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Maximizing Solar PV Efficiency under Partial Shading and Climate Variations: A Novel Hybrid PSO-ROA for Photovoltaic Optimization

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Abstract:

Photovoltaic systems are highly sensitive to environmental factors like partial shading, temperature, and irradiance. These variations affect power output and efficiency. This study proposes a hybrid optimization approach combining Particle Swarm Optimization (PSO) for global search and Red Kite Optimization Algorithm (ROA) for local refinement. The PSO-ROA method improves parameter estimation accuracy in single-diode PV models. Compared to standalone PSO, it enhances Maximum Power Point Tracking (MPPT) precision, especially under partial shading. It minimizes power losses and ensures stable convergence. Sensitivity analysis shows that performance improves with moderate temperatures (60°C–80°C) and high irradiance (500 W/m²). The hybrid approach achieves near-perfect alignment at the Maximum Power Point (MPP). Although computation time increases, the trade-off results in higher accuracy and robustness. These findings confirm that the PSO-ROA hybrid method is an effective solution for optimizing photovoltaic systems. It ensures reliable performance across varying environmental conditions.

Keywords: Single-diode solar model, Particle Swarm Optimization (PSO), Red Kite Optimisation Algorithme (ROA), Hybrid optimization, Partial shading, Root Mean Square Error (RMSE).

1. Introduction

The photovoltaic effect was first observed by Becquerel in 1839. In 1876, Adams developed a selenium-based solar cell, proving that solid-state materials could generate electricity from sunlight. Fritts later improved this by creating junctions using selenium and gold, pioneering the use of p-n junctions in photovoltaic technology [1]. Photovoltaic (PV) systems convert sunlight into direct current (DC) electricity. Their efficiency depends on technology and environmental conditions. A PV module consists of multiple solar cells connected in series or parallel. Electrical performance is determined by key parameters, guiding the design and fabrication of PV devices.

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The single-diode photovoltaic (SD-SPV) model is widely used for its balance between accuracy and simplicity. It relies on five parameters: photocurrent (Iph), saturation current (Io), series resistance (Rs), shunt resistance (Rsh), and ideality factor (Ns). Accurate parameter estimation is crucial for optimizing PV performance. Several methods exist, including Analytical approaches such as the Lambert W function and nonlinear least squares fitting estimate parameters but struggle with nonlinear PV models and require high computational resources[2]. Metaheuristic optimization techniques offer a better alternative. Particle Swarm Optimization (PSO)[3], Genetic Algorithms (GA)[4], Differential Evolution (DE)[5], and Biogeography-Based Optimization (BBO)[6]enhance global search, improving accuracy. Bio-inspired algorithms further refine optimization. Wind Driven Optimization (WDO) [7] outperforms traditional methods like Pattern Search (PS), GA, and Simulated Annealing (SA). The Barnacles Mating Optimizer Algorithm (BMOA)[8] achieves better efficiency than the Successive Discretization Algorithm (SDA) and Imperialist Competitive Algorithm (ICA). Accelerated Particle Swarm Optimization (APSO)[9] improves Maximum Power Point Tracking (MPPT) under partial shading, reducing convergence time and enhancing tracking accuracy.

Hybrid techniques combine global exploration with local refinement. The GA-PSO hybrid optimizes single diode PV models with higher accuracy than standalone methods[10]. Bird Mating Optimization (BMO) is effective for PV parameter extraction[11]. PSO, integrated with the Shuttleworth-Wallace model and a temperature-vegetation index (TVI) scheme, reduces Root Mean Squared Error (RMSE) and bias in PV predictions[12]. Recent advancements refine hybrid methods. The PSO-Rat Search Algorithm[13] and Enhanced Prairie Dog Optimization (En-PDO) integrate reinforcement learning and least squares mechanisms, improving parameter optimization[14]. These techniques enhance PV system performance across diverse conditions.

SD-SPV parameter optimization is still a challenge to overcome despite the opportunities presented by the available advances in photovoltaic module modeling. Traditional approaches are more sensitive to the initialization and often get stuck in local minima. Heuristic algorithms provide a more efficient solution. On the one hand, swarm intuition-inspired PSO is good at global exploration, while red kite optimization (ROA) motivated by the hunt of red kite is inclined to refine localized search. We propose a hybrid PSO-ROA based approach to obtain stable and accurate parameter estimation by combining the global search ability of PSO with the local contraction property of ROA. This study takes a structured approach to improving reliability by reducing the Mean Squared Error (MSE) and Root Mean Squared Error (RMSE). The hybrid method combines the strengths of two algorithms: Particle Swarm Optimization (PSO) for broad, global exploration and the Red Kite Optimization Algorithm (ROA) for fine-tuned local search. The analysis unfolds in several steps. First, the optimization process is carried out using both standalone PSO and the hybrid PSO-ROA approach. Their performance is then compared based on RMSE, fitness scores, and computational efficiency. Next, a sensitivity analysis is conducted to understand how temperature and irradiance fluctuations affect system performance under different environmental conditions. Finally, the study examines the impact of partial shading, highlighting how the hybrid optimization method leads to better energy extraction and more stable power output.

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1 The single diode Solar Photovoltaic Model

1.1 Mathematical Representation

The photovoltaic (PV) cell is represented by the equivalent circuit shown in Fig. 1. This model includes a current source that simulates the light-generated (photocurrent) component, capturing the cell's response to solar irradiance. Losses are accounted for by a series resistance and a shunt resistance. The electrical behavior of the cell is governed by five key parameters: the diode ideality factor (*m*), the photocurrent (*Iph*), the series resistance (*Rs*), the shunt resistance (*Rsh*), and the diode saturation current (*Is*). This configuration is commonly referred to as the 1M5P model and is widely used due to its balance between simplicity and accuracy in simulating PV cell performance.

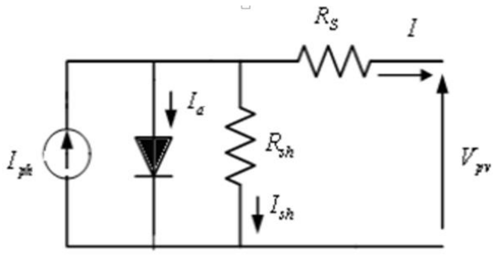

Fig. 1 Equivalent model of single diode solar cell with series and shunt resistances (1M5P)

The single-diode model provides a simplified representation of solar PV systems. The output current (*I*) of the PV cell is described by the following equation:

$$I = I_{ph} - I_0\left(e^{\frac{V+IR_S}{nV_t}} - 1\right) - \frac{V+IR_S}{R_{sh}} \quad (1)$$

The output current equation of a photovoltaic (PV) cell is fundamental in characterizing its electrical behavior and overall performance. The output current (*I*) is a function of the terminal voltage (*V*), the photocurrent (*Iph*), and the diode saturation current (I_0), which accounts for leakage under reverse bias conditions. Internal electrical losses are represented by the series resistance (*Rs*), associated with ohmic losses, and the shunt resistance (*Rsh*), which models leakage pathways across the junction. The diode ideality factor (*n*), typically ranging between 1 and 2, quantifies the deviation from ideal diode behavior. The thermal voltage (*Vt*) is defined by the relation *Vt* = *kT/q*, where *k* is Boltzmann's constant (1.38×10^{-23} J/K), *T* is the absolute temperature in Kelvin, and *q* is the elementary charge (1.602×10^{-19} C). Collectively, these parameters govern the electro-physical processes within the PV cell.

A significant challenge in modeling PV cells arises from the exponential term in the diode equation, which introduces a high degree of non-linearity. This non-linearity is inherent to the thermodynamic and quantum mechanical behavior of the diode, resulting in an exponential relationship between voltage and current. Consequently, small variations in environmental conditions, such as temperature and irradiance, can lead to substantial fluctuations in the output current. These characteristics complicate the parameter estimation process, rendering traditional techniques—

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particularly those relying on linearization or gradient-based methods—ineffective. Such methods often converge to local optima or yield inaccurate parameter values due to the complex, high-dimensional, and irregular nature of the solution space. To address these limitations, advanced metaheuristic optimization techniques have been increasingly employed. Algorithms such as Particle Swarm Optimization (PSO) and the Red Kite Method (RKM) offer robust search capabilities and are well-suited for handling the no-convexities and no-linearities inherent in PV cell modeling. These methods enhance the accuracy and reliability of parameter estimation, ultimately improving the fidelity of PV system simulations and performance predictions.

2 Optimization technique

Metaheuristic optimization methods solve complex problems by finding the optimal solution $f_{obj} = f(\vec{X})$, either minimizing or maximizing it. These methods manipulate decision variables $\vec{X} = [x_1, \ldots, x_m]$. within constraints. Equality constraints $h_i\vec{X} = 0$ for $= 1, \ldots, n_e$, and inequality constraints $g_i\overrightarrow{X \geq} 0$ for $j = 1, \ldots, n_i$, define feasible solutions. Boundary conditions $\vec{X}_l \leq \vec{X} \leq \vec{X}_u$, set the lower and upper limits for decision variables. These constraints guide the search toward an optimal solution while maintaining feasibility.

Particle swarm optimization (PSO)

Particle Swarm Optimization (PSO) is a nature-inspired algorithm modeled after the collective behavior of bird flocks. In this approach, a group of particles, each representing a potential solution, collaborates to explore the search space. Each particle adjusts its movement based on its own experience (*pBest*) and the collective knowledge of the swarm (*gBest*), allowing the group to progressively move toward an optimal solution. The particles' movements are governed by specific equations that update their velocity and position. The velocity update takes into account both cognitive and social influences. These are controlled by acceleration coefficients c_1 and c_2, typically set so that $c_1 + c_2 = 4$, which helps strike a balance between exploration and convergence. A random factor (*rand*), ranging between 0 and 1, is introduced to maintain diversity in the swarm and prevent premature convergence. Proper velocity tuning is crucial: too low a velocity can slow down convergence, while too high a velocity can lead to instability. The swarm size is also an important parameter, typically ranging from 10 to 50 particles, balancing search performance and computational efficiency. The equations governing the velocity and position updates are as follows:

$$p = p + v \tag{2}$$

$$v = v + c1 * rand * (pBest - p) + c2 * rand * (gBest - p) \tag{3}$$

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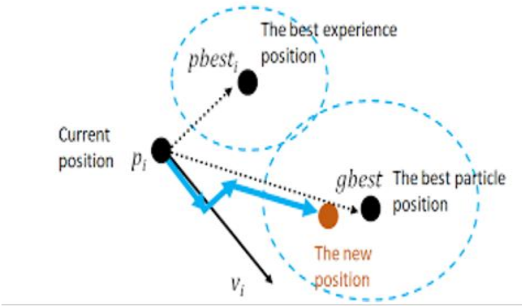

Fig. 2 Principle of PSO method

2.1 Red kite optimization (RKO)

Red Kite Optimization (ROA) is a bio-inspired algorithm that mimics the foraging strategy of red kites to solve complex optimization problems. It operates in two phases: high-altitude exploration and low-altitude exploitation. In the exploration phase, the algorithm looks across a broad search space to pinpoint areas with potential solutions. Once promising regions are identified, it enters the exploitation phase, refining those solutions to increase accuracy. This balance between exploring new possibilities and focusing on improving existing solutions boosts optimization efficiency. ROA is particularly well-suited for solving non-linear equations in photovoltaic (PV) systems, where traditional methods often struggle with high computational costs and getting trapped in local optima. Inspired by the hunting behavior of red kites, ROA strikes an effective balance between global searching and local refinement. This unique strength makes it an excellent choice for optimizing PV system parameters.

In the exploration phase, the position of a kite (xi) is updated using the following equation:

$$x_i^{(t+1)} = x_i^{(t)} + w * rand * (G - x_i^{(t)}) \tag{4}$$

In Red Kite Optimization (ROA), several key parameters guide the exploration phase. The current position, *xi*, represents a kite's location within the search space, while the group center, *G*, serves as a reference point, steering the kites toward more promising areas. An adaptive weighting factor *w*, adjusts the intensity of exploration, striking a balance between broad searching and more focused precision. The inclusion of a random term, *rand*, introduces variability, promoting diversity in the kites' position updates. This approach helps avoid premature convergence by encouraging a thorough exploration of the search space, ensuring that a wide range of potential solutions is considered.

In the exploitation phase, the position is refined based on individual and collective experiences:

$$x_i^{(t+1)} = x_i^{(t)} + a * rand * \left(pBest - x_i^{(t)}\right) + b * rand * (gBest - x_i^{(t)}) \tag{5}$$

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The coefficients a and b drive the exploitation phase. a steers each kite toward its personal best position **(**pBest**),** refining individual performance. b directs kites toward the swarm's best position (gBest**),** ensuring collective progress. These coefficients work together to balance individual refinement and group optimization. By fine-tuning positions in promising regions, they accelerate convergence toward the best solution.

4 Hybrid PSO-ROA Method

4.1 Principles of Hybridization

The hybrid PSO-ROA method merges global exploration with local refinement for efficient optimization. PSO particles first scan the search space broadly, using individual and collective knowledge to identify promising regions without getting trapped prematurely. Once potential solutions emerge, ROA kites take over, applying precise adjustments and controlled random variations to fine-tune the results. The system continuously updates and compares the best solutions from both approaches, maintaining an optimal balance between wide-ranging discovery and meticulous improvement. This combination yields faster convergence than either method could achieve separately, as PSO prevents oversight of potential solutions while ROA ensures no promising lead goes unexploited. The result is robust optimization that thoroughly explores possibilities while delivering precise final answers.

4.2 Algorithm steps

The hybrid PSO-ROA algorithm in Figure 3 is designed to optimize photovoltaic (PV) system parameters efficiently by combining the strengths of Particle Swarm Optimization (PSO) and the Red Kite Optimization Algorithm (ROA). It's structured for both flexibility and performance, with smart parameter tuning and a clear flow.

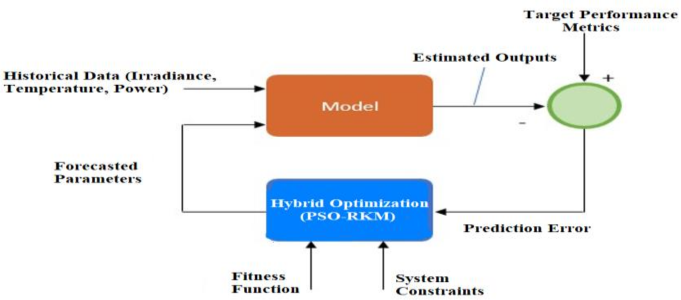

Fig. 3 The hybrid optimization algorithm

The process kicks off with an initialization phase, where PSO particles and ROA kites are randomly placed in the search space. PSO then takes the lead in a global search, using swarm intelligence to explore and identify promising areas. Once potential regions are found, ROA takes over to refine the solutions locally, improving accuracy and speeding up convergence. The algorithm keeps track of both the best solution each particle has found (pBest) and the best overall solution (gBest). These are continuously updated through each iteration until a convergence condition is met or until it's

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clear no further improvement is happening, thanks to advanced stopping criteria.

To stay adaptive, PSO's inertia weight decreases over time, helping it shift from wide exploration to more focused searching. ROA, on the other hand, fine-tunes its own parameters to zero in on local optimizations with greater precision.

This hybrid system is built around several core blocks:

1. **Forecast & Prediction Block:** It uses a mix of historical and forecasted data—irradiance, temperature, and power outputs—to predict system behavior. Adaptive learning and real-time data updates make it resilient to changing environmental conditions.
2. **Optimization Block:** PSO explores, ROA exploits. Together, they work in phases: first finding good regions, then refining the best solutions. Parameters adjust dynamically throughout to keep the search efficient and accurate.
3. **Fitness Function:** The goal is to minimize the Mean Squared Error (MSE) between predicted and actual outputs. It also respects real-world system limits like voltage and current, which are updated in real time based on operating conditions.
4. **System Interactions:** The different parts of the system talk to each other. Predictions feed into performance tracking. Errors guide adjustments in the optimization process. Constraints shape the search space for viable solutions.
5. **Monitoring & Visualization:** The system tracks how fitness scores evolve through both PSO and ROA. It compares measured and predicted current (Ipv) and power (Ppv) to check how well the algorithm is converging and adapting to real-world changes.

This hybrid PSO-ROA setup is a smart, adaptive solution for optimizing PV systems. It balances exploration and precision, learns from real-time data, and avoids wasting time on computations when there's no progress.

4.3 Optimization Methods for Nonlinear and Constrained Problems

Optimization methods solve complex engineering and scientific problems by finding the best solution under given constraints. In the hybridization of Particle Swarm Optimization (PSO) and the Red Kite Optimization Algorithm (ROA), techniques like Sequential Quadratic Programming (SQP), Active-Set, Interior-Point, SQP Legacy, and Trust-Region-Reflective improve local search efficiency and ensure optimal solutions. PSO explores the solution space globally but lacks precise local refinement. Advanced optimization methods address this limitation by fine-tuning solutions within feasible regions [15]. SQP is particularly effective for nonlinear constrained optimization. It iteratively solves quadratic subproblems to approximate the objective function while maintaining feasibility. This makes SQP useful when PSO has identified a promising solution but requires additional refinement for higher accuracy [16]. These optimization methods enhance the hybrid PSO-ROA framework by ensuring effective global exploration and precise local refinement. The integration of these methods ensures that the solution is not only globally optimal but also satisfies all constraints with high precision, making the hybrid approach highly effective in solving complex real-world optimization problems.

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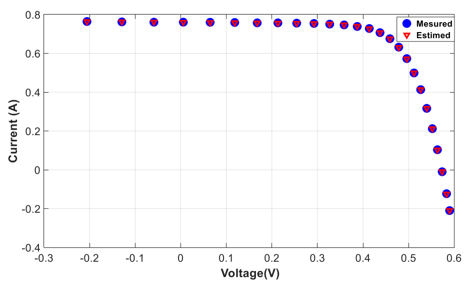
5. Result and discussion

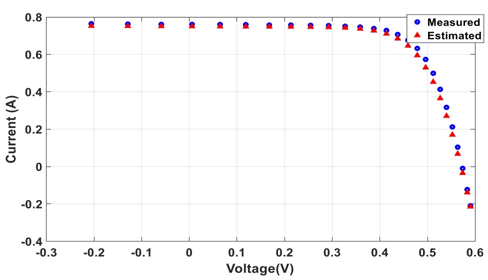
5.1 Experimental Setup

The static characteristics of a single-diode model were used to capture the PV module behavior using simulation software. The diode model parameters are optimized using metaheuristic algorithms, specifically PSO and RK-PSO. The experimental conditions considered include Isc = 0.764 A, Voc = 0.59 V, G = 1000 W/m², T = 25°C, Np = 1, and Ns = 5. The experimental PV module was tested in a controlled environment with a data acquisition system. The PV module specifications include: Pmax = unknown, Isc = 0.764 A, Voc = 0.59 V, and voltage-current characteristics measured at different operating points. To ensure accurate testing, the specular and natural lighting effects on the PV module surface were minimized using a shaded box, while passive cooling techniques controlled temperature fluctuations. A K-type thermocouple with a resolution of 0.5°C was used to measure temperature, and real-time voltage and current data were recorded using a data logger and voltmeter with a 1-second sampling interval. For I-V characteristic data simulation, the initial diode model parameter values were required but were not directly available from the PV module datasheet. Instead, they were estimated using PSO-based optimization, assisted by computational software.

5.2 Optimization Process and Convergence Analysis

The principles of HPSO-RKM are integrated to enhance the Single-Diode Solar Photovoltaic (SD-SPV) model. The effectiveness of PSO, RKM, and their hybrid approach (HPSO-RKM) is evaluated under temperature conditions (25°C). The objective is to optimize the five unknown parameters (Iph, Io, Rsh, Rs, Ns) of the SD SPV model to maximize the power yield of the PV system. The optimization is carried out using a hybrid PSO RKM method, where PSO performs a global search and RKO refines the results through local exploitation. Performance is measured using Root Mean Square Error (RMSE), Mean Squared Error (MSE), and Best Fitness. Optimized parameters obtained from MATLAB simulations are applied directly to the PV model to enhance its output precision.





PSO+ROA **PSO**

Fig. 4 I(V) Curves

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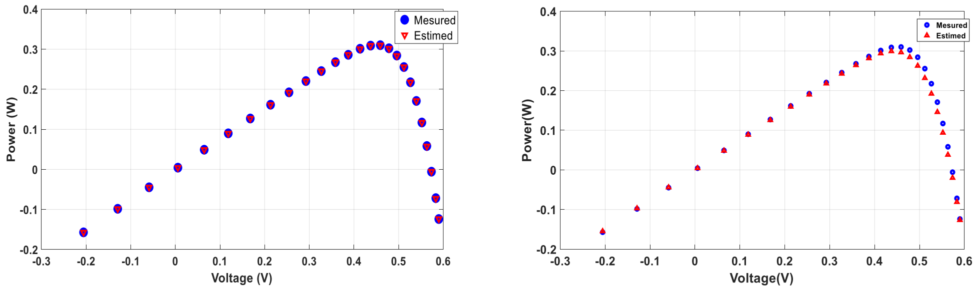

PSO+ROA **PSO**

Fig. 5 P(V) **Curves**

Figures 4 and 5 present a comparison between measured and estimated values of current and power. The close alignment between these values confirms the reliability of the hybrid method. This is especially important at the Maximum Power Point (MPP), where the PV system exhibits strong non-linear behavior. The hybrid approach effectively captures this complexity. It combines wide-range exploration from PSO and ROA with focused refinement from a local method like fmincon. Compared to standalone PSO, the hybrid method shows significantly lower deviations, particularly in non-linear regions. These results demonstrate that integrating global and local search strategies leads to faster, more accurate convergence.

The hybrid PSO+ROA method outperforms standalone PSO in optimizing PV models. It achieves lower RMSE values for current (0.0007756 A) and power (0.00032733 W) compared to PSO’s higher errors (0.03 A, 0.01 W). The best fitness value (0.0007756) significantly improves over PSO’s 0.06, proving the hybrid method finds better solutions. While the hybrid approach increases computation time (1374.3933 seconds), the accuracy gain justifies the cost. This method effectively balances exploration and refinement, making it a more reliable choice for PV model optimization.

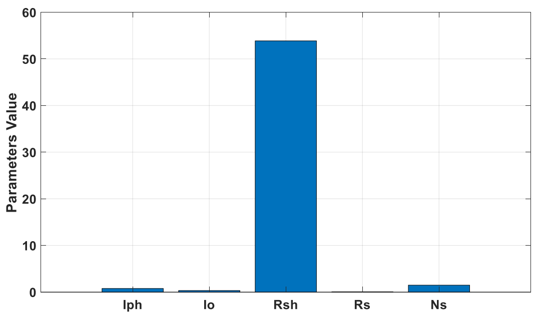

Fig. 6 Optimized Parameters

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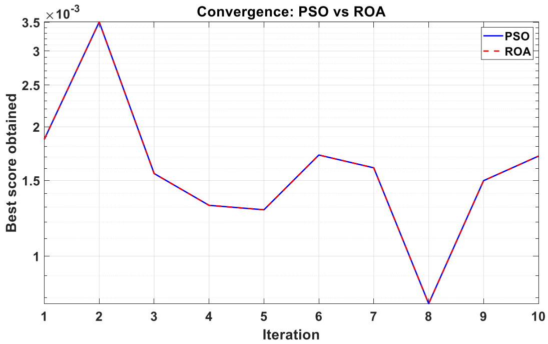

Fig. 7 Convergence PSO vs ROA Curves

Figure 6 shows the values of the optimized parameters (*Iph*, *I*0, *Rsh*, *Rs*, *Ns*) found by the hybrid approach.

Figure 7 shows the fitness value (RMSE) decreasing over iterations for PSO and ROA. The blue line represents PSO, while the red dashed line represents ROA. The hybrid PSO-ROA method accurately models the single-diode solar PV system. The close match between measured and estimated power and current confirms its precision in parameter estimation, especially for non-linear behavior. Optimized parameters such as Rsh and Ns play a key role in improving the accuracy of the PV model. The bar chart shows how these adjustments lead to better performance. Convergence analysis also confirms that the hybrid PSO-ROA method outperforms standalone PSO and ROA. It follows a more stable and consistent path across iterations, which means better predictions and more efficient parameter tuning

5.3 Performance Evaluation and Practical Implications

Figure 8 shows the error histogram. It compares the distribution of estimation errors between the hybrid and standalone methods. The results are clear. The hybrid PSO-ROA approach has a tighter spread of errors, mostly centered around zero. This indicates higher accuracy and better model reliability. In contrast, the standalone PSO shows wider error distribution, pointing to lower precision.

A neural network was also used to support the model. It was trained to map estimated power output (Ppv_estimated) to actual measured values (Ppv_measured). The Levenberg-Marquardt algorithm was used for training. Performance was measured using Mean Squared Error (MSE). The dataset included 18 training samples, 4 for validation, and 4 for testing. Results show that the network, when combined with the hybrid optimization, contributes to better system accuracy.

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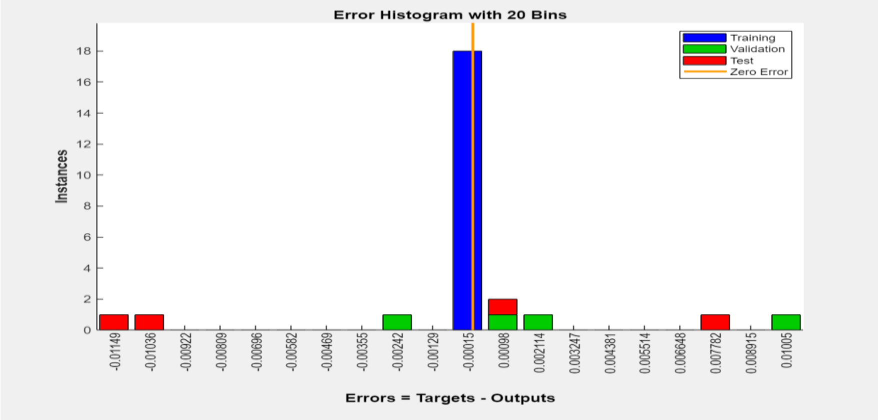

Fig. 8 Error histogram

The training phase achieved an MSE of $5.2839e^{-9}$ and a correlation coefficient (R) of 1.0000, indicating a near-perfect fit. The validation phase had an MSE of 3.1444e-05 and R = 0.9996, confirming strong generalization. The test phase showed an MSE of $7.757e^{-5}$ and R = 0.9877, maintaining high predictive accuracy. The low MSE and high R-values confirm the model's reliability. A slight increase in test MSE suggests minor overfitting, but the model remains effective for accurate Ppv_measured predictions.

Table 1 compares the Hybrid PSO+ROA approach with standalone PSO for optimizing the single-diode PV model. The hybrid method demonstrates superior performance, ensuring better accuracy and stability.

Table 1 Comparison of PSO and Hybrid PSO+ROA for Photovoltaic (PV) Model Optimization

Metric	PSO	Hybrid PSO+ROA
RMSE (Current - Ipv)	0.03 A	**0.0007756 A**
RMSE (Power - Ppv)	0.01 W	**0.00032733 W**
Best Fitness Value	0.06	**0.0007756**
Computation Time (s)	119.164 s	**1374.3933 s**
Accuracy at MPP	Notable deviations	**Near-perfect alignment**
Global Exploration	Moderate	**Efficient (PSO)**
Local Refinement	Limited	**Precise (ROA + fmincon)**
Generalization (R)(test)	0.9953	**0.9877**
MSE (Training)	0.2116	**5.2839e-09**
MSE (Validation)	0.0363	**3.1444e-05**

The comparative analysis between PSO and Hybrid PSO+ROA demonstrates the benefits of hybridization. The hybrid approach significantly reduces the Root Mean Square Error (RMSE) for

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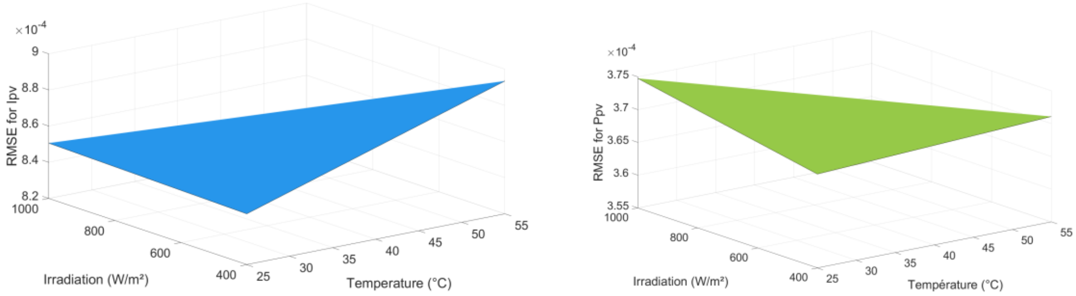
current (Ipv) and power (Ppv), leading to more accurate Maximum Power Point Tracking (MPPT). The best fitness value improves from 0.06 (PSO) to 0.0007756 (Hybrid PSO+ROA), confirming its precision.

The hybrid method requires more computation time (1374.3933 s) compared to PSO (119.164 s) due to the added local refinement step. However, this ensures near-perfect accuracy at the Maximum Power Point (MPP), whereas standalone PSO shows larger deviations. PSO handles global exploration efficiently, while ROA and fmincon enhance local refinement.

The training Mean Squared Error (MSE) drops from 0.2116 (PSO) to 5.2839e-09 (Hybrid PSO+ROA), and the test MSE decreases from 0.0840 to 7.757e-05, confirming the hybrid approach's robustness. The generalization performance remains high, with correlation coefficients (R) of 0.9953 for PSO and 0.9877 for Hybrid PSO+ROA, ensuring reliable predictions across different conditions. These results confirm that Hybrid PSO+ROA enhances MPPT accuracy, improves local refinement, and increases overall system efficiency, making it a strong optimization method for photovoltaic systems.

5.4 Sensitivity Analysis to Temperature and Irradiance Variations

Figures 9 illustrate the influence of temperature and irradiance on the performance of the photovoltaic (PV) model, assessed using key metrics: RMSE for current (Rm), RMSE for power (Pm), and overall fitness.



(Ipv) (Ppv)

Fig. 9 Impact of Temperature and Irradiance on RMSE

Temperature and irradiation significantly affect photovoltaic (PV) performance. Root Mean Square Error (RMSE) for current (Rm), power (Pm), and fitness values indicate that higher irradiation improves accuracy, reducing RMSE and enhancing fitness. Strong sunlight optimizes performance. High temperatures, especially at 100°C, degrade accuracy by increasing RMSE and reducing fitness. This decline is linked to lower cell efficiency and thermal stress. The best results occur at moderate temperatures (60°C to 80°C) with high irradiation (500 W/m²), minimizing errors and ensuring stable convergence.

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Sensitivity analysis confirms the hybrid PSO+ROA model's adaptability to environmental changes. It balances global exploration and local refinement, maintaining accuracy across different conditions.

5.5 Impact of Partial Shading on PV Performance

To complete this study, we have incorporated the effect of partial shading, which significantly influences photovoltaic performance by reducing current output and increasing initial errors. As shading increases, system accuracy declines. The hybrid PSO-ROA optimization reduces these impacts. It ensures precise parameter estimation and maintains stable performance. This confirms its effectiveness in optimizing PV systems under varying shading conditions.

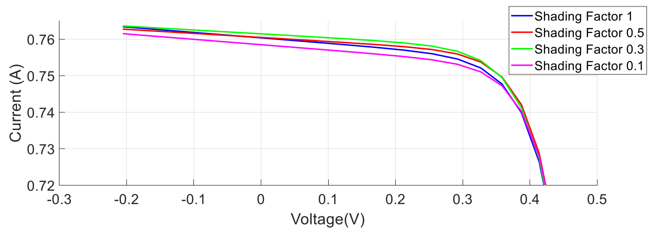

Fig. 10 I-V curves for different shading factors

Fig.10. show the I-V curves for different shading factors (1.0, 0.5, 0.3, and 0.1) show that as the shading factor decreases, the overall current (A) slightly decreases. However, the general trend of the curves remains similar, indicating that the photovoltaic system maintains its operational behavior despite partial shading. The voltage at which the current drops significantly remains almost unchanged, suggesting that the system maintains a relatively stable open-circuit voltage across different shading conditions.

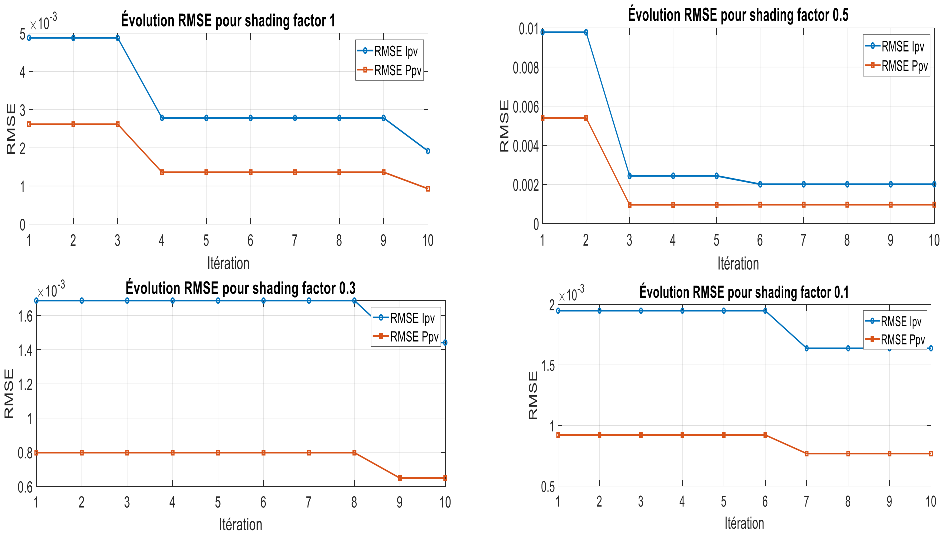

Fig. 11 RMSE of I-V characteristics for different shading factors

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The four bottom graphs shows in figure 11 represent the evolution of the RMSE (Root Mean Square Error) for I-V characteristics over 10 iterations. Initially, the RMSE is high, especially for shading factor 1, but it decreases progressively, showing that the optimization process is effective. After a few iterations (around iteration 3 or 4), the RMSE stabilizes at a low value, indicating that the optimization algorithm converges efficiently to an optimal solution. The shading factor influences the initial RMSE values, with higher shading factors leading to higher RMSE values initially, but they all eventually stabilize at an acceptable level.

6 CONCLUSION

This study optimized photovoltaic performance using a hybrid PSO-ROA approach. The method improved parameter estimation, minimized errors in I-V and P-V characteristics, and ensured stable convergence. It achieved precise predictions and reliable Maximum Power Point Tracking (MPPT) under different conditions.

The hybrid approach significantly outperformed standalone PSO. It reduced RMSE for current and power, improving accuracy at the Maximum Power Point (MPP). Although computation time increased due to ROA-based refinement, the gain in precision justified the trade-off.

Partial shading analysis showed that increased shading reduced current output and increased errors. The hybrid optimization mitigated these effects, maintaining accuracy. Sensitivity analysis confirmed that high irradiance improved performance, while extreme temperatures (100°C) degraded efficiency. The best results appeared at moderate temperatures (60–80°C) and high irradiance (500 W/m²), ensuring minimal errors and optimal convergence.

The hybrid PSO-ROA method balanced global exploration and local refinement. It delivered high accuracy across varying environmental conditions. These findings confirm its effectiveness in optimizing photovoltaic systems, even under partial shading and fluctuating climate conditions.

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