

PARAMETER ESTIMATION OF THE THREE-DIODE PHOTOVOLTAIC MODEL USING THE FLOW DIRECTION ALGORITHM

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ABSTRACT

Accurate parameter identification of photovoltaic (PV) models is essential for reliable performance prediction and optimization of energy systems. However, estimating the parameters of advanced equivalent circuit models is challenging due to the nonlinear and multimodal nature of their current–voltage (I–V) characteristics. This study proposes a parameter extraction approach based on the Flow Direction Algorithm applied to the Three-Diode Model (TDM). The method minimizes the root mean square error (RMSE) between measured and simulated I–V data while ensuring physically consistent parameter sets. The approach is validated using two benchmark photovoltaic devices: the **RTC** France solar cell and an amorphous silicon thin-film solar cell. For the **RTC** France cell, the proposed method achieves an RMSE of 7.3511×10^{-4} when fitting the experimental I–V characteristics using the TDM. For the amorphous silicon cell, the algorithm obtains an RMSE of 2.2939×10^{-5} , demonstrating a very close agreement between the measured and simulated electrical characteristics. These results confirm that the FDA-based optimization approach provides accurate parameter estimation for complex PV models, enabling reliable photovoltaic modeling and supporting improved performance analysis and energy system optimization.



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1. INTRODUCTION

Photovoltaic (PV) technology has become a cornerstone of modern renewable energy systems due to its sustainability, reliability, and steadily declining costs. Accurate modeling of PV devices is essential for performance evaluation, system design optimization, and efficient integration into energy networks. Among the various modeling approaches, equivalent circuit models—such as the single-diode, double-diode, and three-diode configurations—are widely adopted because they provide a practical balance between modeling simplicity and predictive accuracy. However, estimating the parameters of these models remains a challenging task due to the nonlinear and high-dimensional nature of the optimization problem. Conventional optimization techniques often encounter difficulties in obtaining accurate and stable solutions, particularly under varying environmental conditions. Consequently, metaheuristic optimization algorithms have emerged as effective alternatives, offering strong capabilities for exploring complex search spaces and avoiding local minima. Within this framework, the Flow Direction Algorithm (FDA), inspired by hydrological runoff processes, provides an efficient strategy for parameter optimization. By simulating water flows toward a basin outlet, FDA effectively balances global exploration and local exploitation, enabling reliable convergence toward optimal solutions. In this study, FDA is applied to parameter identification for both monocrystalline silicon like **RTC** France and amorphous silicon (**a-Si**) thin-film photovoltaic cells. The performance of the algorithm is evaluated through comprehensive statistical analysis and compared with several state-of-the-art optimization techniques reported in the literature. Accurate modeling and parameter identification of photovoltaic modules are fundamental for maximizing energy harvesting, predicting long-term performance, and ensuring operational reliability under diverse and fluctuating environmental conditions.

Over the past decade, extensive research efforts have focused on developing robust and efficient methods for estimating the unknown parameters of diode-based PV models. Among these models, the Three-Diode Model (TDM) has attracted significant attention because of its superior ability to capture the complex nonlinear characteristics of PV cells, although it introduces a more challenging parameter extraction problem. The inherent difficulty of photovoltaic (PV) parameter identification arises from the multidimensional, nonlinear, and multimodal nature of the associated search space. Consequently, metaheuristic optimization techniques have become widely adopted due to their ability to efficiently explore complex solution landscapes. Over the past few years, numerous enhanced optimization strategies have been introduced to improve the precision and robustness of PV model parameter estimation. For example, the Improved African Vultures Optimization (I-AVO) algorithm, which integrates Opposition-Based Learning and Orthogonal Learning mechanisms, has demonstrated promising results when combined with the Newton–Raphson method for parameter refinement [1]. Likewise, the augmented Mountain Gazelle Optimizer (AMGOIB3H) has shown strong reliability and fast convergence when tested with experimental PV datasets [2]. Other studies have explored the incorporation of chaotic dynamics to enhance the exploration–exploitation balance of optimization algorithms. Approaches such as the Chaotic Dragonfly Algorithm [3] and the Fractal Henon Chaotic Harris Hawks Optimization (FCHHHO) method [4] have reported improved convergence behavior and greater robustness in parameter extraction tasks. In addition, a wide range of optimization techniques has been successfully applied to PV parameter estimation, including improved variants of the Whale Optimization Algorithm (IWOA and WOA) [5], [6], the Equilibrium Optimizer (EOA) [7], Ranking-based Generalized Normal Distribution Optimization (RGNDO) [8], the Innovative Optimization Algorithm (INFO) [9], the Crayfish Optimization Algorithm (COA) [10], the Improved Mountain Gazelle Optimizer (IMGO) [11], Mother Tree Optimization with Climate Change (MTO-CL) [12], the Puma Optimization Algorithm [13], and the bio-dynamics Grasshopper Optimization Algorithm (BDGOA) [14].

Additional approaches have also been explored, including Improved Teaching–Learning-Based Optimization (ITLBO) [15], the Interior Search Algorithm (ISA) [16], Classified Perturbation Mutation-Based Particle Swarm Optimization (CPMPSO) [17], the Fractional Chaotic Ensemble Particle Swarm Optimizer (FC-EPSO2) [18], and the Hybrid Successive Discretization Algorithm (HSDA) [19]. Furthermore, the Mountain Gazelle Optimizer has been applied to single-, double-, and triple-diode PV models for accurate solar cell and module parameter extraction [20]. Collectively, these contributions highlight the continuous progress toward achieving high-precision parameter identification with minimal modeling error under different PV technologies and operating conditions. More recently, hybrid frameworks combining optimization techniques with machine learning models have attracted increasing attention. In particular, the integration of deep learning architectures, such as Convolutional Neural Network–Long Short-Term Memory (CNN–LSTM) networks, with multiple optimization algorithms has improved prediction accuracy and facilitated early fault detection in large-scale PV systems [21]. At the same time, advances in equivalent circuit modeling—including scalable triple-diode circuits [22] and lumped-parameter three-diode models tailored for industrial silicon solar cells [23]—have strengthened the physical representation of PV behavior, especially in capturing temperature-dependent effects and the contributions of different current components. Despite these advances, achieving consistent parameter identification across real operating conditions remains challenging. Factors such as partial shading, temperature variations, and device aging introduce additional nonlinearities that complicate the estimation process. Therefore, further improvements in optimization strategies are required to enhance both the accuracy and reliability of parameter identification for practical PV applications. The main contributions of this study can be summarized as follows:

- **Application of the Flow Direction Algorithm (FDA) for parameter extraction:** The FDA is employed to estimate the unknown parameters of the Three-Diode Model (TDM).
- **Experimental validation using benchmark datasets:** The proposed methodology is validated using experimental measurements from a standard RTC France monocrystalline silicon solar cell and an amorphous silicon (a-Si) thin-film photovoltaic cell.
- **Comparative performance assessment:** The proposed approach is evaluated against several state-of-the-art methods, demonstrating improved accuracy relative to conventional formulations.

The remainder of this paper is organized as follows. Section 2 presents the mathematical modeling of the photovoltaic devices and the formulation of the cost function. Section 3 describes the parameter estimation methodology and the implementation of the Flow Direction Algorithm. Section 4 presents the results and discussion, including statistical analysis and comparisons with existing approaches. Finally, Section 5 concludes the paper and outlines potential directions for future research.

II. PHOTOVOLTAIC MODELING AND PROBLEM FORMULATION

II.1 THREE-DIODE EQUIVALENT CIRCUIT REPRESENTATION OF A PV MODULE

Accurate modeling of photovoltaic (PV) devices is essential for robust parameter identification and reliable performance evaluation. This section outlines the mathematical formulation of the three-diode model (TDM) for both the PV cell and its extension to the module level. The primary emphasis of this work is the precise extraction of the TDM parameters for the PV cell/module, together with the formulation of the objective function employed in the optimization process. Figure 1 illustrates the three-diode equivalent circuit of a photovoltaic (PV) panel, comprising a current source, three parallel-connected diodes, and both series and shunt resistances. The corresponding mathematical formulation is expressed as follows:

$$I = I_{ph} - I_{d1} \left(\exp \left(\frac{V + I \cdot R_s}{n_1 \cdot V_t} \right) - 1 \right) - I_{d2} \left(\exp \left(\frac{V + I \cdot R_s}{n_2 \cdot V_t} \right) - 1 \right) - I_{d3} \left(\exp \left(\frac{V + I \cdot R_s}{n_3 \cdot V_t} \right) - 1 \right) - \frac{V + I \cdot R_s}{R_{sh}} \quad (1)$$

Let I_{ph} denote the photocurrent, $I_{d_1}, I_{d_2}, I_{d_3}$ the reverse saturation currents of the three diodes, and n_1, n_2, n_3 their respective ideality factors. The quantities R_s and R_{sh} correspond to the series and shunt resistances. The thermal voltage is defined as $V_t = \frac{K \times T}{q}$, where T represents the absolute cell temperature, K is the Boltzmann constant, and q denotes the elementary charge. Accordingly, the three-diode model (TDM) is governed by nine unknown parameters ($I_{ph}, I_{d_1}, I_{d_2}, I_{d_3}, n_1, n_2, n_3, R_s, R_{sh}$) which must be accurately identified to ensure precise representation of PV cell behavior.

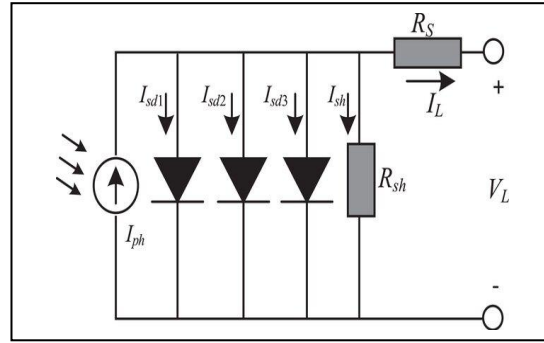


Figure 1: Three-diode (TDM) equivalent circuit model of the photovoltaic (PV) module.
Source: Authors, (2026).

II.2 OBJECTIVE FUNCTION FORMULATION

The estimation of unknown parameters in photovoltaic models is an optimization problem. The goal is to minimize the error between measured and predicted current-voltage (I-V) data. This requires a suitable objective function to quantify the error. A common metric for this task is the root mean square error (RMSE). The RMSE provides a statistical measure of the average discrepancy. It calculates the difference between observed and simulated current values. This metric is expressed as follows:

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^N (I_{mi} - I_{ci}(V_{mi}, I_{mi}, \theta))^2} \quad (2)$$

In this formulation, N denotes the total number of experimental I-V data points, I_{mi} represents the measured current at voltage V_i , $I_c(V_i, \theta)$ corresponds to the model-calculated current at the same voltage obtained using the Newton-Raphson method [24-26], and θ defines the parameter vector to be optimized. The optimization relies on the RMSE criterion, which minimizes squared deviations between measured and predicted values, strongly penalizes large errors, and provides a reliable indicator of how accurately photovoltaic models reproduce actual device behavior.

III. FLOW DIRECTION ALGORITHM FOR PV PARAMETER ESTIMATION

Estimating photovoltaic (PV) model parameters is challenging due to the nonlinear and high-dimensional nature of the problem. Metaheuristic optimization techniques are particularly effective for this task, as they can explore complex solution spaces and avoid entrapment in local minima. Among these, the Flow Direction Algorithm (FDA) [27], [28] is a physics-inspired method based on hydrological runoff processes in drainage basins. The algorithm simulates water flowing downslope toward a basin outlet, which represents the global minimum of the objective function. FDA employs the D8 flow-direction approach as presented in figure 1, in which each cell in a discretized basin has eight neighbors, and runoff is directed toward the neighbor with the steepest descent.

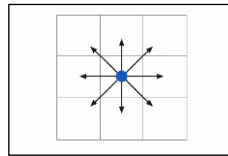


Figure 2: D8 neighborhood around the runoff flow cell.
Source: [28].

In FDA, each candidate solution corresponds to a flow in an n-dimensional search space, and its fitness value is analogous to the flow's elevation. Each flow interacts with neighboring positions within a defined radius, and its movement velocity is proportional to the slope between the current position and the neighbor. Flows move toward better-performing neighbors or, if none exist, toward either the global best solution or a randomly selected flow. The neighborhood radius is reduced linearly over iterations to balance global exploration and local exploitation, while the coefficient applied to the global best accelerates convergence.

Mathematically, the population is initialized randomly within the search bounds:

$$\text{FlowY}_i = \text{lb} + \text{rand} \times (\text{ub} - \text{lb}) \quad (3)$$

Where FlowY_i is the position vector of the i-th flow. Neighboring positions are generated as

$$\text{Neighbor}\mathbf{Y}_j = \text{Flow}\mathbf{Y}_i + \text{rand}_n \times \Delta \quad (4)$$

With rand_n following a normal distribution and Δ representing the neighborhood radius. Flow positions are then updated using

$$\text{Flow}\mathbf{Y}_i^{\text{new}} = \text{Flow}\mathbf{Y}_i + \mathbf{v} \times \frac{\text{Neighbor}\mathbf{Y}_j - \text{Flow}\mathbf{Y}_i}{\|\text{Neighbor}\mathbf{Y}_j - \text{Flow}\mathbf{Y}_i\|} \quad (5)$$

$$\mathbf{v} = \text{rand}_n \times \mathbf{S} \quad (6)$$

Where $\mathbf{S}$ represents the slope vector between the flow and its neighboring flows. The dual-strategy decision rule ensures flows move toward better solutions while maintaining exploration:

$$\begin{aligned} \text{if } f(\text{Flow}_t) < f(\text{Flow}_i): \text{Flow}\mathbf{Y}_i^{\text{new}} &= \text{Flow}\mathbf{Y}_i + \text{rand}_n \times (\text{Flow}_t - \text{Flow}\mathbf{Y}_i) \\ \text{else: } \text{Flow}\mathbf{Y}_i^{\text{new}} &= \text{Flow}\mathbf{Y}_i + 2 \times \text{rand}_n \times (\text{BestFlow}\mathbf{Y} - \text{Flow}\mathbf{Y}_i) \end{aligned} \quad (7)$$

Through this hydrology-inspired mechanism, FDA effectively balances exploration and exploitation, enabling the identification of near-optimal or global solutions in complex, nonlinear optimization problems. Its effectiveness has been demonstrated across various engineering applications, including control system optimization, wireless sensor networks, and power system regulation. The main steps of FDA can be summarized as follows:

1. Initialize the flow population randomly within the search space and set Δ to its initial value.
2. Evaluate the fitness function for each flow.
3. Generate neighbors for each flow within the neighborhood radius Δ .
4. Update flow positions based on neighbor performance or the best global solution using the decision-making strategy.
5. Reduce Δ progressively according to a linear schedule to shift from global exploration to local exploitation.
6. Update the global best solution found so far.
7. Check the termination condition (e.g., maximum iterations or convergence criterion); if not satisfied, return to step 3.

By simulating hydrological runoff dynamics, FDA effectively balances exploration and exploitation, enabling the identification of near-optimal or global solutions in complex, nonlinear optimization problems. Its effectiveness has been demonstrated across diverse engineering applications, including control system optimization, wireless sensor networks, and power system regulation.

IV. RESULTS AND DISCUSSIONS

In these experimental investigations, the algorithm was configured with a population size of **100** and a maximum of **3000** iterations. Under these conditions, two photovoltaic (PV) configurations were investigated. The first case study involves a 57 mm-diameter monocrystalline silicon solar cell from R.T.C. France, tested at an irradiance of 1000 W/m² and a cell temperature of 33 °C. The second case concerns an amorphous silicon (**a-Si**) thin-film photovoltaic cell, evaluated at 25 °C under an irradiance of 1000 W/m². The lower and upper limits of the seven model parameters are presented in Table 1.

Table 1: Range of variables considered during the simulation process.

Parameters	RTC		a-Si	
	l_b	u_b	l_b	u_b
$I_{ph}(A)$	0	1	0	2
$I_{d1}, I_{d2}, I_{d3}(\mu A)$	0	1	0	100
$R_s(\Omega)$	0	0.5	0	5
$R_{sh}(\Omega)$	0	100	0	2000
n_1, n_2, n_3	1	2	1	60

Source: Authors, (2026).

The proposed Flow Direction Algorithm (FDA) was validated using the previously described photovoltaic (PV) devices under standard operating conditions. The accuracy of the estimated parameters was quantitatively evaluated using the root mean square error (RMSE) between the experimental and simulated current–voltage (I–V) characteristics. This metric provides a reliable measure of the model’s fitting capability across the entire operating range, including the short-circuit, knee, and open-circuit regions. For benchmarking purposes, the FDA was applied to the three-diode model (TDM) and its performance was compared with several recently reported state-of-the-art metaheuristic algorithms listed in the introduction. This framework enables a rigorous evaluation of convergence, stability, and robustness in addressing the nonlinear and multimodal nature of the TDM parameter estimation problem. Optimal parameter values were obtained from the best objective function outcomes across 30 independent trials to ensure statistical reliability. The FDA’s performance was further analyzed using minimum, maximum, mean, and standard deviation (STD) of the RMSE values, collectively assessing precision, consistency, and practical applicability. Tables 2–5 present the optimal parameters of the nine-parameter TDM and the corresponding statistical analysis obtained over 30 runs for the **RTC** and **a-Si** solar cells. The RMSE values demonstrate the superior performance of the FDA.

The results in Table 2, along with the statistical comparison presented in Table 3 for **RTC** cells, provide a comprehensive assessment of metaheuristic algorithms for estimating the three-diode model (TDM) parameters, focusing on fitting accuracy, physical consistency, and robustness against the nonlinear, multimodal optimization landscape. The primary performance metric, the root mean square error (RMSE) between measured and modeled I–V characteristics, shows that the Flow Direction Algorithm (FDA) achieved the lowest RMSE (Best: 7.3511×10^{-4} , Worst: 7.5303×10^{-4} , Mean: 7.3773×10^{-4} , STD: 5.0229×10^{-6}), outperforming COA, IMGO, ITLBO, ISA, CPMP SO, RGND O, and FC-EP SO2, while even small RMSE reductions remain significant near the knee and open-circuit regions. All algorithms converged on a photocurrent ($I_{ph} \approx 0.7605 \text{ A}$), but diode saturation currents (I_{d1}, I_{d2}, I_{d3}) exhibited higher variability due to parameter correlation and multimodality; FDA produced smoother scaling of diode currents and ideality factors, with n_2 and n_3 approaching physically consistent values of 2. Series resistance ($R_s \approx 0.038 \Omega$) remained stable across algorithms, and shunt resistance (R_{sh}) stayed within realistic ranges for FDA and most competitive methods, demonstrating both numerical accuracy and physical plausibility. The TDM's nine-dimensional, strongly coupled, non-convex search space challenges many optimizers, with COA and IMGO showing higher RMSE likely due to premature convergence, whereas FDA's balanced exploration–exploitation strategy navigates the landscape effectively, achieving performance comparable to methods like FC-EP SO2 without excessive complexity. Overall, FDA provides the best compromise between convergence accuracy and parameter stability, with reduced dispersion in sensitive parameters highlighting its robustness. Accurate parameter extraction directly benefits predictive PV modeling, maximum power point tracking, performance analysis under varying conditions, and fault detection, showing that even marginal RMSE improvements, when accompanied by physically consistent parameters, enhance downstream applications. Collectively, these findings confirm FDA's suitability for high-precision TDM parameter identification and its broader applicability to other nonlinear energy system modeling problems.

Table 2: Optimal parameters for TDM of **RTC** Cells.

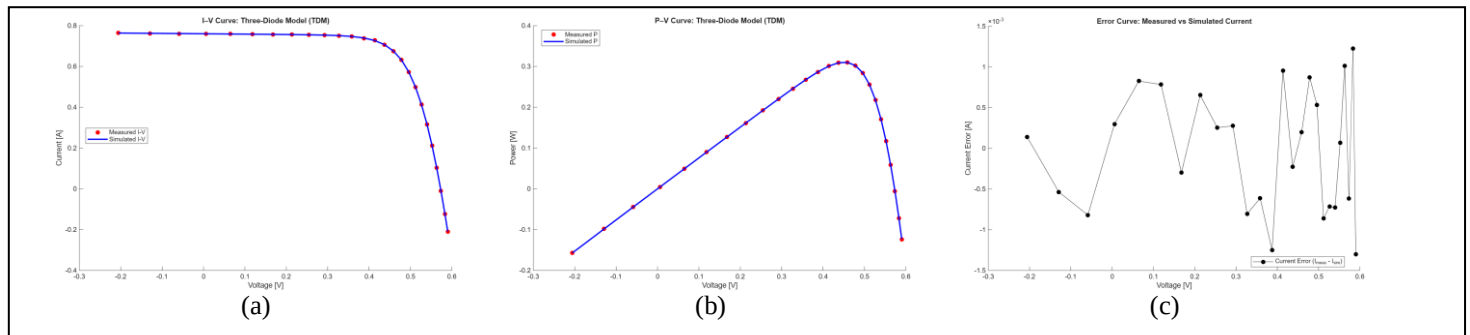
Cell	Parameters	FDA	COA [10]	IMGO [11]	ITLBO [15]	ISA [16]	CPMP SO [17]	RGND O [8]	FC-EP SO2 [18]
RTC	$I_{ph} (\text{A})$	0.760812	0.7604	0.7605	0.760500	0.760500	0.760500	0.760500	0.76080
	$I_{d1} (\mu\text{A})$	1.0	1.39 e-03	1 e-03	2.98 e-02	1.21 e-01	9.62 e-02	9.08 e-02	8.2596 e-02
	$I_{d2} (\mu\text{A})$	1.0	2.3325 e-01	8.18 e-03	9.17 e-01	1.00 e-03	3.73 e-01	1.96	6.9148 e-01
	$I_{d3} (\mu\text{A})$	9.81 e-02	1.01 e-03	4.5409	1.86 e-03	1.68	1.67	1.58 e-01	4.4036 e-01
	$R_s (\Omega)$	0.03789	0.03784	0.04019	0.0381	0.0377	0.0379	0.0380	0.037215
	$R_{sh} (\Omega)$	57.7760	51.1585	82.1867	59.7254	59.5672	61.1542	61.3221	55.742
	n_1	2	1.3818	1.3932	1.3101	1.3995	1.3812	1.3766	1.3740
	n_2	2	1.4502	1.2093	1.7186	1.9936	1.9995	2.000	1.8449
	n_3	1.3816	1.948	1.9994	1.6611	2.000	1.9993	2.000	1.8333
	RMSE	7.3511 e-04	9.2288 e-04	9.2975 e-04	7.6180 e-04	7.5344 e-04	7.5082 e-04	7.5068 e-04	7.4025 e-04

Source: Authors, (2026).

Table 3: Results of the statistical comparison of **RTC** Cells (FDA).

Models	RMSE Best	RMSE Worst	RMSE Mean	RMSE STD
TDM	7.351100 e-04	7.530318 e-04	7.3772949 e-04	5.022918 e-06

Source: Authors, (2026).

Figure 3: Numerical and experimental results for the **RTC** France solar cell: (a) current–voltage (I–V) characteristics, (b) power–voltage (P–V) characteristics, and (c) error between the measured and estimated currents.

Source: Authors, (2026).

Figure 3 presents the I–V and power–voltage (P–V) characteristic curves of the TDM, along with the voltage–point error curves obtained using FDA. The results demonstrate that the simulated current and power values closely match the measured data across all voltage points, with minimal errors, confirming the reliability of the proposed FDA method in accurately capturing the actual behavior of solar cells through the TDM model. Table 4 presents the optimal parameters obtained for the **a-Si** solar cell, while Table 5 summarizes the statistical comparison over 30 independent trials. FDA achieved the lowest RMSE (Best: 2.2939×10^{-5} , Worst: 2.594509×10^{-5} , Mean: 2.468451×10^{-5} , STD: 5.649668×10^{-5}), outperforming HSDA and MGO. The photocurrent (I_{ph}) converged around 0.01132 A for all methods, whereas diode saturation currents (I_{d1}, I_{d2}, I_{d3}) and ideality factors (n_1, n_2, n_3) showed greater variability, reflecting the inherent parameter correlation and multimodality of the TDM. Series resistance ($R_s \approx 2.1 \Omega$) and shunt resistance ($R_{sh} \approx 1500 \Omega$) were consistent with physically realistic ranges for FDA.

Table 4: Optimal parameters for TDM of **a-Si** Cells.

Cell	Parameters	FDA	HSDA [19]	MGO [20]
a-Si	$I_{ph}(A)$	0.01131958	0.01133067	0.01133170
	$I_{d1}(\mu A)$	91.9738982	90.5914527	5.512063
	$I_{d2}(\mu A)$	65.0000	10.8816527	5.011604 e-02
	$I_{d3}(\mu A)$	0.0147317	0.0123991	1.056966 e-05
	$R_s(\Omega)$	2.1	2.24712579	0.500
	$R_{sh}(\Omega)$	1500	1108.3322476	600.7897
	n_1	11.29963345	9.99938271	5.0000
	n_2	11.29971624	10	2.710308
	n_3	2.416746678	2.3874133	4.999188
	<i>RMSE</i>	2.2939 e-05	2.4439838 e-05	4.097395 e-05

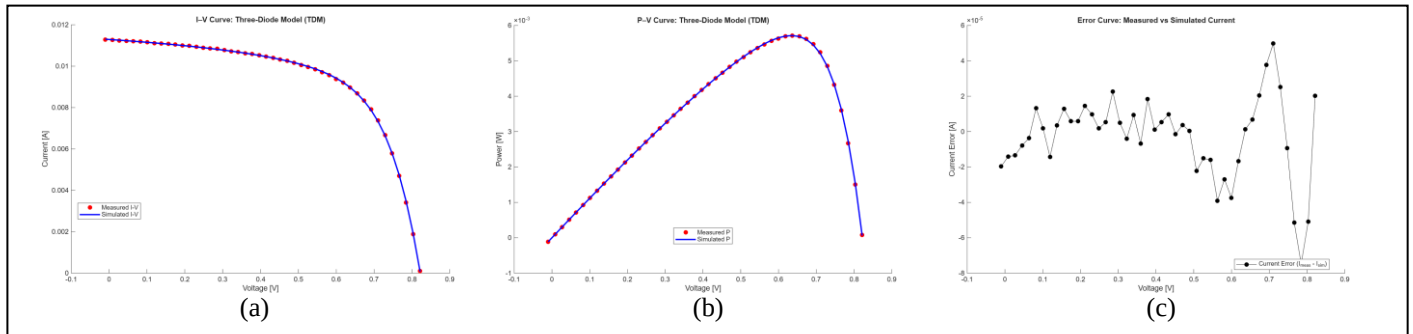
Source: Authors, (2026).

Table 5: Results of the statistical comparison of **a-Si** Cells.

Models	RMSE <i>Best</i>	RMSE <i>Worst</i>	RMSE <i>Mean</i>	RMSE <i>STD</i>
TDM	2.2939 e-05	2.594509 e-05	2.468451 e-05	5.649668 e-05

Source: Authors, (2026).

Figure 4 presents the I–V and power–voltage (P–V) characteristic curves for the **a-Si** cells along with the voltage-point error curves obtained using FDA. The results demonstrate that the simulated current and power values closely match the measured data across all voltage points, with minimal errors, confirming that FDA reliably captures the actual behavior of **a-Si** solar cells. These findings indicate that FDA not only minimizes RMSE but also produces parameter sets that are physically interpretable and electrically coherent, confirming its robustness and suitability for high-precision modeling of **a-Si** photovoltaic devices.

Figure 4: Numerical and experimental results for the **a-Si** cell: (a) current–voltage (I–V) characteristics, (b) power–voltage (P–V) characteristics, and (c) error between the measured and estimated currents.

Source: Authors, (2026).

In summary, the comparative analysis for both **RTC** and **a-Si** photovoltaic cells demonstrates that the Flow Direction Algorithm (FDA) consistently outperforms other state-of-the-art metaheuristic methods in terms of RMSE, convergence stability, and physical plausibility of the extracted parameters. The statistical results from Tables 3 and 5 confirm the reliability and robustness of FDA across multiple independent trials, while the I–V and P–V curves in Figures 3 and 4 illustrate excellent agreement between simulated and experimental data, with minimal voltage-point errors. Overall, FDA not only provides highly accurate parameter identification for both monocrystalline and amorphous silicon cells but also ensures physically consistent and electrically coherent parameter sets, highlighting its applicability to complex, nonlinear photovoltaic models. These findings support the use of FDA for precise PV system modeling, maximum power point tracking simulations, performance assessment under varying environmental conditions, and potential fault detection and degradation studies, demonstrating its practical value for both research and industrial applications.

V. CONCLUSIONS

In this study, the Flow Direction Algorithm (FDA) was proposed for high-precision identification of critical parameters in three-diode model (TDM) photovoltaic cells. Simulation experiments were conducted on two PV cell types: the monocrystalline **RTC** France cell and the amorphous silicon (**a-Si**) thin-film cell. The FDA was benchmarked against several state-of-the-art metaheuristic algorithms. For the **RTC** cells, FDA achieved the lowest RMSE of 7.3411×10^{-4} , outperforming all compared methods and providing the most reliable solution for TDM parameter optimization. Similarly, for **a-Si** cells, FDA achieved an RMSE of 2.426899×10^{-5} , confirming its superior accuracy and robustness. The I–V and P–V characteristic curves further validated the FDA results, demonstrating excellent agreement between simulated and experimental data with minimal errors, indicating that FDA accurately captures the actual behavior of both monocrystalline and amorphous solar cells. These findings confirm that FDA not only ensures highly accurate and physically consistent parameter estimation but also maintains robustness in the nonlinear, multimodal search space inherent to TDM PV models. Given its demonstrated effectiveness and feasibility, FDA constitutes a powerful tool for PV system modeling, maximum power point tracking, performance evaluation under varying environmental conditions, and potential fault detection.

Future research will focus on improving FDA performance through hybridization with other metaheuristic or local search strategies to further enhance convergence speed, solution diversity, and global optimization capability. Looking forward, the proposed algorithm can be extended to address high-dimensional renewable energy optimization problems with complex constraints and applied to modified or emerging PV models reported in the literature, highlighting its potential for broader applications in energy system analysis and optimization.

VI. AUTHOR'S CONTRIBUTION

Conceptualization: Naas Dif, Ismail Dif and Obeidi Thameur.

Methodology: Naas Dif, Ismail Dif and Obeidi Thameur.

Investigation: Naas Dif, Ismail Dif and Obeidi Thameur.

Discussion of results: Naas Dif, Ismail Dif and Obeidi Thameur.

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Approval of the final text: Naas Dif, Ismail Dif and Obeidi Thameur.

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