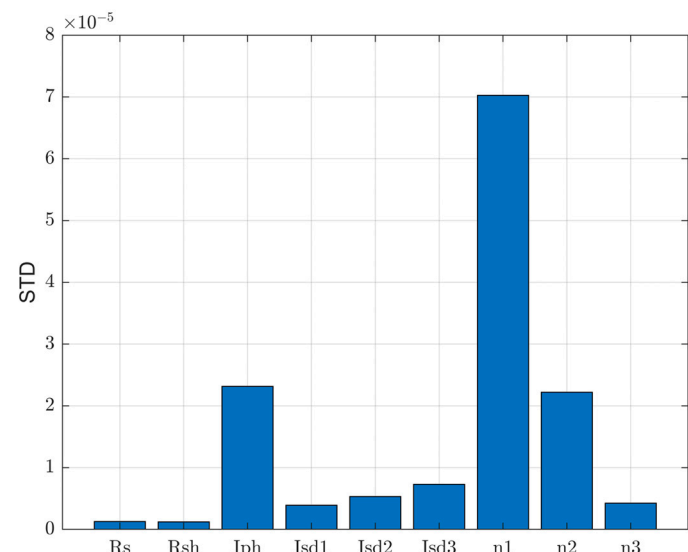


Figure 29. The parameter sensitivity of TDM.

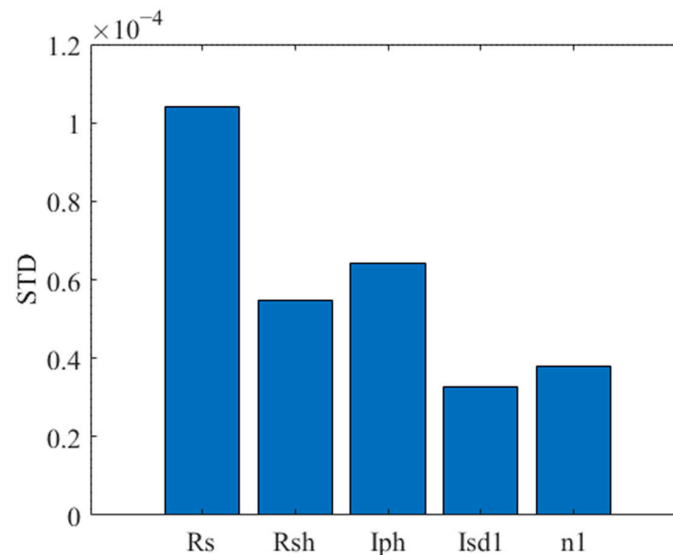


Figure 30. The parameter of PMM model.

4. Conclusions

This research developed a high-precision modeling technique by applying PO for parameter optimization in PV systems. To validate its effectiveness, multiple PV models were constructed, including SDM, DDM, TDM, and PMM. PO with four other advanced metaheuristic algorithms, was employed to estimate system parameters. A detailed set of statistical methods was used to evaluate the robustness, accuracy, and convergence performance of each algorithm. The results demonstrated that the search mechanism of PO is well suited for PV parameter optimization, achieving highly stable solution results across all evaluated models. After validation, PO-optimized parameters were applied to simulate PV performance under varying temperature scenarios and to identify the corresponding MPP in each case. In addition, the study further discusses the parameter sensitivity of the models. This study provides detailed metaheuristic-method modeling techniques, which can serve as a standard research structure for developing unknown commercial photovoltaic systems.

Author Contributions: Conceptualization, E.-J.L. and Y.-H.H.; methodology, W.-L.L.; software, C.-K.W.; validation, W.-L.L.; investigation, C.-K.W.; data curation, C.-I.L.; visualization, W.-L.L.; writing—original draft preparation, E.-J.L.; writing—review and editing, Y.-H.H.; project administration, E.-J.L. All authors have read and agreed to the published version of the manuscript.

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Data Availability Statement: The data that support the findings of this study are available on request from the corresponding author.

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Conflicts of Interest: The authors declare no conflicts of interest.

Abbreviations

Acronym

PV	Photovoltaic
MPP	Maximum power point
PO	Puma optimizer
WOA	Whale optimization algorithm
HBA	Honey badger algorithm
HHO	Harris Hawks optimization
SDM	Single diode model
DDM	Double diode model
TDM	Triple diode model
PMM	Photovoltaic module model
RMSE	Root means square error

Symbol

I_{ph}	Photocurrent
R_s	Series resistance
R_{sh}	Shunt resistance
I_{sd}	Reverse saturation current
n	Ideality factor
K	Boltzmann constant
T	Temperature in Kelvin
q	Elementary charge
I_L	Terminal current
V_L	Terminal voltage
$rand$	Random number between 0 and 1
$randn$	Random number from the standard normal distribution

Subscript

i	The i-th agent
t	The t-th iteration
Old	The old best solution
New	The new best solution
Dim	The dimension of models

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