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Adaptive intelligent PSO-Based MPPT technique for PV systems under dynamic irradiance and partial shading conditions

Muhammad Gul E. Islam[1,2], Mohammad Faridun Naim Tajuddin[1,2], Azralmukmin Azmi[1,2], Rini Nur Hasanah[3], Shahrin Md. Ayob[4], Tole Sutikno[5]

[1]Department of Electrical System Engineering, Faculty of Electrical Engineering and Technology (FKTE), University of Malaysia Perlis (UniMAP), Perlis, Malaysia
[2]Centre of Excellence for Renewable Energy (CERE), Universiti Malaysia Perlis, Perlis, Malaysia
[3]Department of Electrical Engineering, Faculty of Engineering, University of Brawijaya, Malang, Indonesia
[4]Faculty of Electrical Engineering, Universiti Teknologi Malaysia, Johor, Malaysia
[5]Department of Electrical Engineering, Faculty of Industrial Technology, Universitas Ahmad Dahlan, Yogyakarta, Indonesia

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ABSTRACT

This research introduces an adaptive improved particle swarm optimization (AIPSO) approach for maximum power point tracking (MPPT) approach designed to enhance energy harvesting from photovoltaic (PV) systems under dynamic irradiance conditions. The proposed AIPSO algorithm addresses the challenges associated with traditional MPPT methods, particularly in scenarios characterized by fluctuating solar irradiance, such as step changes and partial shading. By incorporating a robust reinitialization strategy along with updated velocity and position equations, the algorithm demonstrates superior performance in terms of convergence accuracy, tracking speed, and tracking efficiency. This modification enables the algorithm to effectively escape local maxima and explore a wider search space, leading to improved convergence and optimal power point tracking. Furthermore, the adaptive nature of the PSO enhances the algorithm's ability to respond to real-time changes in environmental conditions, making it particularly suitable for large-scale PV systems subjected to varying atmospheric factors. Here, "adaptive" denotes coefficient scheduling (C3) and a re-initialization trigger that responds to irradiance regime changes; "intelligent" denotes robust regime-shift detection and safe duty-ratio clamping. Across uniform, step-change, and partial shading conditions, the proposed AIPSO achieves fast reconvergence and high tracking efficiency with negligible steady-state oscillations, as summarized in the results. Building on this contribution, future research will focus on evaluating its scalability across different PV architectures and large-scale grid integration with real hardware setup.

Corresponding Author:

Mohammad Faridum Naim Tajuddin
Department of Electrical Engineering, Faculty of Electrical Engineering & Technology (FKTE)
Universiti Malaysia Perlis (UniMAP)
Pauh Putra Campus, 02600, Arau, Perlis, Malaysia
Email: faridun@unimap.edu.my

1. INTRODUCTION

PV systems have garnered significant attention as a feasible and eco-friendly energy source due to the growing global demand for clean and renewable energy solutions [1]. This increasing interest is driven by the need to lessen dependence on traditional fossil fuels and mitigate the environmental impacts of conventional energy production methods. However, optimizing the energy output of PV systems remains a critical challenge, particularly tracking the MPP under fluctuating environmental conditions [2]. These conditions, such as variations in temperature and sunlight intensity, can change rapidly and substantially, affecting the system's performance [3]. The output of PV arrays is inherently nonlinear and highly reliant on temperature and solar irradiance, creating a complex relationship between voltage and power generation [4]. To address this complexity and ensure that PV systems operate at their maximum potential, the implementation of efficient maximum power point tracking (MPPT) algorithms is necessary [5]. MPPT algorithms play a key role in accurately identifying and maintaining the MPP, thereby boosting the overall efficiency, effectiveness, and stability of PV systems. By ensuring optimal power extraction, these algorithms help harness the full potential of solar energy, making PV systems more reliable source of clean renewable energy [6].

MPPT methods are essential for maximizing the performance of PV systems, particularly in large-scale solar energy projects where system efficiency directly impacts energy production and economic feasibility [7]. By precisely tracking the MPP, MPPT algorithms not only optimize power output but also contribute to reducing system costs, an important consideration in the deployment of large PV arrays [1]. A wide array of MPPT techniques, ranging from direct to indirect methods, have been proposed in the literature, each with its inherent advantages and limitations. This paper investigates the practical considerations of these techniques, addressing factors such as system complexity, computational demands, and sensitivity to environmental changes. It aims to identify the most suitable MPPT approach for specific applications and operational scenarios [6]. While conventional MPPT techniques, such as Perturb and Observe, hill climbing, and Incremental Conductance, are relatively easy to implement and require minimal hardware, they face significant limitations in locating a global MPP under partial shading (PS) conditions [8]. These techniques often struggle to navigate multiple local maxima in the PV curve, a common occurrence in real-world PV systems subjected to shading from objects like trees, buildings, or clouds. Such partial shading can lead to substantial fluctuations in power output, thereby reducing the system's overall performance [9]. To overcome these challenges, advanced techniques leveraging artificial intelligence (AI), such as neural networks (NNs), genetic algorithms (GAs), and fuzzy logic (FL), have been proposed. However, these AI-based methods often demand high computational resources, complex implementation, and extensive tuning, which may not be feasible for all applications [10].

In response to these challenges, metaheuristic algorithms like PSO, grey wolf optimization (GWO), and simulated annealing (SA) have gained popularity as viable alternatives. These techniques are known for their simplicity, efficiency, and ability to solve complex optimization problems without extensive computational power [11]. This study focuses on the application of PSO to MPPT, particularly in environments with varying irradiance conditions, and explores the effectiveness of reinitialization strategies to enhance the algorithm's performance and robustness under challenging operating conditions [12]. PSO is a powerful stochastic optimization approach inspired by the behavior of swarms, where multiple agents (particles) work collaboratively to explore a solution space [13]. Each particle adjusts its position according to its own best-found solution (Pbest) and the best global solution (Gbest) determined by the swarm. This cooperative mechanism helps guide the search process, balancing exploration and exploitation to avoid premature convergence to local optima [3]. The study leverages PSO to optimize PV system performance under various irradiance conditions, including standard, step-change, and partial shading scenarios, ensuring adaptability to real-world conditions. Compared to traditional MPPT methods, PSO shows better performance in terms of convergence rate, stability, and optimal power extraction, making it a more effective approach for maximizing energy output in photovoltaic systems [14].

Despite the advantages, the standard PSO algorithm has several limitations when applied to MPPT. First, it often suffers from premature convergence, where particles get trapped in local optima under partial shading or rapidly changing irradiance. Second, its convergence speed is not always sufficient during sudden step changes in sunlight, delaying the system's ability to reach the true maximum power point. Third, the standard velocity and position update equations lack adaptability, reducing robustness under highly dynamic conditions. These shortcomings limit the practical effectiveness of standard PSO in real-world PV environments [15]. To address these gaps, this study introduces an AIPSO that integrates a reinitialization strategy and modified velocity, position updates, thereby enhancing global search capability, convergence speed, and tracking reliability.

Recognizing the importance of enhancing PSO-based MPPT algorithms, this paper proposes an adaptive intelligence-based PSO (AIPSO) algorithm to further improve convergence rates, tracking accuracy, and overall system efficiency. The proposed AIPSO introduces two key modifications: a reinitialization strategy to effectively handle step-change irradiance conditions and improved velocity and position update equations [15]. These modifications enhance the algorithm's convergence behavior and accuracy in tracking the MPP [16]. Additionally, the inclusion of an improvisation factor in the velocity equation improves tracking speed and overall system performance [17]. The reinitialization strategy, in particular, proves valuable in addressing sudden changes in irradiance, ensuring more reliable and efficient operation under dynamic environmental conditions [18], [19].

This study focuses on the key contributions: i) An adaptive PSO update with C3 and are initialization trigger; ii) A buck–boost design and parameter bounds linked to duty ratio control; iii) Evaluation under uniform, step change, and PSC with convergence time, efficiency, and oscillation metrics; and iv) practical limits and deployment guidance. The remaining sections are structured as follows: Section 2 presents the methodology employed in the study, including a comprehensive overview of the standard PSO algorithm. Section 3 presents the results and performance evaluation of AIPSO, comparing it with other MPPT techniques. Finally, Section 4 provides conclusions and future recommendations in this domain.

2. METHODOLOGY

The overall methodology used in this research is illustrated in Figure 1. The workflow includes a series of systematic steps designed to develop and validate an enhanced maximum power point tracking (MPPT) scheme utilizing the AIPSO algorithm for PV systems. Each phase of the research is described as follows.

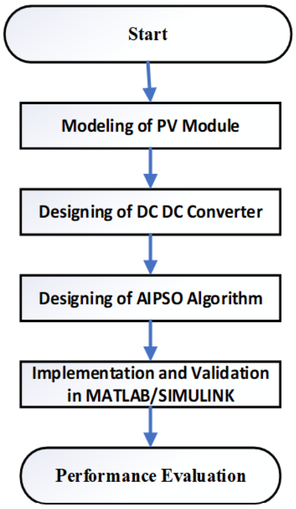

Figure 1. General workflow

2.1. Modeling of PV module

Modeling PV systems is essential in forecasting their electrical performance under various environmental conditions, such as changes in temperature and irradiance. PV systems are generally represented using equivalent circuit models that capture the electrical properties of solar cells, including their current-voltage (I-V) characteristics [20]. These models can be empirical, based on experimental data, or analytical, relying on mathematical formulas to describe the behavior of the PV cells. More advanced models take into account factors such as temperature variations, shading, and system inefficiencies [21]. Precise modeling is crucial for optimizing design, estimating energy production, and evaluating long-term system performance in practical settings [22]. After reviewing the literature, a PV system is designed apart from MPPT and power converter. Comprehensive information about the solar PV module is summarized in Table 1 [19]

Table 1. Parameters of PV module

Parameters	Value
P_{max} (W)	240
N_{cell}	60
$V_{open\ circuit}$ (V)	37.1
$I_{short\ circuit}$ (A)	8.58
V_{mp} (V)	29.7
I_{mp} (A)	8.07

2.2. Designing and simulation of DC-DC buck-boost converter

This section presents the design of a DC-DC buck-boost converter tailored for photovoltaic (PV) applications. The buck-boost topology is selected for its ability to operate in both step-up and step-down modes, making it highly suitable for PV systems [23]. This dual-mode functionality ensures stable power delivery under fluctuating solar irradiance conditions, particularly in systems employing MPPT [24]. The buck-boost converter also offers higher efficiency compared to buck and boost converters, reducing energy losses and enhancing system performance [25]. The converter is designed to operate in continuous conduction mode (CCM) across the entire input range to maintain low current ripple and enhance reliability. Figure 2 represents the schematic diagram of the DC-DC buck-boost converter associated with the PV array module. Key design considerations include the selection of appropriate switching frequency, inductor sizing, and control strategy to optimize efficiency and maintain acceptable voltage and current ripple levels under all operating conditions [26]. Design parameters, as summarized in Table 2, are determined through detailed analytical calculations provided in the subsequent sections.

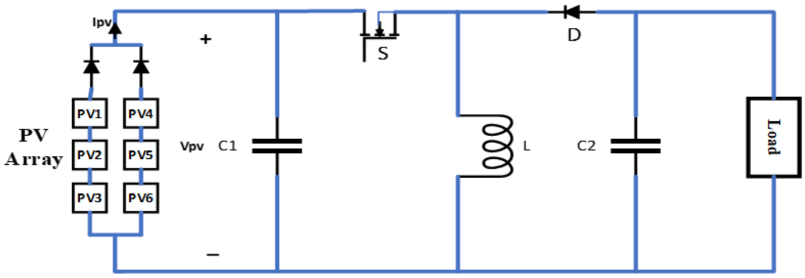

Figure 2. Schematic of DC-DC buck boost converter

In photovoltaic (PV) applications, both the input voltage, V_i and output voltage, V_o vary continuously, and the duty cycle, D fluctuates accordingly. As a result, conventional steady-state equations are not directly applicable for designing a buck-boost converter in such dynamic conditions [27]. For the designing of DC-DC buck boost converter some of general assumptions are described in Table. 2. These assumptions are made while considering real time behavior of PV modules and environmental conditions. As the irradiance is not uniform throughout the day and hence the power extraction also varies accordingly. The switching frequency, current ripple, and voltage ripple factors are chosen as per standard hardware setup for improved performance.

Table 2. General assumptions for designing of buck boost converter

Input power (P_{in})	100 W to 1000 W
Input voltage (V_{in})	10 V to 100 V
Switching frequency, f_{sw}	25 kHz
Maximum inductor current ripple, Δi_L	40%
Output voltage ripple, $\Delta V_o/V_o$	15%

i) Step 1: Load resistance range determination

Since the output voltage is not regulated, it varies with duty cycle and input voltage. To establish the boundary conditions for power delivery, we start with:

$$P_{\text{out}} = \frac{V_o^2}{R} \Rightarrow R = \frac{V_o^2}{P_{\text{out}}} \tag{1}$$

Using the buck-boost output relationship:

$$V_o = \frac{-D}{1-D} \cdot V_{in} \tag{2}$$

Assuming practical duty cycle limits of $0.1 \le D \le 0.9$ the worst-case output voltage:

$$-90 \text{ V} \le V_o \le -11.1 \text{ V} \tag{3}$$

This results in a range of load resistance:

$$0.123\, \Omega \le R_o \le 81\, \Omega \tag{4}$$

For this design, a fixed load of 10 Ω is selected, which comfortably lies within the valid operating region.

ii) Step 2: duty cycle range

Using the formula:

$$D = \frac{|V_o|}{|V_o| + V_{in}} \tag{5}$$

The range of duty cycle:

$$0.240 \leq D \leq 0.909 \tag{6}$$

iii) Step 3: inductor sizing

To ensure the converter operates in continuous conduction mode (CCM) under all conditions, the inductor is sized to limit the ripple current to 40% of the average input current. The ripple current is calculated as (7).

$$\Delta i_L = 0.4 I_L \tag{7}$$

Using this ripple, the required inductance is given by (8):

$$L = \frac{D \cdot V_{in}}{f_{sw} \cdot \Delta i_L} \tag{8}$$

where D is the duty cycle, V_{in} is the input voltage, and f_{sw} is the switching frequency, set at 25 kHz. The inductor was sized based on the range of input voltage and power. Among all cases, the low power at high voltage scenario demands the largest inductance to maintain continuous current flow. Therefore, to ensure reliable CCM operation across all voltages and power levels, an inductor value of 1 mH is selected. This guarantees that the inductor current never falls to zero, thereby maintaining stable converter performance over the entire duty cycle range.

iv) Step 4: Output capacitor sizing

The output capacitor is selected to limit the voltage ripple to within 1.5% of the output voltage, ensuring stable operation and minimizing stress on the load. The required capacitance is calculated using the standard ripple voltage equation:

$$C_o = \frac{D \cdot I_o}{f_{sw} \cdot \Delta V_o} \tag{9}$$

where ΔV_o is the allowable ripple voltage (1.5% of V_o). To ensure the design is robust, the calculation is based on the worst-case operating condition. To account for real-world factors such as temperature variation, aging, and tolerance drift, a slightly larger capacitor of 470 μF is selected. This ensures that the ripple voltage remains within acceptable limits under all conditions.

v) Step 5: Input capacitor sizing

The input capacitor, C_{in} is critical for reducing high-frequency voltage ripple at the input and for stabilizing the input current drawn from the PV source, especially during fast switching events. The input capacitor is calculated using the following expression:

$$C_{in} = \frac{I_L \cdot D}{V_{in} \cdot f_{sw}} \tag{10}$$

Using the worst-case condition, the calculated capacitance is approximately 364 μF. To ensure practical implementation and account for temperature variations, voltage derating, and standard component availability, a commercially available capacitor value of 470 μF is selected. This choice provides adequate margin above the calculated value, ensuring stable operation and reduced input voltage ripple across all conditions.

Table 3 presents the final design values of the critical components; input capacitance, inductance, output capacitance, and load resistance used in the buck-boost converter. These parametric values were derived from (4), (8), (9), and (10), based on the design constraints. Furthermore, the parameters were tested and validated using a MATLAB/Simulink model under different operating scenarios.

Table 3. Parameters of buck boost converter

Parameters	Value
Input capacitance C_{in}	470 μF
Inductance, L	1 mH
Output capacitance C_o	470 μF
Load resistance, R_o	10 Ω

2.3. Designing of an AIPSO-based MPPT algorithm for variable irradiance conditions

This section explains the design of the proposed AIPSO MPPT algorithm, beginning with the standard PSO and followed by enhancements to improve its performance. The conventional PSO algorithm is known for its simplicity and fast convergence, but it often suffers from premature convergence and reduced accuracy under rapidly changing irradiance conditions. To overcome these limitations, the adaptive improved particle swarm optimization (AIPSO) introduces dynamic adjustment mechanisms for inertia weight and acceleration coefficients, allowing better exploration and exploitation of the search space. The algorithm is further refined by integrating adaptive perturbation strategies to maintain diversity among particles and avoid local optima. Simulation results under variable irradiance profiles demonstrate that AIPSO achieves faster tracking and higher efficiency compared to standard MPPT techniques.

2.3.1. Standard PSO

PSO is an optimization approach presented by Regaya *et al.* [28]. The position, velocity, and fitness value of a particle define its properties. A particle's position and speed are dynamically modified by its own experience as well as by the motion of other particles [29]. PSO can attain optimization through repeated iterations. The velocity and position of particles are revised based on (11) and (12) [30].

$$V_i(t+1) = W \times v_i(t) + C_1 \times r_1 \times (P_i - X_i(t)) + C_2 \times r_2 \times (G - X_i(t)) \tag{11}$$

$$X_i(t+1) = X_i(t) + V_i(t+1) \tag{12}$$

$V_i\,(t+1)$ is the updated velocity of particle i at iteration t +1, V_i (t) is the current velocity of particle i at iteration t, ω is the inertia weight, balancing exploration and exploitation. C_1 is cognitive coefficient and C_2 is called as a social coefficient [31]. The r_1 and r_2 are random numbers between [0,1]. P_i is the personal best and G is the global best position of a particle, and X_i(t) is the particle’s current position at iteration t. The slow convergence speed and difficulties locating the GMPP are the issues with the traditional PSO technique. During the iterations, W, r_1, and r_2 stay constant since they are assigned to fixed values based on experience. Although a large value of W results in a more resilient global search, the high particle speed can cause fluctuations in the global region and reduce the local search potential [32]. A lower value of W can cause a more resilient local search, however its global search capability decreases, which can cause an early convergence towards local optimum. However, the impact of initial particle position randomization on the particle swarm's ability to locate the global maximum can’t be disregarded. The random initial particle placements may converge to local maximum values abruptly [33].

2.3.2. Improvised velocity and position updates

The standard equations for updating the velocity and position in PSO are presented in (11) and (12), which form the foundation of the algorithm's iterative improvement process. However, in the proposed AIPSO, significant modifications have been introduced to enhance the algorithm's performance by incorporating additional factors into the update equations. Specifically, the velocity update equation in AIPSO is adjusted to include a new term C3·(G − Pi), which accounts for the dynamic influence of the difference between the Pbest and the Gbest position, thereby balancing exploration and exploitation [34]. This modification is presented in (13):

$$V_i(t+1) = W \times v_i(t) + C_1 \times r_1 \times (P_i - X_i(t)) + C_2 \times r_2 \times (G - X_i(t)) + C_3 \times (G - X_i(t)) \tag{13}$$

Similarly, the position update equation has been refined in AIPSO to incorporate a scaling factor of 0.6, which controls the magnitude of the velocity's contribution to position updates [35]. This change ensures a more gradual adjustment in particle positions, preventing abrupt changes that could destabilize the optimization process. The updated position equation is given in (14):

$$X_i(t+1) = X_i(t) + 0.6 \times V_i(t+1) \tag{14}$$

The term adaptive is used because it augments PSO with an adaptive coefficient C3 in the velocity update (13) and a re-initialization trigger when the PV power deviates from its running median. It stated intelligent because it detects regime shifts (step irradiance/PSC) robustly via a median-based deviation test and clamps the duty-ratio search to [0.05,0.95] to avoid infeasible operating points while preserving access to the GMPP.

These tailored adjustments to the equations of velocity and position updates form the core of the proposed AIPSO algorithm. The MPPT operates on the duty ratio D; converter limits and ripple relations above bound the search and inform the adaptive gain C3 near steep power gradients. As demonstrated in the results section, these modifications lead to a significant improvement in optimization performance, offering faster convergence and better solutions in comparison to the standard PSO algorithm.

2.3.3. Converter level modeling and ripple consideration

The fixed-frequency PWM FSW = 25 kHz has been used with D ∈ [0.05 – 0.95]. In continuous conduction mode, the inductor-current ripple and output-voltage ripple follow first-order bounds as stated in (15), and (16) respectively.

$$\Delta \mathrm{IL} = \frac{\mathrm{Vin.D}}{\mathrm{L.fsw}} \tag{15}$$

$$\Delta \mathrm{Vo} = \frac{\mathrm{Io.D}}{\mathrm{C.fsw}} \tag{16}$$

These relations interpret the component values already listed in the paper and explain the observed power ripple during step irradiance/PSC. MPPT duty updates are slew-limited to avoid excessive low-frequency power ripple.

2.3.4. Reinitialization strategy

PSO is widely regarded as one of the most effective algorithms for MPPT in photovoltaic systems [36]. However, a significant limitation of PSO is its inability to effectively respond to both sudden and gradual changes in irradiance conditions, which can severely impact the overall efficiency of the system. To tackle this issue, a reinitialization technique has been proposed to enhance PSO's tracking capabilities in fluctuating irradiance environments [37]. This technique involves reinitializing the algorithm whenever a change in irradiance is detected, allowing it to more accurately track the MPP and improve overall system efficiency [38]. The reinitialization process is triggered when the change in power exceeds or equals 5% of the total power, as described in (17).

$$\left|\frac{P_i(k)-P_i(k-1)}{P_i(k-1)}\right| > \Delta P \tag{17}$$

This condition ensures that the system adapts quickly to significant changes in irradiance, improving performance and stability. The proposed reinitialization strategy contributes to enhanced tracking efficiency and overall optimization of the system.

2.3.5. Proposed AIPSO

Figure 3 illustrates the flowchart of the proposed AIPSO based MPPT approach, specifically designed for PV systems operating under variable irradiance conditions. The adaptive nature of the AIPSO algorithm allows it to dynamically balance the trade-off between exploring the search space and exploiting promising regions, making it particularly effective for complex, nonlinear optimization problems [29]. The algorithm's performance is optimized by tuning several critical parameters, including the cognitive coefficient (C_1), social coefficient (C_2), improvisation coefficient (C_3), inertia weight (W), and population size [39]. These parameters, summarized in Table 4, are essential for achieving an optimal balance between convergence speed and tracking accuracy, thereby enhancing the efficiency of MPPT operation [28]. The introduction of an improvisation coefficient in the velocity and position update equations improves the algorithm's convergence rate compared to conventional PSO. This modification not only accelerates convergence but also enhances the system's ability to adapt to dynamic changes in irradiance conditions, thereby improving overall MPPT efficiency [40].

Table 4. Parameters of PSO algorithm

Parameters	Values	Parameters	Values
Cognitive coefficient, C_1	1.4	Inertia weight, W	0.5
Social coefficient, C_2	1.7	Number of particles	3
Improvising coefficient, C_3	0.6		

The AIPSO algorithm begins by initializing key parameters, including the inertia weight, W, C_1, C_2, and the improvisation factor, C_3. A population of particles, each representing a potential solution, is then generated. During each iteration, the fitness of each particle is evaluated using a predefined objective function [41]. If a particle discovers a new personal best solution, its personal best position (Pbest) is updated accordingly [42]. Similarly, the global best position (G_{best}) is updated based on the best solution identified across the entire swarm. Subsequently, each particle's velocity and position are updated based on its P_{best}, the current G_{best}, and the improvisation factor. This iterative process continues until a predefined termination criterion is met—either a maximum number of iterations or a satisfactory fitness value. The final Gbest position represents the optimal solution to the MPPT optimization problem [29].

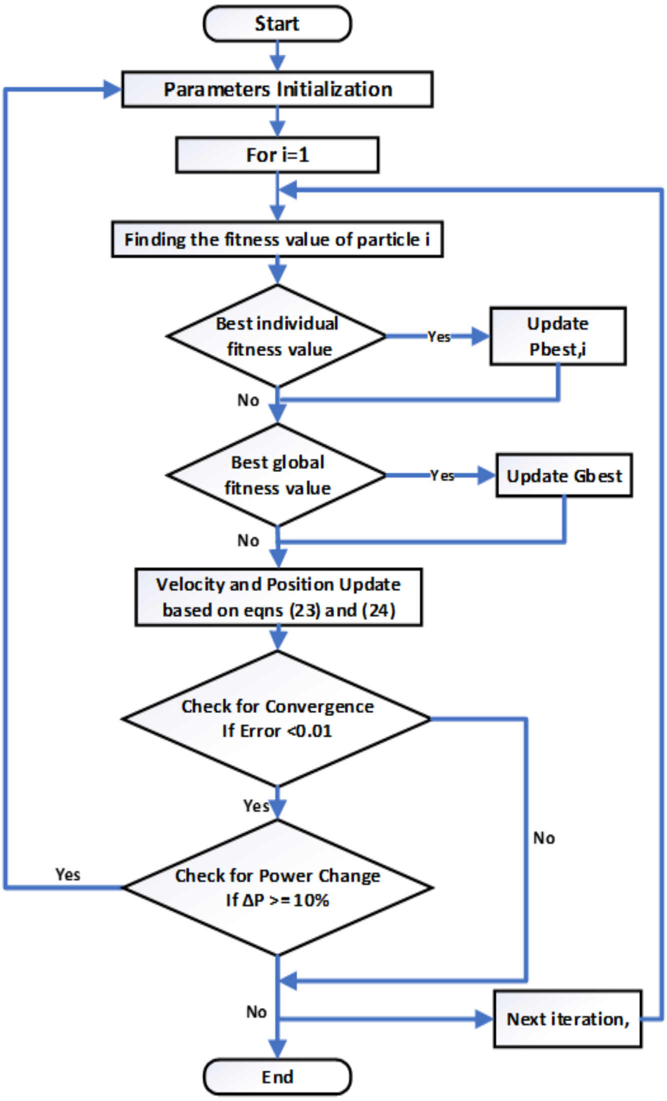

Figure 3. Flow chart of adaptive PSO based MPPT algorithm

2.4. Implementation and validation in MATLAB Simulink

MATLAB/Simulink was utilized to simulate and validate the effectiveness of the proposed method. Initially, a buck-boost converter was simulated to establish a baseline for comparison. Subsequently, a standard PV system configuration, incorporating a DC-DC converter, was simulated and validated. To assess the resilience of the PSO algorithm, it was subjected to both step changes and gradual variations in irradiance conditions. The results indicated that the standard PSO algorithm struggled to accurately locate the MPP under dynamic conditions. To address this limitation, a new adaptive intelligent strategy was implemented, significantly enhancing the algorithm's ability to adapt to changing conditions and improving the efficiency and convergence of the PV system under varying irradiance conditions [43]. Finally, the effectiveness of the AIPSO-based MPPT system was evaluated under partial shading conditions, demonstrating its capability in tracking the GMPP. Figure 4 illustrates the complete Simulink model of the PV system, including the buck-boost converter and the PSO-based MPPT algorithm.

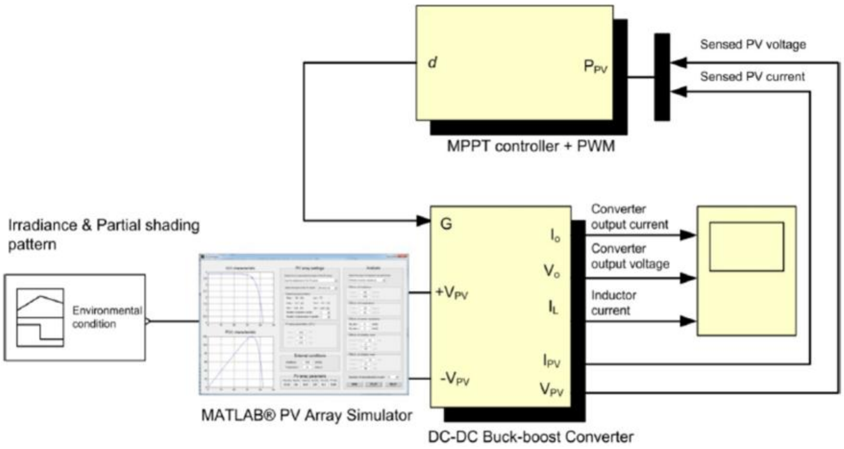

Figure 4. Simulink model of PV system with MPPT

3. RESULTS AND DISCUSSION

MATLAB software is used to verify the results for five different conditions including, constant irradiance without MPPT, constant irradiance condition with MPPT, step change irradiance condition, and PS condition step by step. The analysis focused on the system's efficiency in tracking maximum power and the tracking duration. The tracking duration refers to the time taken for the system to find the optimal solution. AIPSO's faster convergence with zero steady-state oscillations reduces low-frequency PV power ripple transferred to the DC link. This lowers current-loop effort in a grid-tied inverter and avoids PLL perturbations. Because MPPT runs well below switching and current-loop bandwidths, interaction is unlikely. Table 5, presents the definitions of metrics used in results and discussion section to validate the effectiveness and show comparison of proposed AIPSO with other standard algorithms. Similarly, Table 6 describes the irradiance test profiles used in this study to validate the effectiveness of the proposed AIPSO algorithm.

Table 5. Metric definitions

Metrics	Definition
Convergence time	The first time to attain the maximum power point.
Power	The maximum extracted power
Efficiency %	The percentage of extracted power from ideal power. Efficiency % = (P_{out}/P_{ideal}) *100
Steady state oscillations	The small fluctuations after it reaches the maximum power point.

Table 6. Test profiles used in this study

Test scenarios	Irradiance (W/m^2)	Temperature (ºC)	Remarks
Uniform irradiance condition	1000 W/m^2	25 ºC	Standard Testing Condition
Step up irradiance change condition	(333-666-1000) W/m^2	25 ºC	sudden change in irradiance condition after few seconds
Step down irradiance change condition	(1000-666-333) W/m^2	25 ºC	sudden change in irradiance condition after few seconds
Partial shading Case 1	(500, 400, 1000) W/m^2	25 ºC	Three PV modules with different irradiance levels are used to initiate partial shading
Partial shading Case 2	(500, 600, 1000) W/m^2	25 ºC	Three PV modules with different irradiance levels are used to initiate partial shading

3.1. Uniform irradiance condition without MPPT

In this section, a PV system integrated with a DC-DC buck-boost converter is simulated under uniform irradiance conditions without using any MPPT algorithm. The goal is to determine the range of duty cycle values that yield maximum output power for each irradiance level. The simulation was initially conducted at an irradiance level of 100 W/m² and an ambient temperature of 25 °C. The duty cycle was manually varied from 0 to 1 in fine increments, and the corresponding output power was recorded. This procedure was systematically repeated for all fixed irradiance levels ranging from 100 W/m² to 1000 W/m² in 100 W/m^2 steps. Analysis of the results revealed that the optimal duty cycle—corresponding to the maximum power point—consistently falls within the range of 0.35 to 0.65 across all tested irradiances. Table 7 summarizes the most suitable duty cycle values for each uniform irradiance condition, highlighting the converter's behavior in the absence of an MPPT controller.

Table 7. Most suitable duty cycle values corresponding to MPP without MPPT algorithm

No	Irradiance (W/m^2)	Duty cycle at MPP
1	100	0.36
2	200	0.44
3	300	0.48
4	400	0.53
5	500	0.55
6	600	0.57
7	700	0.59
8	800	0.60
9	900	0.62
10	1000	0.64

3.2. Uniform irradiance condition with MPPT

In this section, the PV system is simulated under uniform irradiance conditions using various MPPT algorithms. The algorithms considered include the conventional HC method, standard PSO, the FA, and the proposed AIPSO method. The simulation was initially conducted at an irradiance level of 100 W/m² and a temperature of 25 °C. Each MPPT algorithm was applied independently, and the resulting performance metrics—such as convergence speed, tracking accuracy, and steady-state oscillation—were recorded. This process was repeated for each fixed irradiance level up to 1000 W/m² in increments of 100 W/m². Figure 5 presents a performance comparison of all four algorithms under a high irradiance condition of 1000 W/m². The figure highlights the superior tracking capability of the proposed AIPSO method, demonstrating faster convergence and minimal oscillation around the maximum power point. A comprehensive summary of the simulation results across all irradiance levels is provided in Table 8. The data clearly indicates that the proposed AIPSO algorithm outperforms the other methods in terms of efficiency, robustness, and accuracy in tracking the maximum power point. Overall, the AIPSO-based MPPT approach exhibits significantly improved dynamic and steady-state performance, validating its effectiveness for PV systems operating under constant irradiance conditions. The simulation results highlight that AIPSO reaches the MPP quickly with negligible steady-state ripple, matching the highest power and efficiency among compared methods.

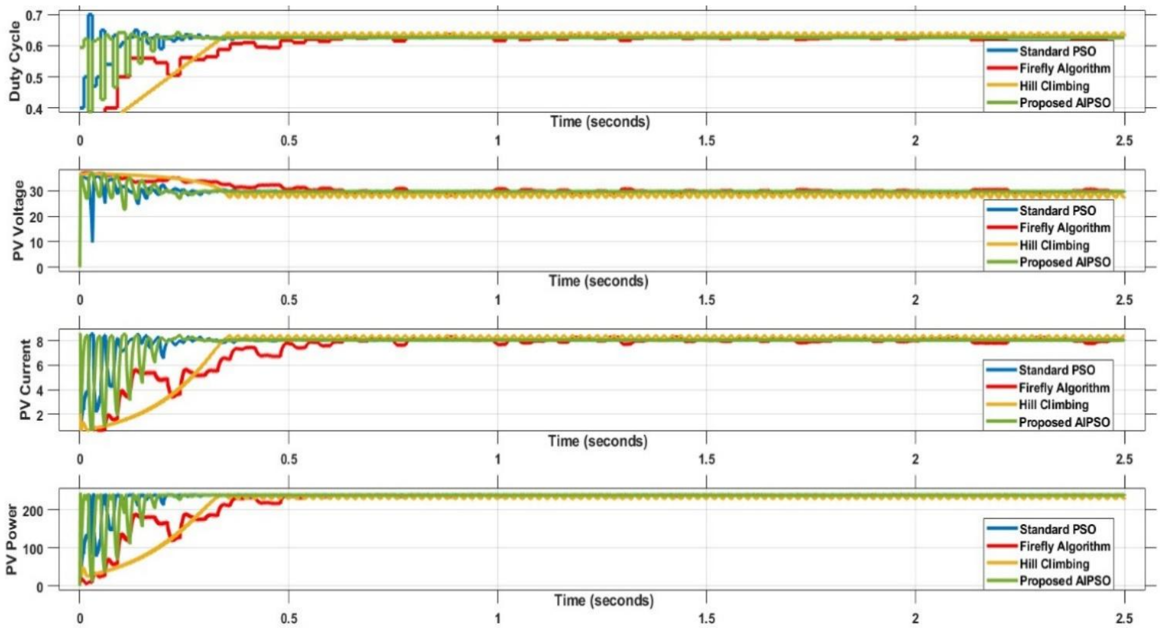

Figure 5. Performance comparison under uniform irradiance conditions (1000 W/m^2)

Table 8. Comparison of different MPPT algorithms under uniform irradiance conditions

Algorithm	Convergence time (s)	Power (W)	Efficiency (%)	Steady state oscillations
Standard PSO	0.33	239.1	99.5	Zero
Firefly algorithm	0.62	238.8	99.1	Low
Hill climbing	0.4	237	98.7	High
Proposed AIPSO	0.22	239.6	99.8	Zero

3.2. Step change irradiance with MPPT

This section investigates the performance of various MPPT algorithms under dynamic irradiance conditions characterized by step changes, including both step-up and step-down scenarios. The simulation results indicate that the standard PSO algorithm struggles to maintain accurate tracking of the MPP during rapid changes in irradiance. Although the PSO algorithm can converge during the initial step change, it fails to consistently track the MPP in subsequent fluctuations. This limitation is illustrated in Figure 5, which highlights the inability of the standard PSO to adapt effectively to dynamic operating conditions. Similarly, the firefly algorithm (FA) exhibited poor performance under step-change conditions, demonstrating increased oscillations and unstable convergence behaviour. These results highlight its inefficiency in handling abrupt variations in solar irradiance. The conventional Hill Climbing (HC) algorithm, while widely used and relatively robust, also displayed minor perturbations around the MPP, which affected overall tracking precision and reduced its effectiveness in such scenarios.

To address these limitations, the proposed AIPSO algorithm incorporates a reinitialization strategy, identified through a comprehensive literature review as an effective enhancement to traditional PSO. This strategy resets the algorithm's parameters upon detecting sudden changes in irradiance, enabling faster re-convergence to the new MPP and improving overall tracking performance. Figure 6 presents the I-V and P-V characteristics for both step-up and step-down irradiance profiles used in the simulation. Figures 7 and 8 illustrate performance comparisons for step-down and step-up scenarios, respectively, based on real-time responses to irradiance shifts. The simulation results demonstrate that AIPSO reaches the MPP quickly and reconverges upon sudden changes in irradiance, with negligible steady-state ripple, achieving the highest power and efficiency among the compared methods.

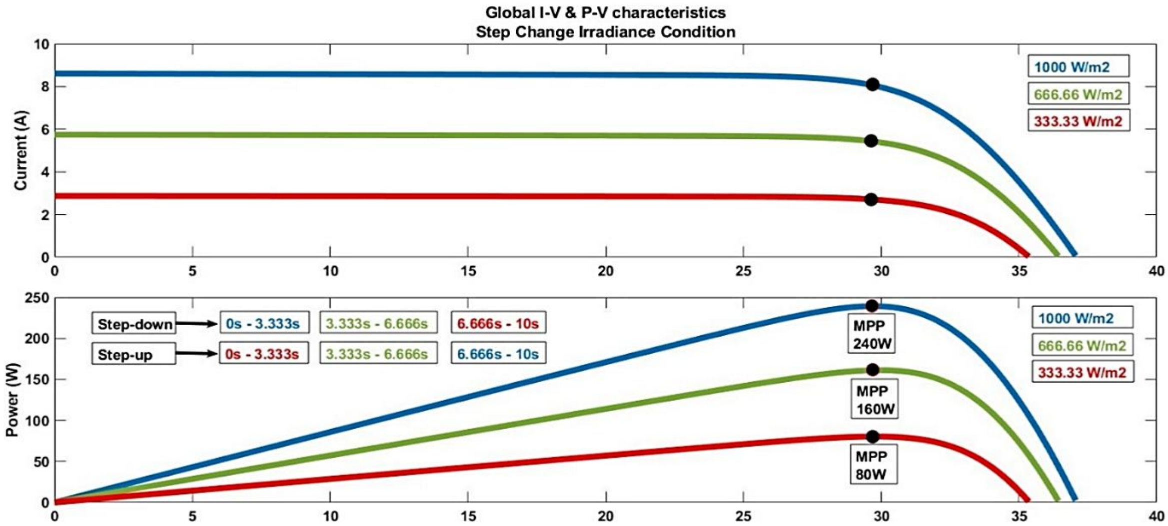

Figure 6. I-V and P-V characteristics curve during a step change in irradiance conditions

Rapid irradiance changes make the MPPT adjust the duty ratio quickly. This can create extra electrical noise (EMI) and brief heat spikes in the switch/diode. Our controller limits duty-ratio slew and reconverges quickly, which reduces both conducted/radiated noise and thermal cycling. In hardware, common mitigations are tight PCB switch/diode loops, input/output LC filters, snubbers, and gate-resistor tuning; optional spread-spectrum PWM can further lower peak emissions without affecting the MPPT logic. A full EMI/thermal characterization is planned for future hardware tests. A summary of the performance metrics is provided in Table 9. The results confirm that AIPSO achieves superior convergence speed, high tracking accuracy, and stable operation, making it a highly effective MPPT solution for PV systems operating in dynamically changing environments.

3.4. Partial shading condition

Partial shading occurs when a portion of a PV array or module is obstructed from direct sunlight, leading to a significant reduction in overall energy yield [44]. This phenomenon can be caused by various factors, such as nearby buildings, trees, or the accumulation of dust and debris on the panel surface. In a series-connected PV array, even minor shading on a single cell can adversely impact the performance of the entire string. The output of the series string is limited by the weakest (i.e., most shaded) cell, resulting in reduced power generation, increased localized heating, and the formation of hotspots [45].

In this study, a PV system equipped with a buck-boost DC-DC converter is simulated under PS conditions. The system consists of three PV panels exposed to different irradiance levels across two scenarios. In Case 1, the panels receive irradiance levels of 500 W/m², 400 W/m², and 1000 W/m², respectively. In Case 2, the irradiance levels are set to 500 W/m², 600 W/m², and 1000 W/m². Figure 9 illustrates the corresponding I-V and P-V characteristics under these shading conditions, while Figures 10 and 11 provide a comparative analysis of the MPPT algorithms tested, including the proposed method.

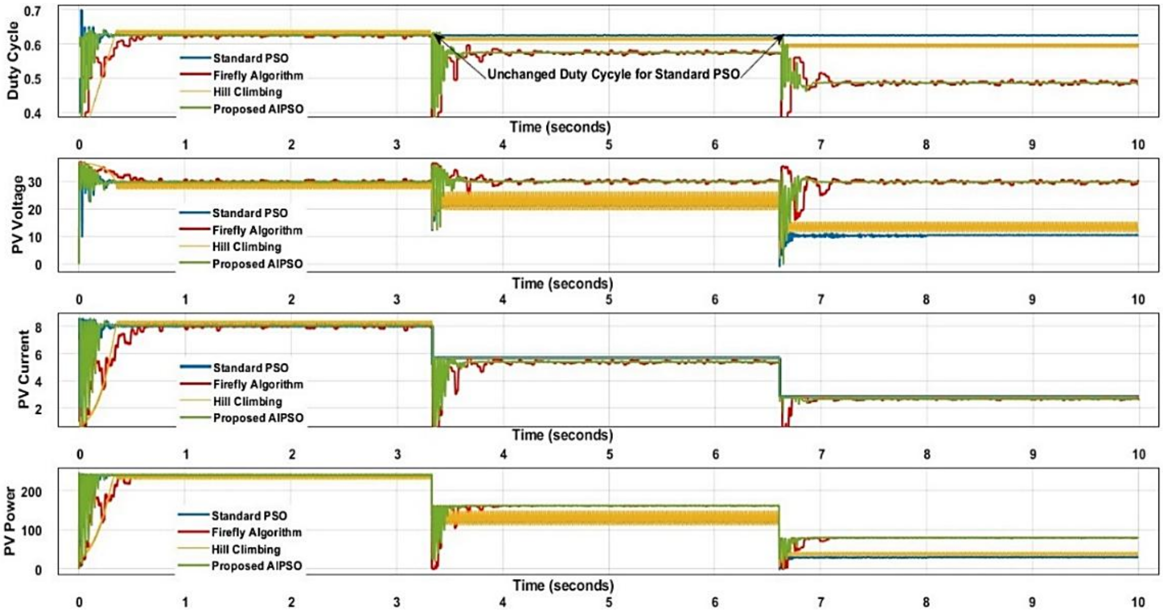

Figure 7. Performance comparison during step change in irradiance (step-down)

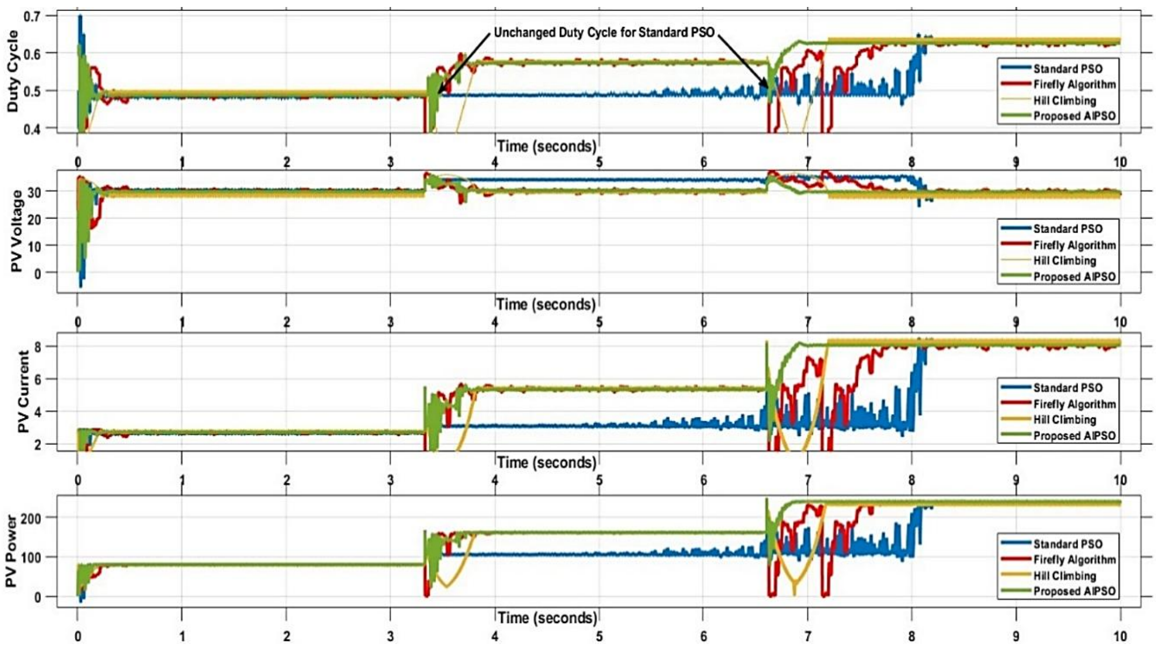

Figure 8. Performance comparison during step change in irradiance (step-up)

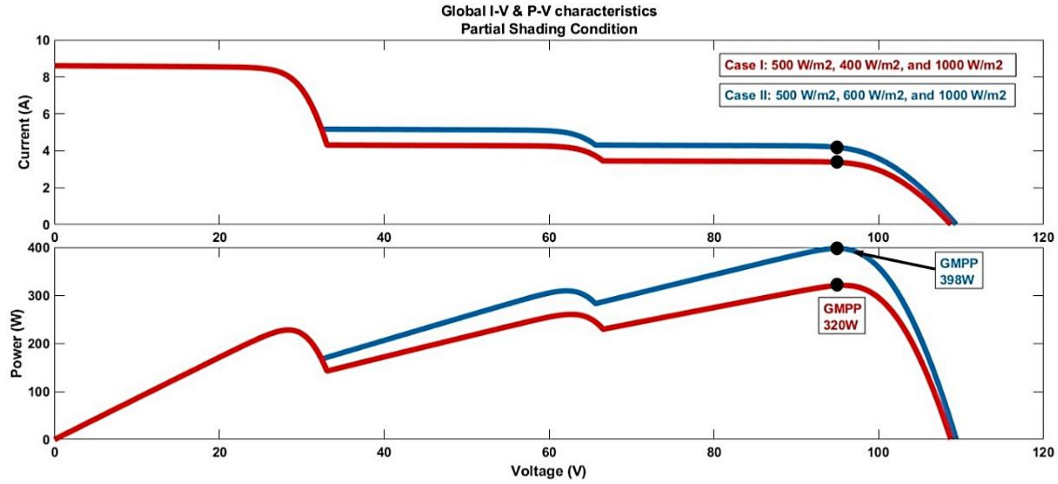

Figure 9. IV and PV characteristics during partial shading conditions (Case 1 and 2)

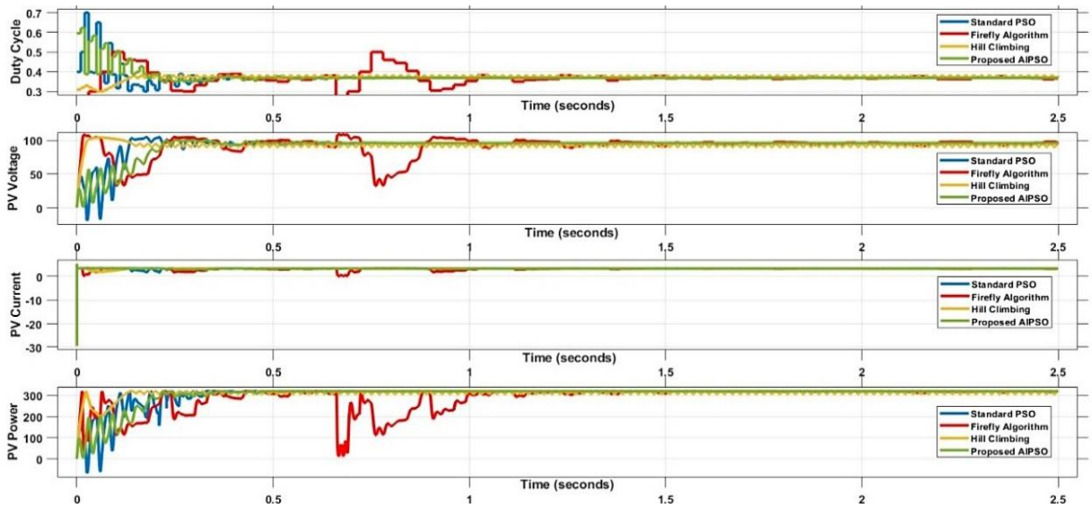

Figure 10. Performance comparison of PS irradiance condition by (Case 1)

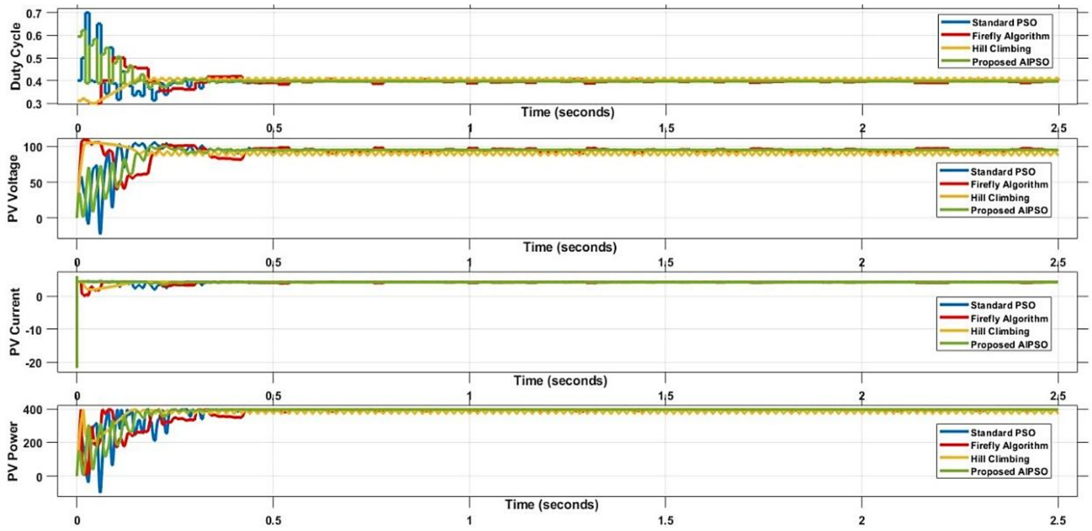

Figure 11. Performance comparison of the PS irradiance condition by (Case 2)

Table 9. Comparison of different MPPT algorithms under step-down change in irradiance condition

Step change condition	Step change response time (s)	Algorithm	Convergence time (s)	Power (w)	Efficiency (%)	Steady state oscillations
Step-down Change Irradiance Condition	0-3.3	Standard PSO	0.20	239.2	99.6	Zero
		Firefly algorithm	0.42	239.3	99.6	Low
		Hill climbing	0.20	237.7	99.0	High
		Proposed AIPSO	0.14	239.7	99.6	Zero
	3.3-6.6	Standard PSO	(Unchanged) Staying at previous value	118.0	73.7	Zero
		Firefly algorithm	0.56	159.4	99.6	Low
		Hill climbing	0.14	125.2	78.2	High
		Proposed AIPSO	0.15	159.7	99.8	Zero
	6.6-10	Standard PSO	(Unchanged) Staying at previous value	33.5	41.8	Zero
		Firefly algorithm	0.45	78.9	98.6	Low
		Hill climbing	Inaccurate Convergence	40.2	50.2	High
		Proposed AIPSO	0.3	79.8	99.8	Zero
Step-up Change Irradiance Condition	0-3.3	Standard PSO	0.10	78.6	98.3	Zero
		Firefly algorithm	0.25	78.2	97.7	Low
		Hill climbing	0.12	78.7	98.4	High
		Proposed AIPSO	0.09	79.7	99.6	Zero
	3.3-6.6	Standard PSO	(Unchanged) Staying at previous value	105	65.6	Zero
		Firefly algorithm	0.54	159.4	99.6	Low
		Hill climbing	0.50	159.5	99.7	High
		Proposed AIPSO	0.47	159.7	99.8	Zero
	6.6-10	Standard PSO	1.8	237.5	98.5	Zero
		Firefly algorithm	1.0	238.8	99.1	Low
		Hill climbing	0.7	237	98.7	High
		Proposed AIPSO	0.3	239.6	99.8	Zero

To evaluate the effectiveness of the proposed AIPSO algorithm, its performance is benchmarked against conventional techniques, including standard PSO, the FA, and the HC method. The simulation results show that the AIPSO algorithm achieves convergence in under 0.3 seconds, outperforming the other methods in terms of speed, stability, and tracking accuracy. Table 10 summarizes the comparative performance metrics, including convergence time, tracking accuracy, response speed, and power output efficiency.

Table 10. Comparison of different MPPT algorithms under partial shading irradiance condition

Case	Algorithm	Convergence time (s)	Power (W)	Efficiency (%)	Steady state oscillations
Case 1	Standard PSO	0.36	319.1	99.6	Zero
	Firefly algorithm	1.10	318.7	99.4	Low
	Hill climbing	0.25	312.2	97.4	High
	Proposed AIPSO	0.23	319.8	99.9	Zero
Case 2	Standard PSO	0.28	397.2	99.6	Zero
	Firefly algorithm	0.41	397.1	99.2	Low
	Hill climbing	0.25	379.4	94.4	High
	Proposed AIPSO	0.23	397.8	99.9	Zero

Moreover, to check the adaptability of the proposed AIPSO, the recent literature of the last 3 years is presented in Table 11, which clearly states the effectiveness of the proposed AIPSO and benchmarks the adaptability in terms of tracking accuracy, tracking speed, overall efficiency, and steady state oscillations. The hybrid methods are found to be promising and effective in terms of different environmental conditions, but the integration requires training, huge memory, and maintenance. AIPSO achieves comparable gains through adaptive scheduling and re-initialization without auxiliary learners, which simplifies deployment on resource-constrained controllers. The findings clearly demonstrate that the proposed AIPSO algorithm not only tracks the GMPP more rapidly but also exhibits superior precision and robustness under partial shading conditions compared to the other algorithms tested. The simulation results highlight that AIPSO avoids locking in local peaks and found GMPP effectively with zero steady state oscillations.

Table 11. Recent MPPT techniques under partial shading conditions

Method	Partial shading scenario	Convergence time (s)	Efficiency (%)	Remarks	References
P-PSO	Varying irradiance, partial shading	0.8 s	99.45	Faster and more efficient than standard PSO. However Proposed AIPSO outperforms P-PSO in terms of tracking time and overall efficiency.	[46]
Modified ANN	Multiple Partial Shading cases	0.87 s	99.1	Modified ANN provide superior performance than that of standard ANN, however, the proposed AIPSO outperforms in terms of tracking and efficiency.	[47]
Hybrid POA-PO	Partial shading	0.77 s	99.32	The hybrid POA-PO algorithm presents better results applicability, but lack in performance comparison with proposed AIPSO in terms of efficiency, tracking time and steady state oscillations.	[48]
Hybrid PSO-ANN	Complex partial shading	0.69 s	99.40	The hybrid approach is found to be very helpful and effective in different scenarios. However, the proposed AIPSO outperforms in terms of tracking time and efficiency.	[49]

4. CONCLUSION

In conclusion, this study introduced an adaptive intelligent particle swarm optimization (AIPSO) algorithm for MPPT in photovoltaic systems, integrating an enhanced velocity-position update mechanism and a reinitialization strategy to address the limitations of conventional methods under dynamic irradiance conditions. The algorithm was benchmarked through simulations under constant, step-change, and partial shading scenarios, demonstrating superior convergence speed, tracking accuracy, and overall efficiency compared to standard PSO, Firefly algorithm, and Hill Climbing. Notably, AIPSO consistently identified the global MPP, even under complex shading conditions, with convergence times under 0.3 seconds. Its adaptive behavior, low computational cost, and strong performance under varying conditions suggest high practical viability for real-world PV applications, from residential systems to large-scale solar farms.

Despite these promising outcomes, this work is limited to simulation-based validation, and hardware implementation may reveal additional challenges such as sensor noise, converter non-idealities, and computational delays. Furthermore, scalability for very large PV arrays and long-term stability under real-world operating conditions remain open questions. Future research will therefore focus on hardware prototyping, field testing, and exploring hybrid and distributed MPPT strategies to further strengthen robustness and scalability.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Muhammad Gul E. Islam	✓	✓	✓		✓	✓		✓	✓	✓	✓		✓	
Mohammad Faridun Naim Tajuddin	✓	✓	✓	✓	✓	✓		✓	✓	✓	✓	✓		✓
Azralmukmin Azmi	✓	✓	✓		✓	✓	✓	✓		✓	✓		✓	
Rini Nur Hasanah	✓			✓		✓			✓			✓		
Shahrin Md. Ayob		✓		✓	✓	✓				✓		✓		
Tole Sutikno		✓		✓	✓		✓			✓		✓		✓

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

The authors state no conflict of interest.

DATA AVAILABILITY

Data availability is not applicable to this paper as no new data were created or analyzed in this study.

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BIOGRAPHIES OF AUTHORS

Muhammad Gul E. Islam is a dedicated research assistant and MSc/Ph.D. student at the Department of Electrical System Engineering, Faculty of Electrical Engineering and Technology, Universiti Malaysia Perlis (UniMAP). His current research focuses on photovoltaic systems and advanced techniques in maximum power point tracking (MPPT), key areas driving innovation in renewable energy. He earned his Bachelor of Science in Electrical Engineering from the International Islamic University Islamabad Pakistan (IIUI) in 2022. Throughout his academic and professional journey, Muhammad has developed strong practical expertise in PCB design and fabrication, as well as in the maintenance and operation of electrical systems. He can be contacted at email: muhammadgulislam@gmail.com.

Mohammad Faridun Naim Tajuddin received the B.Eng. and M.Eng. degrees from the University of Malaya (UM), Malaysia, in 2004 and 2007 respectively, and the Ph.D. degree from the Universiti Teknologi Malaysia (UTM), Malaysia, in 2015. He is currently with the Faculty of Electrical Engineering & Technology, Universiti Malaysia Perlis (UniMAP). He has published refereed manuscripts in various reputable international journals. His research interests include power electronics control, photovoltaic modeling and control, intelligent control, and optimization techniques. He is also acting as a Reviewer for various reputed journals, such as the IEEE, Applied Energy (Elsevier), Renewable and Sustainable Energy Reviews, Neurocomputing, and Energy Reports. He can be contacted at email: faridun@unimap.edu.my.

Azralmukmin Azmi received the B.Eng. degree from the University Malaysia Perlis (UniMAP), in 2007, M.Eng. degree from Universiti Teknologi Malaysia (UTM), in 2009 and Ph.D. degree from UniMAP, in 2022. He is currently with the Faculty of Electrical Engineering & Technology, UniMAP. His research interests include artificial intelligence and optimization algorithm in power systems, power electronics and renewable energy. He can be contacted at email: azralmukmin@unimap.edu.my.

Rini Nur Hasanah (Senior Member, IEEE) received the bachelor's degree in electrical engineering from the Institut Teknologi Bandung (ITB), Bandung, Indonesia, in 1994, and the master's and Ph.D. degrees in electriomechanics from the École Polytechnique Fédérale de Lausanne (EPFL), Switzerland, in 2001 and 2005, respectively. Currently, she is a Professor with the Department of Electrical Engineering, Universitas Brawijaya, Malang, Indonesia, focusing on electrical power system engineering. Her research interests include electrical power engineering, electromechanics, renewable energy, power electronics, and energy management. She can be contacted at email: rini.hasanah@ub.ac.id.

Shahrin Bin Md. Ayob was born in Kuala Lumpur, Malaysia. He received the degree in electrical engineering, the master's degree in electrical engineering (power), and the Ph.D. degree from Universiti Teknologi Malaysia, in 2001, 2003, and 2009, respectively. He is currently an Associate Professor with the Faculty of Engineering, School of Electrical Engineering, Universiti Teknologi Malaysia. He is also a registered Graduate Engineer under the Board of Engineer Malaysia (BEM). His current research interests include solar photovoltaic systems, electric vehicle technology, fuzzy systems, and evolutionary algorithms for power electronics applications. He can be contacted at email: e-shahrin@utm.my.

Prof. Ir. Tole Sutikno, Ph.D., MIET, IPM., ASEAN Eng. is a full professor in the Department of Electrical Engineering at Universitas Ahmad Dahlan (UAD) in Yogyakarta, Indonesia. He has held this position since 2023, having previously served as an associate professor from 2008. He earned his bachelor's degree from Universitas Diponegoro in 1999, his master's degree from Universitas Gadjah Mada in 2004, and his Ph.D. in Electrical Engineering from Universiti Teknologi Malaysia in 2016, where his doctoral research focused on advanced digital power electronics and intelligent control systems. From 2016 to 2021, he served as the Director of the Institute for Scientific Publishing and Publications (LPPI) at UAD, where he led initiatives to strengthen research visibility, journal management, and international collaboration in scholarly publishing. Since 2024, he has served as the head of the master's program in electrical engineering at UAD, following his leadership of the undergraduate program in electrical engineering in 2022. He is also the founding leader of the Embedded Systems and Power Electronics Research Group (ESPERG), which actively collaborates with both national and international institutions on topics such as fault-tolerant embedded systems, FPGA-based control, and renewable energy integration. He is widely acknowledged for his contributions to digital design, industrial electronics, motor drives, robotics, intelligent systems, and AI-based automation. His interdisciplinary research emphasizes practical deployments in industrial and healthcare contexts, covering FPGA applications, embedded systems, power electronics, and digital libraries. He has published 380 peer-reviewed articles in high-impact journals and conferences indexed by Scopus. As of 2025, Google Scholar indicates over 6,000 citations, with an h-index of 36 and an i10-index of 174. In recognition of his global research impact, he has been listed among the Top 2% of Scientists Worldwide by Stanford University and Elsevier BV from 2021 to the present, a distinction based on standardized citation metrics across all scientific disciplines. He can be contacted at email: tole@te.uad.ac.id.