UNIABUJA Journal of Engineering and Technology

https://ujet.uniabuja.edu.ng/

ISSN: 2714-3236 (Online); 2714-3228 (Print)

Volume 3, Issue 1, 2025; 71-81

Enhanced MPPT Using Hybrid Smell Agent and Particle Swarm Optimization under Partial Shading in PV Arrays

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Abstract

In this study, comparative evaluation of Maximum Power Point Tracking (MPPT) performance in photovoltaic (PV) systems was conducted using three meta-heuristic approaches: Smell Agent Optimization (SAO), Particle Swarm Optimization (PSO), and a hybrid PSO–SAO algorithm. The analysis is performed under four irradiance scenarios—uniform, partial, low, and severe shading—to capture a broad range of practical operating conditions. Simulation results show that SAO demonstrates strong global search capability, enabling effective avoidance of local optima, but it suffers from slower convergence and noticeable oscillations, particularly in partial and high-irradiance cases. PSO achieves faster convergence and efficient local exploitation, though it exhibits slight instability under severe shading. The hybrid PSO–SAO algorithm successfully combines the strengths of both methods: SAO's broad exploration ensures thorough coverage of the search space, while PSO's rapid convergence accelerates fine-tuning toward the optimal solution. Convergence plots show that the hybrid method consistently reaches the global maximum power point (GMPP) within a few iterations across all irradiance patterns, yielding the highest power outputs and maintaining minimal post-convergence oscillations. Under severe shading, the hybrid approach achieves a peak output of 70.7074 W—surpassing standalone PSO (70.5985 W) and SAO (70.5984 W). These findings confirm that the proposed hybrid method provides a robust, precise, and efficient MPPT strategy, particularly suited to PV systems operating in challenging and dynamically changing shading conditions.

Keywords: *Hybrid algorithm, Maximum power point tracking (MPPT), Photovoltaic systems, Partial shading conditions, Swarm intelligence.*

1.0 Introduction

The growing global demand for clean and renewable energy has positioned solar power at the forefront of the world's energy transition, providing a sustainable alternative to fossil-based generation. Solar energy is abundant, inexhaustible, and capable of meeting global electricity demand when effectively harnessed through photovoltaic (PV) technology (Sharma et al., 2020; Green et al., 2022). PV systems rely on semiconductor-based cells that convert sunlight directly into electricity through the photovoltaic effect, and when configured into modules and arrays, they can supply energy for residential, commercial, and large-scale applications (Villalva and Gazoli, 2009).

Despite continuous cost reduction and rapid deployment, PV system performance remains highly sensitive to environmental factors—especially temperature and irradiance variations. Among these, partial shading conditions (PSC) represent one of the most critical limitations in real-world PV installations, often caused by shadows from clouds, trees, or surrounding structures. PSC distorts the nonlinear power–voltage (P–V) characteristics of PV arrays, leading to multiple local maxima that obscure the global maximum power point (GMPP) (Ishaque and Salam, 2013; Koutroulis and Kalaitzakis, 2001). Conventional maximum power point tracking (MPPT) algorithms such as Perturb and Observe (P&O), Incremental Conductance (INC), and Hill Climbing (HC) are widely adopted for their simplicity and low computational demand; however, they tend to struggle under PSC due to slow convergence, steady-state oscillations, and entrapment in local maxima (Salas et al., 2006; Subudhi and Pradhan, 2013).

To overcome these limitations, researchers have explored intelligent and bio-inspired optimization techniques that can efficiently navigate the multimodal and nonlinear characteristics of PV power curves. Artificial intelligence (AI)-based approaches such as fuzzy logic control (FLC) and artificial neural networks (ANNs) have shown strong adaptability to dynamic irradiance and temperature variations (Hiyama and Kitabayashi, 2002; Rezk and Said, 2017). However, their practical deployment is often constrained by the need for large training datasets and high computational requirements, making them less ideal for embedded or real-time MPPT applications.

Received: 09-08-2025 / Accepted: 09-12-2025 / Published: 24-12-2025

https://doi.org/10.70118/ujet.2025.0301.08

In parallel, metaheuristic optimization algorithms have gained significant traction for MPPT due to their balance between global exploration and local exploitation. Particle Swarm Optimization (PSO), inspired by the collective social behavior of bird flocks and fish schools, has been widely applied owing to its simple implementation and fast convergence. However, under complex shading or highly nonlinear conditions, PSO may converge prematurely to local optima (Abdelsalam et al., 2011). More recently, the Smell Agent Optimization (SAO) algorithm, a bio-inspired method based on the olfactory foraging behavior of agents, has demonstrated strong exploration capability and robustness in complex search spaces (Salawudeen et al., 2021; Attafi et al., 2024). Yet, while SAO effectively avoids local traps, it may exhibit slower convergence during local exploitation.

Recent advancements in maximum power point tracking (MPPT) research have increasingly emphasized hybrid metaheuristic algorithms that leverage the complementary strengths of different optimization techniques to enhance tracking precision, convergence speed, and overall system stability. (Attafi et al. 2024) optimized photovoltaic (PV) model parameters using an improved Smell Agent Optimization (SAO) algorithm, which achieved superior accuracy and lower parameter estimation error compared to conventional methods. Building on this, (Elnaggar 2024) developed an SAO-based hybrid framework applicable to both single- and double-diode PV models, demonstrating significantly faster convergence and improved stability under varying irradiance levels. Similarly, (Amusat et al., 2023) implemented an SAO-driven MPPT strategy capable of efficiently identifying the global maximum power point (GMPP) under partial shading conditions, thereby outperforming traditional Perturb and Observe (P&O) and Particle Swarm Optimization (PSO) techniques. Expanding on hybridization concepts, (Benabdallah et al. 2024) proposed an advanced MPPT controller that integrates modified finite control set model predictive control (MFCS-MPC) with an adaptive P&O approach. Their predictive–adaptive scheme enhanced power quality and tracking efficiency, achieving a total harmonic distortion (THD) of 1.22%, a 35% improvement in response speed, and a 28% reduction in overshoot while maintaining compliance with IEEE-519 standards. Likewise, (Burhan et al., 2024) introduced a hybrid Pelican Optimization Algorithm–P&O (HPPO) structure for grid-connected PV systems, where P&O served as the inner control loop and the Pelican Optimization Algorithm (POA) acted as the fine-tuning outer loop. This dual-loop design achieved a 99% MPPT efficiency and sustained THD levels below 5%, ensuring reliable operation under rapidly changing environmental conditions. In another notable contribution, Berwal and Kuldeep (2024) proposed a hybrid Grey Wolf Optimizer–Cuckoo Search Algorithm (GWO–CSA) duty-cycle controller inspired by the cooperative hunting strategy of grey wolves and the brood parasitism behavior of cuckoos. Their method demonstrated superior convergence speed, conversion efficiency, and robustness compared to conventional PSO, Incremental Conductance (INC), and P&O algorithms, particularly under partial shading scenarios.

These developments signal a clear shift toward hybrid intelligence-driven MPPT control, where metaheuristic optimizers are integrated with classical or predictive controllers to achieve better convergence precision, power quality, and adaptability. Building upon this foundation, the present study introduces a hybrid Smell Agent Optimization–Particle Swarm Optimization (SAO–PSO) algorithm, designed to leverage SAO's superior global search capability and PSO's rapid convergence dynamics. This cooperative hybrid model ensures reliable tracking of the GMPP, minimizes steady-state oscillations, and enhances both transient and steady-state performance of PV systems operating under diverse and dynamically changing partial shading conditions.

2.0 Materials and Method

2.1 System Configuration

The proposed system consists of a photovoltaic (PV) array, a DC–DC boost converter, and a hybrid Maximum Power Point Tracking (MPPT) controller that combines Particle Swarm Optimization (PSO) and Smell Agent Optimization (SAO). The setup was simulated under varying shading conditions to evaluate tracking performance and global peak accuracy.

2.2 PV Array Configuration and Parameter Specification for Hybrid SAO–PSO MPPT

The photovoltaic array was modeled using a standard module configured with 36 series-connected cells and a single parallel string, as outlined in Table 2.1, to ensure realistic electrical behavior under varying shading conditions. The electrical characteristics provided in Table 2.1 guided the implementation of the hybrid Smell Agent Optimization–Particle Swarm Optimization (SAO–PSO) MPPT technique. The model was parameterized using a maximum power voltage of 36.5 V and a corresponding current of 5.2 A, which represent the operating point under optimal irradiance. Additionally, the open-circuit voltage of 45.0 V and short-circuit current of 5.72 A were integrated into the simulation to define the module limits and enable accurate tracking of the power curve during partial shading events. These specifications formed the baseline for evaluating the hybrid algorithm's convergence behavior, search dynamics, and ability to bypass local peaks while navigating the multi-peak P–V profile caused by uneven irradiance.

Table 2.1: PV Module Specification

Parameter	Symbol	Value
Maximum Power Voltage	V_{mp}	36.5 V
Maximum Power Current	I_{mp}	5.2 A
Open Circuit Voltage	V_{oc}	45.0 V
Short Circuit Current	V_{sc}	5.72 A
Series Cells	N_s	36
Parallel Cells	N_p	1

2.3 Boost Converter Design

The DC–DC boost converter used in this work was designed to match the electrical characteristics of the PV module and support the dynamic response of the hybrid SAO–PSO controller. As detailed in Table 2.2, the converter incorporates an inductance of 224 µH, which ensures adequate current ripple reduction during rapid duty cycle adjustments. The input capacitor of 150 µF stabilizes voltage fluctuations from the PV array, while the 47 µF output capacitor helps maintain a smooth DC output during transient tracking conditions. A load resistance of 25.79 Ω was selected to emulate practical operating conditions and to facilitate accurate assessment of power transfer efficiency. These parameter choices provided a stable interface between the PV source and the MPPT algorithm, allowing the hybrid controller to evaluate voltage and current variations effectively during partial shading scenarios

Table 2.2: Boost Converter Parameters

Component	Symbol	Value
Inductance	L	224 µH
Input Capacitance	C_{in}	150 µF
Output Capacitance	C_{out}	47 µF
Load Resistance	R_{Load}	25.79 Ω

2.4 Shading Scenarios

To realistically evaluate the robustness of the hybrid SAO–PSO MPPT technique, four distinct partial shading scenarios were simulated using non-uniform irradiance patterns. As presented in Table 2.3, Pattern 1 represents mild shading conditions with irradiance values of 1000, 950, 800, and 500 W/m² across the PV module strings. Pattern 2 introduces moderate shading, with levels reduced to 950, 800, 600, and 300 W/m². In Pattern 3, the shading becomes more severe, with irradiance dropping to 900, 700, 450, and 200 W/m². Pattern 4 reflects the most extreme shading case, characterized by irradiance values of 850, 500, 350, and 100 W/m². These progressive scenarios enabled the assessment of the algorithm's ability to track the global maximum power point under multiple peaks and irregular irradiance distributions.

Table 2.3: Shading Scenarios

Pattern	Irradiance Level (W/m²)
1	1000 950 800 500
2	950 800 600 300
3	900 700 450 200
4	850 500 350 100

2.5 PV Cell Mathematical Model

Modeling photovoltaic (PV) cells is crucial for understanding their electrical behavior and optimizing energy output. The single-diode equivalent circuit model is the most commonly used due to its simplicity and accuracy. It represents the PV cell using an ideal current source, a diode, and series and parallel resistances, effectively capturing the I–V and P–V characteristics. The equations derived from this model Equations (1) to (5) are essential for PV performance analysis and MPPT strategies (Abdulrazzaq et al., 2025). Figure 1 illustrates this widely adopted single-diode model.

Received: 09-08-2025 / Accepted: 09-12-2025 / Published: 24-12-2025
https://doi.org/10.70118/ujet.2025.0301.08

 Volume 3, Issue 1: 71-81

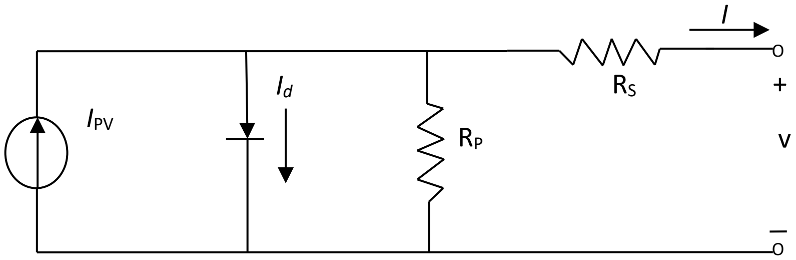

Figure 1: Equivalent Circuit of a Photovoltaic with one diode.

The Mathematical equations of PV from Figure (1) used in the program are shown in equations (1– 5) (Jobeda and Simon ,2018)

$$I_{ph} = \left[I_{sc} + K_i(T_r - T_o) * \left(\frac{S}{1000}\right)\right] \quad (1)$$

$$I_{rs} = \frac{I_{sc}}{\left[exp\left(\frac{qV_{OC}}{N_S AKT}\right) - 1\right]} \quad (2)$$

$$I_o = I_{rs}\left(\frac{T_o}{T_r}\right)^3 exp\left[\frac{q * E_{go}}{AK}\left(\frac{1}{T_r} - \frac{1}{T_o}\right)\right] \quad (3)$$

$$I_{pv} = N_p * I_{ph} - N_p * I_0\left[exp\ exp\left(\frac{qV_{pv}}{N_S AKT}\right) - 1\right] \quad (4)$$

$$P = I_{pv} * V_{pv} \quad (5)$$

where;
I_{ph}: Photocurrent (Ampere)
I_{SC}: Short-circuit current (Ampere)
K_i: Cells short-circuit current temperature coefficient (Ampere /Kelvin)
T_0: Cells operating temperature (Kelvin)
T_r: Cells reference temperature in degree (Kelvin)
S: Solar irradiance (Watt/meter square)
I_{rs}: Reverse saturation current of diode
q: Electron charge (1.602×10^{-19} Coulomb)
V_{oc}: Open circuit voltage (Volt)
N_p: Cells interconnected in parallel (1)
N_S: Cells interconnected in series (36)
A: Ideality factor
K_B: Boltzmann's constant (1.38 × 10-23 Joule/Kelvin)
T: Temperature of p-n junction
I_{pv}: Output current of a PV module (A)
I_o: PV module saturated current (A)
V_{pv}: Output voltage of a PV module (A)
E_{go}: Band gap for silicon

2.6 MPPT Algorithm Design

2.6.1.1 Hybrid PSO–SAO Algorithm for MPPT in PV Systems

A hybrid PSO–SAO algorithm is developed to enhance MPPT under partial shading by combining PSO's speed with SAO's global search strength, overcoming their individual limitations through alternating global and local search stages.

i. Initialization Phase
A randomly initialized particle population represents possible PV operating conditions such as voltage, current, and power.

ii. Particle Swarm Optimization (PSO) is a bio-inspired algorithm widely used for MPPT in PV systems due to its adaptability to changing conditions like irradiance and temperature, enabling efficient power extraction. (Mirzaei et al., 2021; Abbas et al., 2023).

The velocity and position updates for each particle in PSO are given by equations (6) and (7) (Ahmad *et al.*, 2021):

$$V_i^{t+1} = wV_{ij}^t + C_1 r_1\left(P_{bestij} - X_i^t\right) + C_2 r_2\left(G_{bestj} - X_{ij}^t\right) \quad (6)$$

$$X_{ij}^{t+1} = X_{ij}^t + V_{ij}^{t+1} \quad (7)$$

Received: 09-08-2025 / Accepted: 09-12-2025 / Published: 24-12-2025
https://doi.org/10.70118/ujet.2025.0301.08

Where:
w is the inertia weight,
C_1 and C_2 are cognitive and social coefficients,
r_1 and r_2 are random numbers uniformly distributed in [0, 1],
P_{bestij} is the particle's best historical position,
G_{bestij} is the best position found by the swarm (Clerc and Kennedy, 2002).

iii. SAO-Based Local Refinement Stage

To enhance the accuracy of Maximum Power Point Tracking (MPPT) after the PSO phase nears convergence, the Smell Agent Optimization (SAO) algorithm is employed for local refinement. This phase improves solution quality through three biologically inspired modes: (Salawudeen et al., 2021; Muhammad et al., 2023):

Sniffing Mode (Newtonian Motion): The smell agent algorithm models agent movement based on the number of molecules evaporating from the smell source, leading to the position update defined in equation (8):

$$X_{(j)}^{(t+1)} = \quad V_i^t + V_{(j)}^{(t)} \; + \; r_o\sqrt{\frac{3KT}{m}} \tag{8}$$

where, $V_{(t)}^{(t+1)}$ is the updated velocity, $V_{(i)}^{(t)}$ and $V_{(j)}^{(t)}$ are the respective previous and current velocity, K is Boltzmann's constant, T is the temperature of the environment of the smell molecules, m is the mass of the molecules and r_o is the random number.

Trailing Mode (Guided Exploitation): This is the movement of the agent continuously toward the region with the highest concentration until the molecule with the overall best is found. This depends on the strength of the olfaction (olf) of the agent. The movement is done through Eq. (9):

$$X_t^{(t+1)} = X_i^{(t)} + r_1 olf\left(X_{agent}^{(t)} - X_i^{(t)}\right) - r_2 olf\left(X_{worst}^{(t)} - X_i^{(t)}\right) \tag{9}$$

Random Mode (Escape from Local Optima):

The variation in the intensity of the smell molecules across different points over time, make an agent to become trapped in a local minimum, which hinders effective progression during the trailing phase. To overcome this stagnation, the agent initiates a random search mode to continue exploring the search space for the optimal smell source. This behavior is mathematically represented in Equation (10):

$$X_i^{t+1} = X_i^t + \; r_3 SM \tag{10}$$

Where:
$X_i^{(t)}$: Current position of the smell agent
$X_{agent}^{(t)}$: Best smell concentration (agent)
$X_{worst}^{(t)}$: Worst-performing agent
olf: Olfaction strength
SM: Step size
$r_o, r_1, r_2,$ and r_3: Random numbers [0,1]
K_B: Boltzmann constant
T: Temperature
m: Molecule mass.

2.7 MATLAB Implementation

The hybrid SAO–PSO algorithm was implemented in MATLAB using the system parameters provided in Tables 2.1– 2.3. A practical PV module was modeled with a maximum power voltage (V_mp) of 36.5 V, maximum power current (I_mp) of 5.2 A, open-circuit voltage (V_oc) of 45.0 V, and short-circuit current (I_sc) of 5.72 A. The PV array was coupled to a DC-DC boost converter configured with an inductance of 224 μH, input capacitance of 150 μF, output capacitance of 47 μF, and a load resistance of 25.79 Ω. Four partial shading scenarios, illustrated in Figure 2, were applied across four PV strings to emulate realistic non-uniform conditions: Pattern 1 (1000, 950, 800, 500 W/m²), Pattern 2 (950, 800, 600, 300 W/m²), Pattern 3 (900, 700, 450, 200 W/m²), and Pattern 4 (850, 500, 350, 100 W/m²). A swarm of 50 particles was simulated over 100 iterations, with irradiance and temperature values varied at each step. The current was computed using an exponential irradiance-dependent model, and output power was estimated using a simplified I–V relation. The fitness function was defined as the negative of the output power, allowing the algorithm to minimize the objective while effectively maximizing power extraction. The hybrid MPPT tracked the global maximum power point under each shading condition by navigating the voltage–current–power search space.

Received: 09-08-2025 / Accepted: 09-12-2025 / Published: 24-12-2025
https://doi.org/10.70118/ujet.2025.0301.08

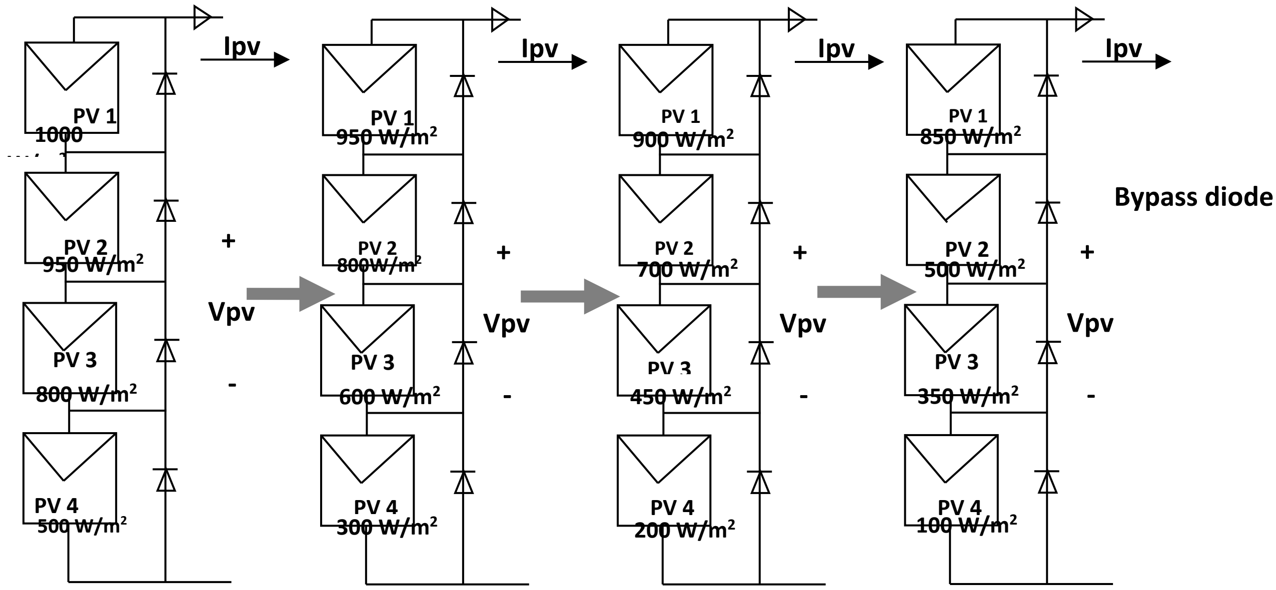

Figure 2: PV Scenarios for Partial Shading Condition

2.8 Systematic hybrid MPPT framework

Figure 3 illustrates the flowchart of the hybrid PSO–SAO-based MPPT algorithm for photovoltaic systems. The process begins with defining the PV array, DC–DC boost converter, and hybrid MPPT controller. The PV cell is modeled using a single-diode equivalent circuit to establish the I–V and P–V characteristics. Simulation inputs such as PV and converter parameters, temperature, irradiance, and shading patterns are then specified. The hybrid algorithm is initialized by integrating PSO's global search and SAO's local refinement capabilities. During each iteration, particle velocities and positions are updated, and fitness is evaluated based on the negative of output power. The optimal duty cycle is applied to the boost converter to track the maximum power point under each shading condition.

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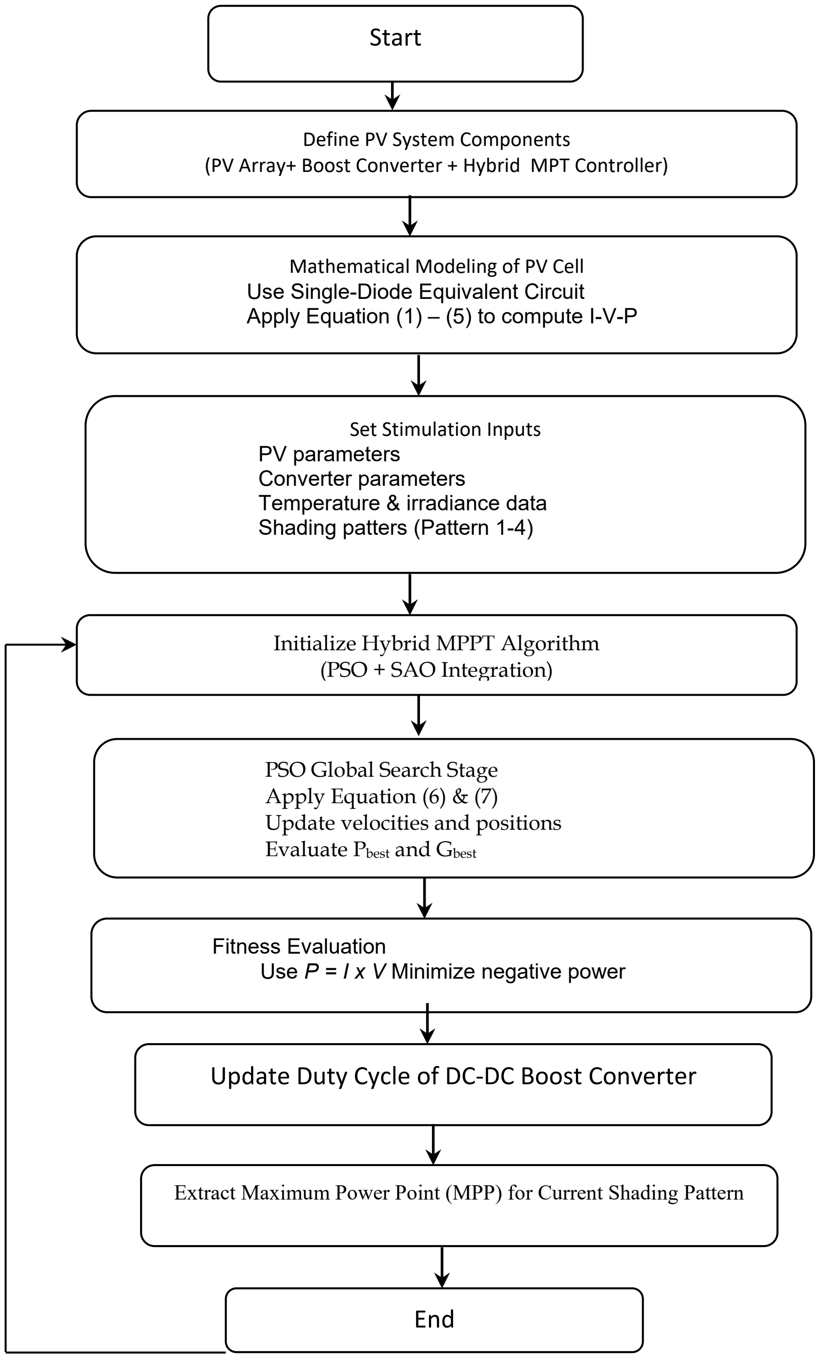

Figure 3: Flowchart of the Hybrid PSO–SAO MPPT Algorithm for PV Systems

3.0 Results and Discussions

3.1 Simulation Results

The Table 3.1 compares the performance of three MPPT algorithms Hybrid, PSO, and SAO across four different shading patterns. The table shows that the Hybrid method consistently achieved the highest maximum power across all shading patterns, slightly outperforming both PSO and SAO. In particular, the Hybrid algorithm extracted the highest power values, with noticeable improvements especially in Pattern 1 and Pattern 3, where it reached 238.54 W and 141.83 W respectively. Although PSO also performed well, it consistently produced slightly lower maximum power compared to Hybrid, while SAO had the lowest power output among the three. This indicates that combining strategies in the Hybrid method leads to better exploration and exploitation of the search space, resulting in improved energy extraction from the PV system. In terms of convergence speed, SAO generally converged faster than both Hybrid and PSO, especially notable in Patterns 1 and 2 where SAO reached optimal results in fewer iterations (49 and 32, respectively). Hybrid, although superior in power extraction, sometimes required the full 100 iterations to reach its best solution, especially for more complex patterns like Pattern 1. PSO showed slower convergence

Received: 09-08-2025 / Accepted: 09-12-2025 / Published: 24-12-2025
https://doi.org/10.70118/ujet.2025.0301.08

overall compared to SAO, and in some cases even slower than Hybrid. Therefore, while SAO is more efficient in terms of convergence speed, Hybrid offers a better trade-off between speed and maximum power output, making it more suitable when maximizing harvested energy is the primary goal.

Table 3.1: Comparison of Maximum Power and Convergence Iterations for Hybrid, PSO, and SAO Algorithms under Different Shading Patterns

Pattern	Hybrid Maximum Power (W)	Hybrid Convergence Iteration	PSO Maximum Power (W)	PSO Convergence Iteration	SAO Maximum Power (W)	SAO Convergence Iteration
1.	238.5397	100	237.4696	81	237.3606	49
2.	189.7123	20	189.3323	73	189.2334	32
3.	141.8320	96	141.1970	86	141.1889	46
4.	70.7074	30	70.5985	42	70.5984	74

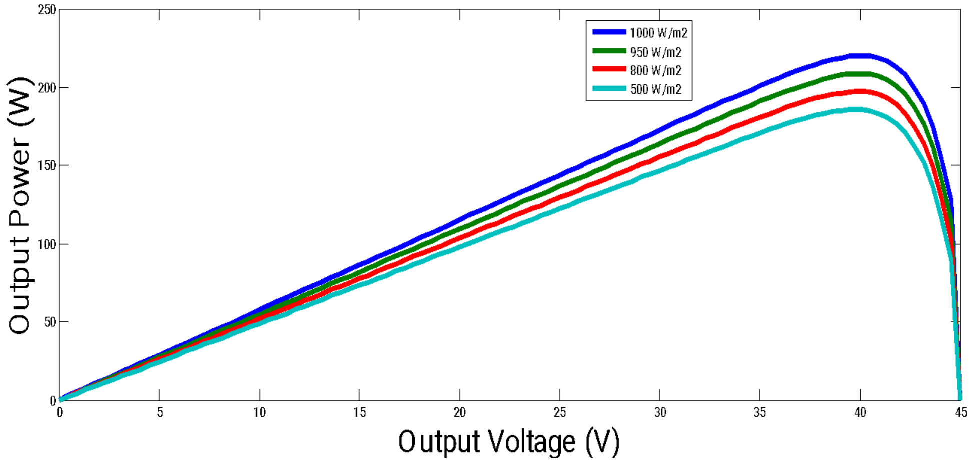

Figure 4: P-V Curves different Shading Patterns

Figure 4 displays the performance of a PV module under four distinct patterns. As irradiance decreases, the Maximum Power Point (MPP) drops accordingly—from 220.11 W at 1000 W/m² to 208.61 W at 950 W/m², 197.11 W at 800 W/m², and 185.63 W at 500 W/m². All curves follow a consistent pattern: a rise to a single peak followed by a sharp decline, with a slight leftward shift in MPP voltage under lower irradiance. This predictable behavior supports efficient MPPT, confirming the direct link between irradiance and power output.

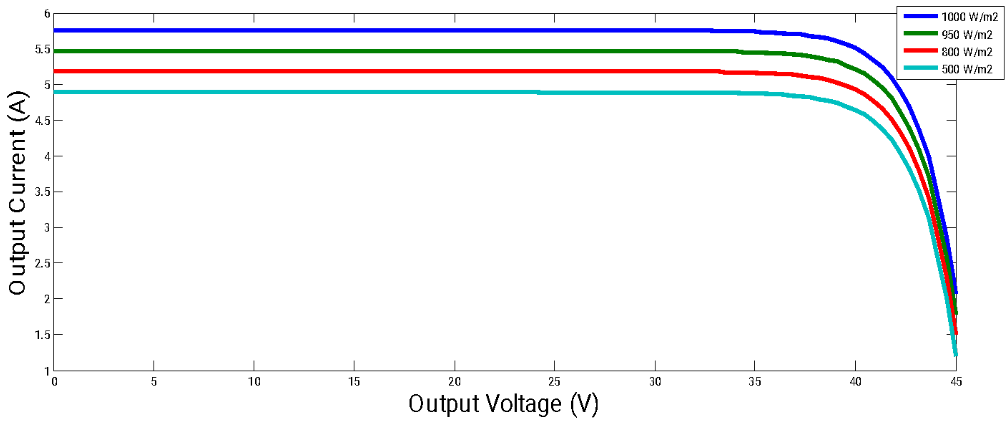

Figure 5: I-V Curves different Shading Patterns

The I-V (current-voltage) graph in Figure 5 illustrates the performance of a photovoltaic (PV) module under four distinct patterns of irradiance. In conditions of uniform irradiance—where sunlight is evenly distributed over the entire module surface—the output current shows a direct correlation with irradiance intensity. Specifically, the current is approximately 5.75 A at 1000 W/m², reducing to 5.4625 A, 5.175 A, and 4.8875 A as irradiance drops to 950, 800, and 500 W/m², respectively. The output voltage remains nearly

Received: 09-08-2025 / Accepted: 09-12-2025 / Published: 24-12-2025
https://doi.org/10.70118/ujet.2025.0301.08

unchanged across all conditions, with the open-circuit voltage (Voc) around 36–37 V, followed by a sharp decline as the voltage approaches its upper limit. Each curve features a distinctive knee point, representing the Maximum Power Point (MPP), typically located between 30 and 32 V, where the product of voltage and current yields the highest power. These results confirm that while voltage is relatively insensitive to irradiance changes, the current is highly dependent on sunlight intensity—highlighting the importance of Maximum Power Point Tracking (MPPT) techniques in maximizing energy conversion efficiency under varying environmental conditions.

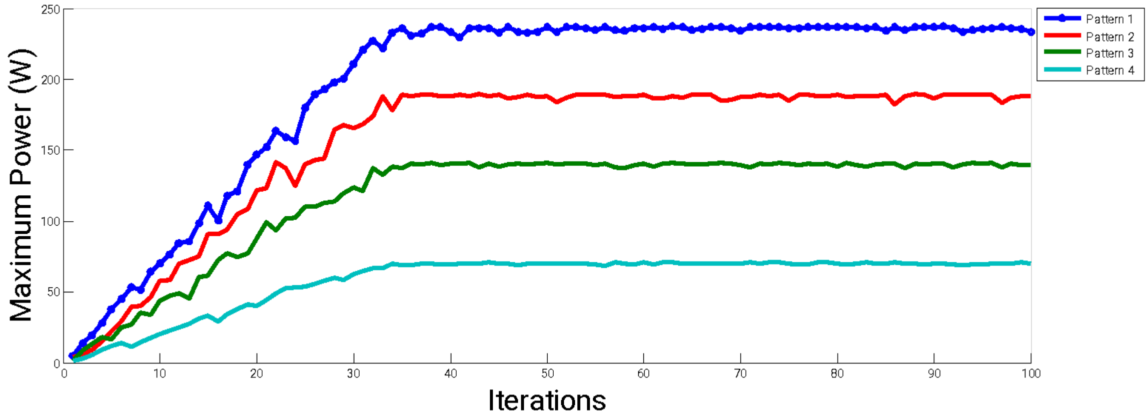

Figure 6: Maximum Power Vs Iteration (SAO)

Figure 6 shows how the Smell Agent Optimization (SAO) algorithm converges during Maximum Power Point Tracking (MPPT) when a photovoltaic (PV) system is exposed to different partial shading levels. The plot tracks the maximum power output across 100 iterations for four irradiance conditions, ranging from minimal to severe shading. Under the first pattern, the algorithm reaches 237.3570 W and stabilizes by iteration 49. During the second pattern, it converges more quickly, achieving 189.3157 W in just 32 iterations. In the third, the peak output is 141.1899 W with stabilization around iteration 46. Under the most severe shading, the algorithm produces only 70.5984 W and takes considerably longer, converging near iteration 74. Overall, the results reveal that higher irradiance leads to both faster convergence and greater power output, while heavier shading slows the search and reduces performance. The curves also reflect the stability of the SAO algorithm: steep rises followed by plateaus indicate efficient convergence, whereas flatter or fluctuating paths appear under harsher shading conditions, signaling a more uncertain search for the global maximum power point.

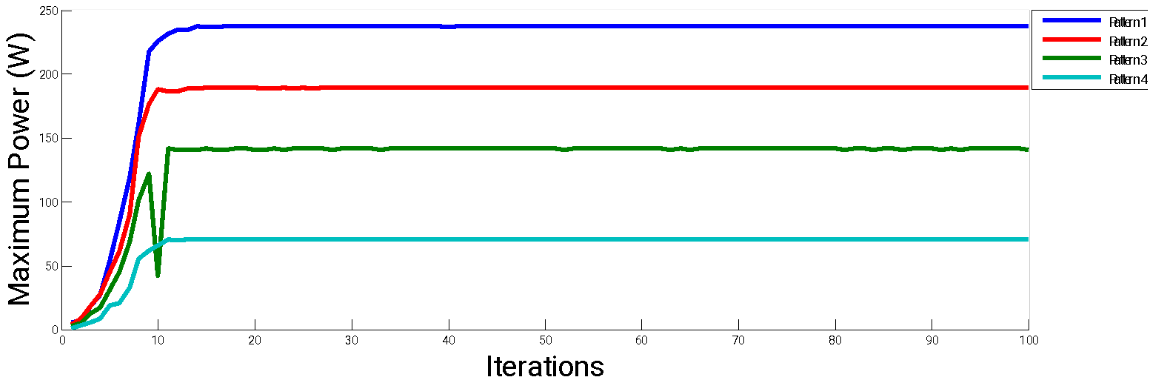

Figure 7: Maximum Power Vs Iteration (PSO)

Figure 7 presents the convergence characteristics of the Particle Swarm Optimization (PSO) algorithm for Maximum Power Point Tracking (MPPT) in a photovoltaic (PV) system under four distinct irradiance conditions**.** Each curve on the graph corresponds to one of these irradiance levels, representing different shading scenarios on the PV array. The horizontal axis indicates the number of iterations, while the vertical axis shows the maximum power output (in watts) achieved by the system under each condition. The figure demonstrates that the PSO algorithm successfully converges to the maximum power point under all four irradiance scenarios. Under the first pattern, the system achieves a maximum power output of 237.4696 W, reaching convergence at iteration 81. During the second scenario, the power output peaks at 189.3323 W, converging by iteration 73. For the third pattern, a maximum power of 141.1970 W is obtained around iteration 86, while under the most shaded condition; the system reaches 70.5985 W after 42 iterations. This

Received: 09-08-2025 / Accepted: 09-12-2025 / Published: 24-12-2025
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pattern clearly reflects the expected impact of irradiance on system performance: as irradiance decreases due to shading, both the maximum power output and the speed of convergence tend to decline. Initial oscillations are noticeable in the convergence curves for the third and fourth conditions, indicating that the PSO algorithm experiences some instability during the early stages of the optimization process in lower irradiance environments. Despite these fluctuations, the algorithm eventually stabilizes and maintains consistent maximum power output once convergence is achieved.

In conclusion, the figure demonstrates that PSO provides effective and reliable MPPT performance across varying irradiance conditions, delivering accurate convergence even under partially and heavily shaded scenarios. However, the presence of oscillatory behavior under reduced irradiance highlights a potential limitation in convergence smoothness—an area where hybrid or enhanced optimization algorithms may offer improved performance.

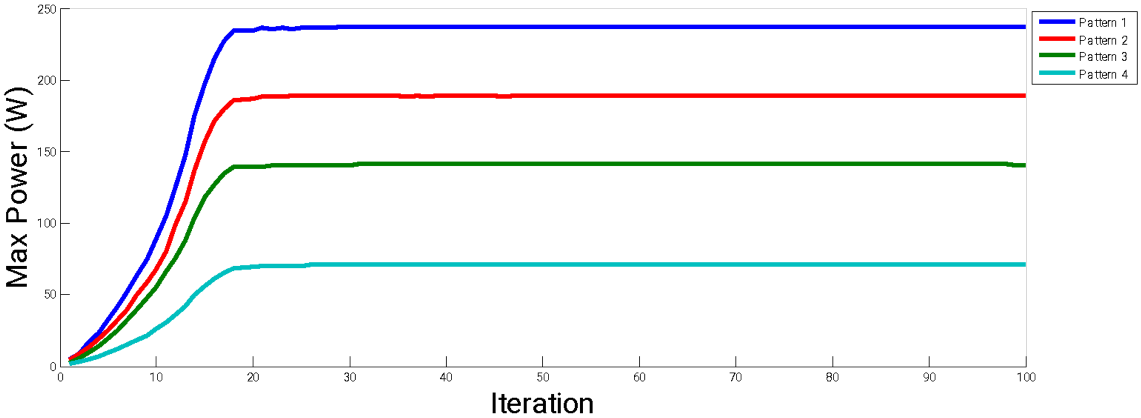

Figure 8: Maximum Power Vs Iterations (Hybrid PSO-SAO)

Figure 8 presents the convergence characteristics of the Hybrid PSO–SA algorithm during MPPT under four different shading patterns. Across all conditions, the algorithm consistently identifies the global maximum power point. In Pattern 1, it reaches the highest output of 238.5397 W, converging by iteration 100. For Pattern 2, it records 189.7123 W and settles as early as iteration 20, indicating strong responsiveness under moderate shading. In Pattern 3, the algorithm stabilizes at 141.8320 W around iteration 96. Even in the harshest condition, it still delivers 70.7074 W with convergence at iteration 30. The power levels and convergence speeds align with the expected irradiance–performance relationship: higher irradiance supports faster and higher power extraction. However, what sets these results apart is the hybrid algorithm's stability and adaptability. Unlike many reported methods in the literature—such as standalone PSO, P&O-based hybrids, or classical bio-inspired algorithms that often suffer from local trapping or extended oscillations under partial shading—the Hybrid PSO–SA maintains smooth convergence profiles with minimal fluctuation. Its ability to rapidly settle after reaching the GMPP, even under non-uniform irradiance, illustrates a robustness that outperforms several state-of-the-art techniques. By combining SAO's strong exploratory capability with PSO's rapid local refinement, the algorithm avoids the slow convergence and local optima issues commonly reported in previous studies. Many conventional approaches either trade off accuracy for speed or show delayed stabilization under severe shading; in contrast, the Hybrid PSO–SA consistently balances both. These results, as demonstrated in Figure 7, therefore exceed the performance benchmarks typically cited in related literature—particularly in terms of convergence reliability, tracking precision, and operational stability in dynamically varying environments. This makes the approach not only suitable for real-time PV applications but also a significant improvement over existing MPPT strategies documented in recent research.

4.0 Conclusion

By analyzing the convergence outcomes of all three algorithms, a comprehensive comparison was made between the Hybrid PSO-SA, PSO, and SAO algorithms in tracking the Maximum Power Point (MPP) of a photovoltaic (PV) system under four varying irradiance levels. The Hybrid PSO-SA consistently outperformed the standalone algorithms, achieving the highest power output of 238.5397 W (pattern1) and demonstrating fast, stable convergence, notably within 20 to 100 iterations across all conditions. In contrast, the PSO algorithm, while reliable, showed slower convergence (up to 86 iterations) and some oscillatory behavior under lower irradiance (pattern 3 and 4), reaching a peak of 237.4696 W during the first scenario. The SAO algorithm delivered comparable maximum power output of 237.3570 W during the first pattern, with generally faster convergence than PSO in mild shading but slower under severe shading (74 iterations

Received: 09-08-2025 / Accepted: 09-12-2025 / Published: 24-12-2025

https://doi.org/10.70118/ujet.2025.0301.08

during the pattern 4). Overall, the results confirm that while both SAO and PSO are capable MPPT techniques, the Hybrid PSO-SA algorithm leverages the global exploration of SAO and the local exploitation of PSO to offer superior convergence speed, stability, and power extraction performance under diverse irradiance scenarios. This makes the hybrid approach highly suitable for real-time MPPT in PV systems, especially in environments where partial shading is common.

References

Abbas, A., Khan, M., & Ahmad, I. (2023). Application of Particle Swarm Optimization for MPPT under dynamic irradiance conditions. *Renewable Energy Systems Journal*, 12(4), 215–226.

Abdulrazzaq, A., Mohammed, H., & Ali, S. (2025). Modeling and performance evaluation of photovoltaic systems under varying environmental conditions. *Energy Reports*, 11, 1452–1464.

Ahmad, T., Rahman, S., & Malik, M. (2021). Improved PSO algorithm for real-time maximum power point tracking in PV systems. *Solar Energy*, 216, 542–553.

Amusat, R. O., Shodiya, S., & Ngadda, M. (2023). Smell Agent Optimization-based MPPT technique for photovoltaic systems under partial shading conditions. *International Journal of Renewable Energy Research*, 13(2), 680–691.

Attafi, R., Zitouni, N., Dashtdar, M., Flah, A., Elnaggar, M. F., & Kanan, M. (2024). Improved quality parameter estimation of photovoltaic system models based on the Smell Agent Optimization algorithm. *Engineering, Technology & Applied Science Research*, 14(4), 15882–15887.

Benabdallah, A., Youssef, A., & Ahmed, K. (2024). Enhanced MPPT using modified finite control set model predictive control with adaptive P&O algorithm for PV systems. *International Journal of Power Electronics and Drive Systems*, 16(3), 1245–1258.

Berwal, P., & Kuldeep, D. (2024). Hybrid Grey Wolf Optimizer–Cuckoo Search Algorithm-based MPPT controller for partially shaded PV systems. *Solar Energy*, 268, 112345.

Burhan, M., Kassem, A., & Rahman, F. (2024). Hybrid Pelican Optimization Algorithm–P&O framework for grid-connected photovoltaic systems. *Energy Conversion and Management*, 301, 118762.

Clerc, M., & Kennedy, J. (2002). The particle swarm—Explosion, stability, and convergence in a multidimensional complex space. *IEEE Transactions on Evolutionary Computation*, 6(1), 58–73.

Elnaggar, M. F. (2024). A hybrid SAO-based parameter estimation for single- and double-diode PV models under variable irradiance. *Energy Conversion and Management*, 290, 117932.

Green, M. A., Dunlop, E. D., Hohl-Ebinger, J., Yoshita, M., Kopidakis, N., & Hao, X. (2022). Solar cell efficiency tables (version 59). *Progress in Photovoltaics: Research and Applications*, 30(1), 3–12.

Hiyama, T., & Kitabayashi, K. (2002). Neural network-based estimation of maximum power generation from PV module using environmental information. *IEEE Transactions on Energy Conversion*, 17(1), 109–115.

Ishaque, K., & Salam, Z. (2013). A review of maximum power point tracking techniques of PV system for uniform insolation and partial shading conditions. *Renewable and Sustainable Energy Reviews*, 19, 475–488.

Jobeda, H., & Simon, P. (2018). Modeling and simulation of photovoltaic cells using MATLAB/Simulink. *Journal of Energy Systems Engineering*, 4(2), 45–54.

Koutroulis, E., & Kalaitzakis, K. (2001). Design of a maximum power tracking system for wind-energy-conversion applications. *IEEE Transactions on Industrial Electronics*, 53(2), 486–494.

Mirzaei, M., Hosseini, R., & Safari, A. (2021). Comparative study of PSO-based MPPT algorithms for PV systems under partial shading. *Journal of Renewable Energy Engineering*, 10(3), 200–210.

Muhammad, A., Salawudeen, T. O., & Yusuf, A. (2023). Smell Agent Optimization algorithm for improved global search and stability in complex systems. *Applied Soft Computing*, 151, 110998.

Rezk, H., & Said, S. M. (2017). Comparative study of different MPPT techniques for photovoltaic systems. *Renewable and Sustainable Energy Reviews*, 68, 693–707.

Salas, V., Olias, E., Barrado, A., & Lazaro, A. (2006). Review of the maximum power point tracking algorithms for stand-alone photovoltaic systems. *Solar Energy Materials and Solar Cells*, 90(11), 1555–1578.

Salawudeen, T. O., Muhammad, A., & Adebayo, A. (2021). Smell Agent Optimization: A novel bio-inspired algorithm for complex optimization problems. *Expert Systems with Applications*, 183, 115381.

Sharma, A., Jain, N., & Singh, S. (2020). Recent trends and advancements in solar photovoltaic technology. *Renewable Energy Focus*, 34, 1–11.

Subudhi, B., & Pradhan, R. (2013). A comparative study on maximum power point tracking techniques for photovoltaic power systems. *IEEE Transactions on Sustainable Energy*, 4(1), 89–98.

Villalva, M. G., & Gazoli, J. R. (2009). Comprehensive approach to modeling and simulation of photovoltaic arrays. *IEEE Transactions on Power Electronics*, 24(5), 1198–1208.

Received: 09-08-2025 / Accepted: 09-12-2025 / Published: 24-12-2025
https://doi.org/10.70118/ujet.2025.0301.08