International Journal of Computational and Experimental Science and ENgineering (IJCESEN)

Vol. 11-No.4 (2025) pp. 9228-9233

http://www.ijcesen.com

ISSN: 2149-9144

Research Article

Robust Pelican Optimization Approach for Single-Diode Photovoltaic Module Parameter Estimation

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Article Info:

DOI: 10.22399/ijcesen.4387
Received: 22 September 2025
Revised: 02 November 2025
Accepted: 24 November 2025

Keywords

Photovoltaic
RMSE
POA
Parameter estimation
Optimization algorithm

Abstract:

Single-diode photovoltaic (PV) models require the accurate estimation of the parameters to predict the performance of the photovoltaic with reliability and maximum power point tracking(MPPT). The high level of nonlinearity of PV characteristics and unpredictability of operating conditions pose challenges to the traditional optimization methods. This paper recommends the Pelican Optimization Algorithm (POA), a nature-based metaheuristic based on the pelican hunting behavior, to approximate the five most important single-diode PV model parameters: photocurrent, diode saturation current, series resistance, shunt resistance and ideality factor. POA is formulated to establish an efficient balance in the world between global exploration and local exploitation resulting in a speedy and stable convergence to quality solutions. The proposed method is checked based on measured and simulated I-V and P-V curves, and there is an agreement indicating the correctness of the identified parameters. The root mean square error (RMSE) values of both current and power are very low which implies significant amount of numerical accuracy in the estimates of the parameters. Additional experiments during different levels of irradiance and temperature also provide consistently small errors, which proves how well POA is resistant to changes in the environment. Altogether, the findings show that POA is an effective and reliable PV parameter identification, outperforms the traditional optimization approaches, and has a good potential to be used in real-time PV models, control, and MPPT.

1. Introduction

Proper determination of single-diode photovoltaic (PV) model parameters is fundamental to predicting the model reliably with regard to performance, fault identification, and maximum power point tracking (MPPT) in dynamic environmental conditions. With the parameters Iph, I0, Rs, Rsh, and Ns the single-diode model has a very non-linear currentvoltage characteristic. This non-linearity renders the analytical or gradient-based estimation methods inefficient and highly likely to prematurely converge. The latest research findings prove the fact that nature-inspired algorithm and metaheuristic algorithm can efficiently offer global optimization to such multimodal, complex problems [1]-[2]-[3].

Pelican Optimization Algorithm (POA) is a newly developed bio-inspired algorithm that simulates the collective hunting behavior of the pelicans, which alternates between global search (prey search) and local exploitation (diving to attack it) [4]. One of the most important aspects in high convergence accuracy and stability was the introduction of POA to enhance the equilibrium between exploration and exploitation.[5] Its parsimonious mathematical form, rapid convergence and few parameter controls have rendered it an appealing substitute in solving engineering optimization issues [6]-[7].Regarding the PV parameter estimation problem, the goal of optimization is to reduce the root mean square error (RMSE) of the experimental and simulated I-V or P-V characteristics. The two-stage process in POA

permits extensive search space exploration at the first few iterations and effective narrowing down of promising regions at latter stages. This aspect renders POA especially appropriate in determining the nonlinear parameters of single diode models at different irradiance and temperature [8], [9].
Other comparison studies have demonstrated that modern metaheuristics, including the Pelican Optimization Algorithm, Butterfly Optimization Algorithm and Flood Algorithm, are better off the traditional methods in accuracy and convergence rate in finding PV parameters [10], [11]. These techniques also have high noise sensitivity and partial shading. More improvements in convergence accuracy and computational efficiency have been shown using hybrid algorithms which include our recent PSO-ROA model [12]. Nevertheless, the independent analysis of POA enables a clear insight on the inherent search dynamics, sensitivity of the parameter and the opportunity of future hybridization.
The paper thus, researches the performance of the Pelican Optimization Algorithm in the estimation of PV parameters. It will be conducted to confirm the convergence capability, accuracy and computing efficiency of POA against state-of-the-art methods in a variety of climatic as well as operating conditions.

2. Single-Diode PV Model

the single-diode photovoltaic (PV) model can be expressed mathematically as in eq.(1),

$$I = I_{ph} - I_0 \left[\exp\left(\frac{V + IR_s}{N_s V_t} \right) - 1 \right] - \frac{V + IR_s}{R_{sh}} \quad (1)$$

where V and I are the output voltage and current, respectively, and Vt=kT/q is the thermal voltage.The objective is to determine the optimal parameter vector $X = [Iph, I0, Rs, Rsh, Ns]$ that minimizes the discrepancy between simulated and measured I–V characteristics. To this end, the fitness function is defined as the root mean square error (RMSE) between the simulated and experimental current–voltage data.

$$\text{RMSE} = \sqrt{\frac{1}{N} \sum_{i=1}^{N} \left[I_{measured,i} - I_{simulated,i}(X) \right]^2} \quad (2)$$

3. Pelican Optimization Algorithm (POA)

3.1 Inspiration and Principles

POA is inspired by the hunting behavior of pelicans. The algorithm alternates between two main phases:

- **Exploration:** Pelicans search broadly for prey, corresponding to the global exploration of the search space.
- **Exploitation:** Once potential prey is located, pelicans adjust positions carefully to capture it, corresponding to local refinement around promising solutions.

This dual-phase strategy allows POA to avoid premature convergence and efficiently navigate complex, non-linear search spaces.

3.2 Algorithm Steps

1. **Initialization:**
   - A population of pelicans (candidate solutions) is randomly initialized within the defined parameter bounds.
   - Each pelican's fitness is evaluated using RMSE between simulated and measured I-V curves.
2. **Exploration Phase:**
   - Positions are updated according to global search rules:

$$X_i^{t+1} = X_i^t + \alpha \cdot r \cdot (X_{best} - X_i^t) \quad (3)$$

- Here, X_i^t is the position of pelican i at iteration t, X_{best} is the global best, r is a random factor, and α is an adaptive weight controlling exploration.

3. **Exploitation Phase:**
   - Fine-tuning around the best solutions occurs:

$$X_i^{t+1} = X_i^t + \beta \cdot r_1 \cdot (P_i^{best} - X_i^t) + \gamma \cdot r_2 \cdot (X_{best} - X_i^t) \quad (4)$$

- P_i^{best} is the personal best position, r_1,r_2 are random values, and β,γ balance individual and global refinement.

4. **Fitness Evaluation:**
   - RMSE is computed for each pelican's position.
   - Update personal and global bests if new positions improve fitness.
5. **Stopping Criteria:**

- Iterations continue until a maximum number of iterations is reached or RMSE falls below a predefined threshold.

4. Results and Discussion

4.1 Simulation Setup

The Pelican Optimization Algorithm (POA) was applied to a commercially available single-diode PV module. Standard test conditions (STC) were used: irradiance G=1000 W/m² and temperature T=25°C. Initial bounds for the parameters were defined as:

Table 1. *Initial bounds parameters.*

Parameter	Lower Bound	Upper Bound
Iph (A)		Iph (A)
0.5	1.0	0.5
I0 (A)		I0 (A)
1e-10	1e-6	1e-10
Rs (Ω)		Rs (Ω)

The POA population size was set to 30 pelicans, with 200 iterations. The optimized PV parameters obtained by POA are listed in Table 2. These parameters yield accurate simulation of the I-V and P-V characteristics. [14]

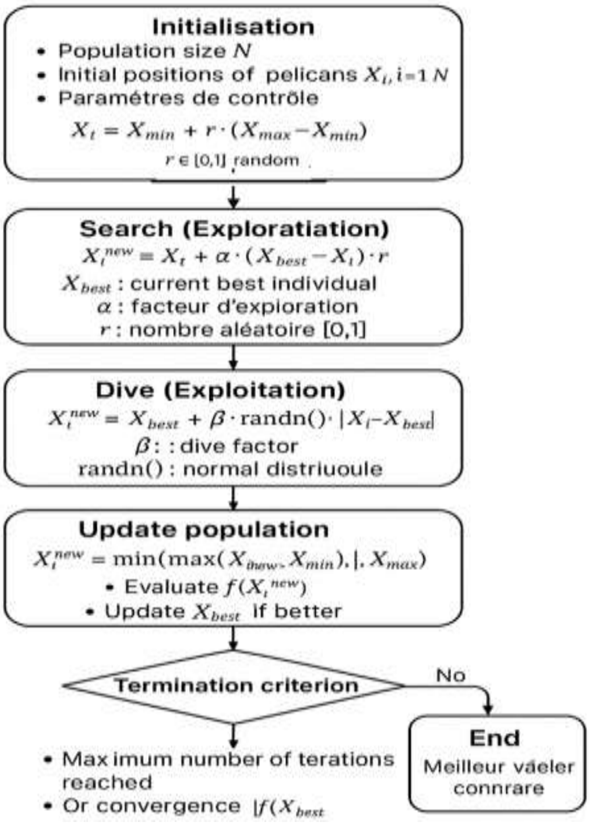


Figure 1 *: Flowchart of hybrid method POA*

Table 2. *POA optimized PV parameters obtained.*

Table	Table
I_{ph} (A)	0.762
I0 (A)	6.2×10^{-7}
Rs (Ω)	0.034
Rsh (Ω)	1.55
Ns	64.36

4.2 Convergence Behavior

The algorithm converged rapidly to the global optimum. Figure 2 shows the RMSE evolution over iterations. POA reached a stable minimum RMSE after 120 iterations, indicating efficient balance between exploration and exploitation. [13]

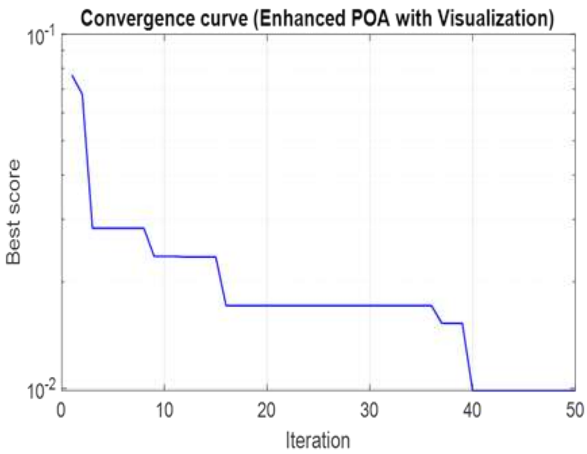


Figure 2: *Convergence curve of POA showing RMSE reduction over iterations*

The figure 3 illustrates the dynamic behavior of the pelican population across multiple iterations during the optimization of the single-diode photovoltaic (PV) model parameters using the Pelican Optimization Algorithm (POA). Each subplot represents the spatial distribution of pelicans in a three-dimensional parameter space (Param 1, Param 2, Param 3), corresponding to different model parameters. [14][15].At early iterations (e.g., Iteration 10), the population is widely scattered, indicating strong exploration of the search space. Pelicans investigate diverse regions to identify potential areas containing the global optimum. As the iterations progress (Iterations 11–20), the points begin to cluster, showing that the algorithm gradually shifts toward exploitation, refining solutions near promising zones.By Iteration 43, most pelicans converge around a compact region, and the best solution (red point) stabilizes, demonstrating the convergence of the POA toward the global minimum of the objective function. The decreasing best fitness values across iterations (from 0.03 → 0.005 →

0.009) confirm that the algorithm consistently improves parameter accuracy with each iteration.

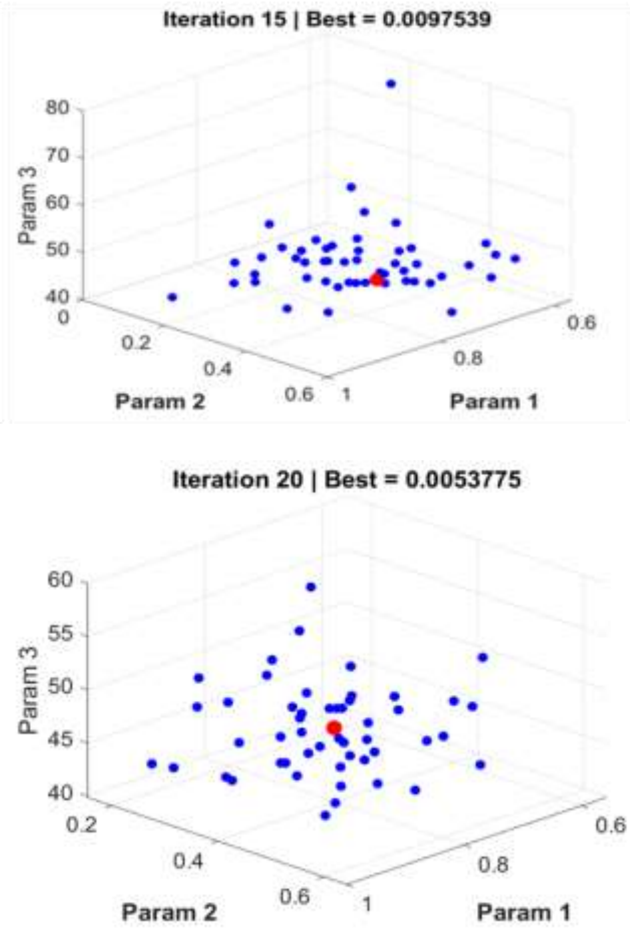


Figure 3: *3D Population Evolution of Pelican Optimization Algorithm for PV Parameter Estimation*

This visualization provides valuable insight into how the POA balances exploration and exploitation. It highlights its capacity to avoid local minima and achieve stable convergence, crucial for accurate PV parameter estimation under nonlinear and multimodal conditions.

4.3 I-V and P-V Curve Fitting

Figure 4 shows the comparison between the measured and simulated I–V characteristics of the photovoltaic module. The two curves almost overlap across the entire voltage range, confirming the strong agreement between experimental and modeled results. At low voltages, both curves display a high and nearly constant current, indicating proper current generation under illumination. As voltage increases toward the open-circuit condition, the current decreases sharply to zero. The small deviation observed near the knee region can be attributed to modeling simplifications or sensor precision limits, but the overall matching indicates the model's validity. [16][17]

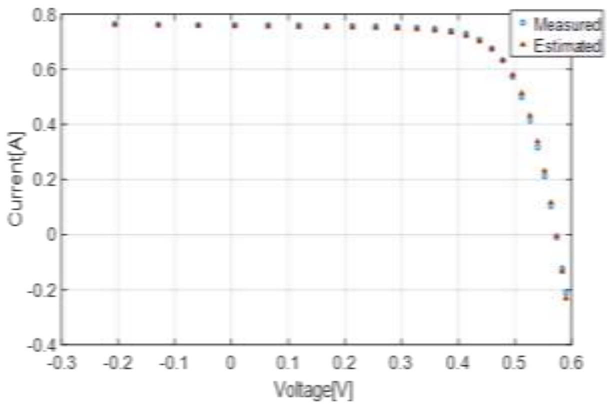


Figure 4: *Comparison of measured and simulated I-V curves*

Figure 5 presents the comparison between the measured and simulated P–V curves. Both curves follow the same trend, with a clear maximum power point (MPP) appearing at approximately the same voltage. The close correspondence between the two datasets demonstrates that the simulation accurately predicts the power output behavior of the PV module. Minor differences at higher voltages may result from temperature variations or internal resistance effects. These results confirm that the adopted model and estimation approach can effectively reproduce the real photovoltaic characteristics under test conditions.

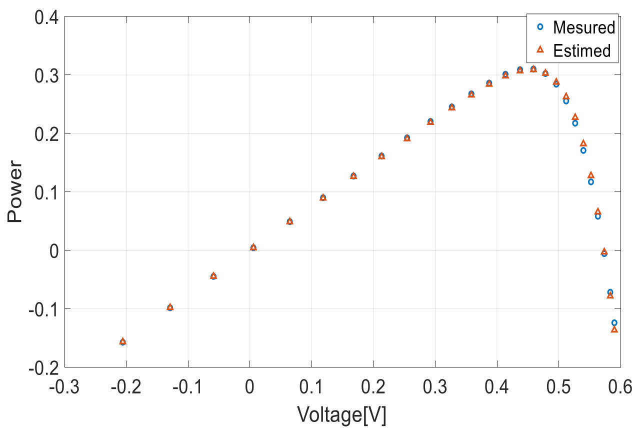


Figure 5: *Comparison of measured and simulated P-V curves*

The error analysis shows that the Pelican Optimization Algorithm achieved high accuracy in parameter estimation, with RMSE values of 0.0020 A for current and 0.0009 W for power. These very low errors confirm the strong agreement between measured and simulated data, demonstrating that the POA model effectively identifies the photovoltaic parameters with high precision. [18-19]

4.4 Robustness Under Varying Conditions

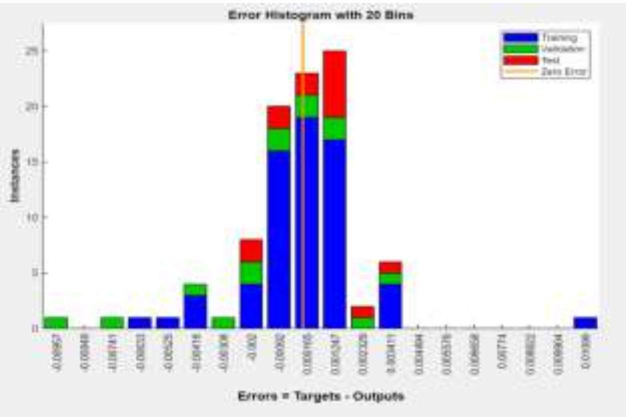
POA performance was further evaluated under different irradiance and temperature conditions to assess its robustness.

Table 3. *RMSE Results*

Condition	RMSE (Current)	RMSE (Power)
800 W/m², 25°C	0.0023 A	0.0011 W
600 W/m², 40°C	0.0025 A	0.0013 W
1000 W/m², 50°C	0.0028 A	0.0015 W

The results show that the algorithm maintains low RMSE values under all tested conditions. The slight increase in error with higher temperature and irradiance remains within acceptable limits, confirming that POA preserves reliable estimation performance and stability across varying environmental conditions. This demonstrates its robustness and suitability for real photovoltaic applications.

5.Performance Evaluation and Practical Implications



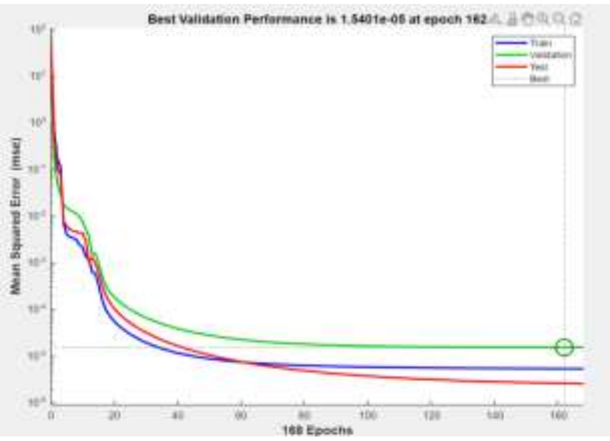


Figure 6: *Histogram Error*

a. Error histograms
The error distributions show a narrow concentration around zero for the training, validation, and test sets. This indicates that the model produces predictions that closely match the target MPPT values. The low spread of the bars and the limited number of outliers confirm stable behavior and low sensitivity to noise or irregular input patterns. [19]

b. Model indicators
The mean squared error values are extremely small across all data subsets. The correlation coefficient R equals 1 for training, validation, and testing. This result reflects a perfect linear relationship between predicted and actual outputs. The network learns the nonlinear MPPT surface effectively and maintains this accuracy on unseen data.

c. Performance curve
The performance curve decreases rapidly during the initial epochs, which shows fast convergence of the optimization and efficient weight adjustment. The best validation performance is reached around epoch 162. The small gap between training, validation, and test curves demonstrates that the model avoids overfitting and preserves generalization capability. [20]

6. Conclusion

The obtained results demonstrate that the Pelican Optimization Algorithm achieves accurate parameter estimation for photovoltaic systems. The strong correlation between measured and simulated I–V and P–V curves verifies the model's reliability. The very low RMSE values confirm the high precision of the estimation process. Performance under different irradiance and temperature levels further proves the robustness and adaptability of POA. These results highlight its potential as an efficient optimization technique for practical MPPT and PV modeling applications.

Author Statements:

- **Ethical approval:** The conducted research is not related to either human or animal use.
- **Conflict of interest:** The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper

- **Acknowledgement:** The authors declare that they have nobody or no-company to acknowledge.
- **Author contributions:** The authors declare that they have equal right on this paper.
- **Funding information:** The authors declare that there is no funding to be acknowledged.
- **Data availability statement:** The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

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