A Hybrid MPPT Algorithm Based on Trisection Search and IPSO

Yulun WU, Lidong LIU

School of Information Engineering,
Chang'an University, Shanxi, People's Republic of China.
(e-mail:2022900972@chd.edu.cn, e-mail: liulidong@chd.edu.cn)

Abstract: This paper introduces an innovative algorithm for maximum power point tracking (MPPT) with a trisection search method is proposed in this paper. The proposed method resolves the drawbacks of conventional MPPT techniques like Perturb & Observe (P&O), especially under partial shading conditions that result in the presence of multiple local maxima on the power curve. Traditional methods often face significant challenges in locating and maintaining the global maximum power point (GMPP), while heuristic methods like Particle Swarm Optimization (PSO) suffer from slow convergence. The proposed IPSO with Trisection Search (IPSO-TS) algorithm combines the global search capability of IPSO with the rapid convergence of the trisection search method, enabling efficient tracking of the GMPP and providing improved performance in both simple and complex irradiance conditions. MATLAB simulations demonstrate the robustness and stability of the algorithm across various scenarios, achieving energy savings of approximately 50% compared to the IPSO algorithm and around 33% compared to EAGPSO during the tracking process.

Keywords: MPPT, Localized shading effects, PV systems, Particle Swarm Optimization (PSO), Trisection search.

1. INTRODUCTION

Amid the growing energy crisis and escalating environmental pollution, the pursuit of clean renewable energy has emerged as a global priority. Solar energy, recognized for being both clean and eco-friendly, has garnered significant attention. Among the primary methods of harnessing solar power are photovoltaic (PV) systems, whose energy conversion efficiency and operational stability play a vital role in maximizing energy utilization. PV efficiency is affected by light intensity, temperature, and shading. Variations in complex light conditions can not only affect the output power of the PV cells but may also cause multiple LMPP to appear on the power output generated by the photovoltaic (PV) system (Refaat et al., 2020; Kanagaraj et al., 2021; Fathabadi et al., 2020). to dynamically optimize the operational parameters of the PV array, ensuring continuous operation at its maximum power point.

To enable PV systems to quickly and effectively track the Maximum Power Point (MPP), researchers have proposed a series of algorithms. Initially, researchers proposed the P&O algorithm (Kim et al., 2001), the Incremental

Circuit parameter-dependent strategies encompassing Kollimalla's fractional short-circuit current framework (FSCC, 2013) and its voltage-domain counterpart — the fractional open-circuit voltage technique (FOCV) recently enhanced by (Aakash et al., 2023); methods (Aakash al., 2023) based on circuit characteristics. These algorithms have been improved derived from studies. (Macaulay et al., 2018) proposed a Variable Step-size P&O algorithm, which improved the effectiveness of the traditional Perturb & Observe (P&O) algorithm in tracking power points. In 2022, Ahmed et al. introduced a Staged Variable step-size search method on open-circuit voltage. While these methods are straightforward to design and apply to track the MPP, they are unable to accurately identify the global maximum power point (GMPP) when partial shading occurs.

To address the inability of traditional algorithms to track the GMPP, researchers began to focus on the application of heuristic algorithms (Mohanty et al., 2016; Safarudin et al., 2014; Jiang et al., 2013; Ahmed et al., 2014). Among them, PSO algorithm (Ishaque et al., 2013; Kennedy et al., 1995), proposed by Kennedy and Eberhart in 1995, is the most widely cited, drawing inspiration from the collective foraging patterns observed in bird flocks. This method guides a swarm of particles through the search space, enabling them to progressively converge toward the optimal solution. On this basis, (Obukhov et al., 2020; Ibrahim et al., 2019) proposed the Constriction Factor PSO (CFPSO) algorithm. (Ishaque et al., 2013) proposed the Deterministic PSO (DPSO) algorithm, which omits random numbers and acceleration coefficients, limiting the velocity variable to a certain value, ΔD_{Max}. (Dileep et al., 2017) proposed the IPSO algorithm, which accelerates the convergence speed through dynamic changes of coefficients. (Mirjalili et al., 2014) proposed In 2014, Mirjalili et al. introduced the Autonomous Group PSO (AGPSO) algorithm, which partitions particles into four distinct groups, each utilizing unique coefficients to enhance the convergence speed. (Refaat et al., 2023) improved the AGPSO algorithm and proposed the Enhanced AGPSO (EAGPSO) algorithm, which improves the efficiency of AGPSO. While heuristic algorithms can effectively track the GMPP under complex conditions, the simplicity and speed advantages of traditional algorithms are sacrificed.

Given the slow efficiency of traditional algorithms and the inadequate convergence speed and simplicity of heuristic algorithms, this paper proposes the IPSO-TS Method. Similar to traditional MPPT algorithms, this method is designed for simple scenarios where the power curve has only one extremum, offering a fast algorithm that significantly improves the search efficiency of traditional methods. Combining IPSO and Trisection search method, the proposed algorithm enhances the tracking efficiency of heuristic algorithms while maintaining the capability to search for the GMPP, thereby providing new insights into MPPT algorithm research.

The structure of this paper is as follows: Section 2 explores how partial shading impacts the performance characteristics of solar photovoltaic arrays. Section 3 provides a review of several different versions of the PSO algorithm. Section 4 explains the principles and processes of the IPSO-TS algorithm in detail. Section 5 presents the experimental results and analysis, which demonstrate the robustness of the proposed IPSO-ST algorithm under the tested partial shading conditions (PSC). Section 6 presents the conclusions.

2. CIRCUIT MODEL

2.1 PV cell model

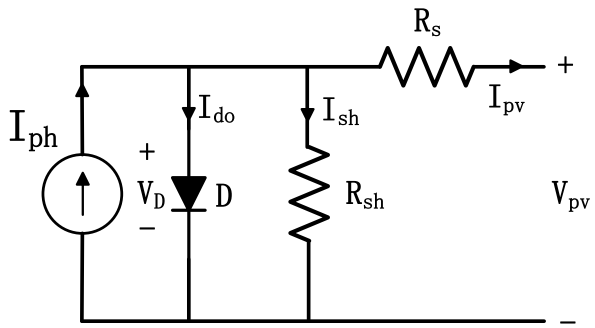


Fig. 1. The single-diode model serves as the equivalent circuit representation for a photovoltaic (PV) cell.

The performance of photovoltaic (PV) systems is susceptible to significant fluctuations in response to changes in weather conditions. Consequently, it is of paramount importance to employ precise modelling techniques to accurately assess the impact of weather variations on system output. Numerous mathematical models in existing research are predominantly derived from equivalent circuit designs. Figure 1 illustrates a standard photovoltaic (PV) cell modeled using a single-diode configuration. The model represents an optimal compromise between accuracy and complexity, with parameters derived from values documented in the literature proposed by (Reddy et al., 2022).

The core equations that define the behavior of a photovoltaic (PV) array, factoring in variations in solar irradiance and cell temperature, are presented below:

$$I_{PV} = I_{Ph}N_{pr} - I_0 N_{pr}\left\{\exp\left[\frac{V_{PV}+I_{PV}R_s\left(\frac{N_{sr}}{N_{pr}}\right)}{mV_tN_{sr}}\right]-1\right\} - \frac{V_{PV}+I_{PV}R_s\left(\frac{N_{sr}}{N_{pr}}\right)}{R_{sh}\left(\frac{N_{sr}}{N_{pr}}\right)} \quad (1)$$

$$I_0 = \frac{I_{SC,T_{ref}}+\alpha_I\left(T_c-T_{ref}\right)}{\left\{\exp\left[\frac{V_{oc,ref}+\alpha_V\left(T_c-T_{ref}\right)}{mV_t}\right]-1\right\}} \quad (2)$$

Here, V_{PV} and I_{PV} represent the output voltage and current of the PV array, respectively. R_s and R_{sh} are the series and shunt resistances, respectively. I_0 denotes the dark saturation current, I_{ph} represents the photocurrent, m is the diode ideality factor, N_{pr} indicates the number of parallel-connected strings, and N_{sr} refers to the number of series-connected modules. Additionally, $V_t = n_s \mathscr{R} T_c/q$ defines the thermal voltage of the PV module, where $\mathscr{R}$ is the Boltzmann constant, q is the charge of an electron, and T_c denotes the module temperature. At standard test conditions (STC), I_{sc},T_{ref} and V_{oc},T_{re} represent the short-circuit current and open-circuit voltage, respectively, while I_{Ph},T_{re} is the photocurrent. Lastly, α_I and α_V are the temperature coefficients for current and voltage.

2.2 Boost circuit model

Boost circuits are often used as post stage converters for MPPT execution in photovoltaic systems. Figure 2 illustrates the fundamental design of a Boost circuit.

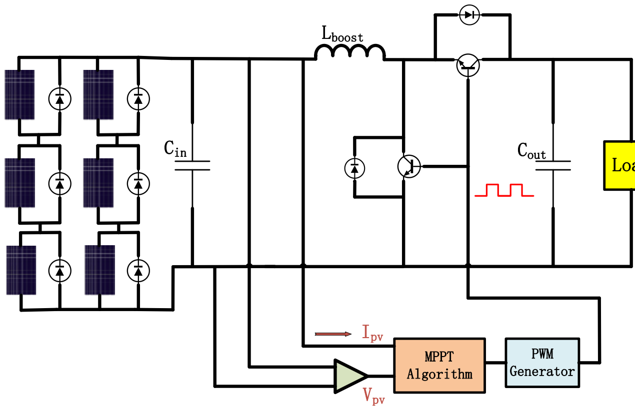


Fig. 2. DC-DC converter with MPPT controller.

In this circuit, V_{PV} represents the input voltage, Cin serves as the input filtering capacitor, and Cout functions as the output filtering capacitor., L_{boost} is the power inductance, The selection of device parameters for the Boost circuit in photovoltaic power generation systems is a crucial factor that affects the system output, and it can also influence the practical application and execution of the MPPT algorithm. (Fathabadi et al., 2020).

2.3 The influence of shading conditions on circuit performance.

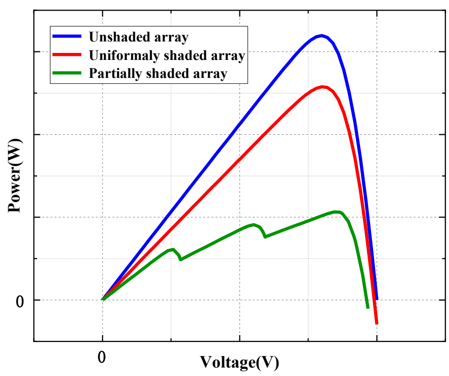


Fig. 3. The power-voltage (P-V) behavior of the photovoltaic array under various partial shading conditions (PSCs).

As illustrated in Figure 3, the P-V curve of a photovoltaic module features a single extremum when it is either fully illuminated or entirely shaded. However, in partial shading scenarios, the curve reveals multiple local maximum power points (LMPPs). Conventional MPPT methods like Perturb & Observe (P&O) and Incremental Conductance (INC) often become confined to an LMPP, thereby failing to effectively locate the global maximum power point (GMPP).

3. A REVIEW OF MPPT METHODS

3.1 PSO

In the Particle Swarm Optimization (PSO) approach, particles signify potential solutions and adjust their positions based on their personal best positions (p_{best}) and the global best position (g_{best}). The position update formula for particles is as follows:

$$v_i^{t+1} = w \cdot v_i^t + c_1 \cdot r_1 \cdot (p_{best,i} - x_i^t) + c_2 \cdot r_2 \cdot (g_{best} - x_i^t) \tag{3}$$

$$x_i^{t+1} = x_i^t + v_i^{t+1} \tag{4}$$

Here, v^t_i denotes the velocity of a particle, x^t_i represents its position, w is the inertia weight, c_1 and c_2 are cognitive and social learning coefficients, and r_1 and r_2 are random values within the range [0,1].

In MPPT problem of photovoltaic systems, PSO algorithm searches within the possible ranges of the voltage and current parameters to achieve maximum system power output. In a boost converter, each particle's position correlates with a duty cycle within the photovoltaic system, with the goal of finding the duty cycle that maximizes power output. PSO continually updates the particles' velocity and position to find the GMPP of system, which avoids the limitation of traditional algorithms that may get trapped in local optima.

Specifically, during each iteration, the position of a particle represents the duty cycle D of the photovoltaic system, and the voltage V and output power P=f(V) at that moment are recorded as the fitness function. The PSO algorithm updates the duty cycle of each particle, adjusting the duty cycle based on the global optimal power value, gradually approaching the maximum power point. The global search capability of PSO enables it to handle the complex, nonlinear behavior of photovoltaic systems, excelling under conditions like partial shading.

3.2 IPSO

IPSO improves efficiency through real-time coefficient changes. The specific formula is as follows:

$$w^k = w_{\max} - \frac{(K + w_{\min})}{K_{\max}} \tag{5}$$

$$c_1 = c_{1\max} - \frac{(K + c_{1\min})}{K_{\max}} \tag{6}$$

$$c_2 = c_{2\max} + \frac{(K + c_{2\max})}{K_{\max}} \tag{7}$$

From the equation, we can observe that the inertia weight and individual learning factor decrease over time, while the social learning factor increases. However, in PSO and IPSO algorithm, the search efficiency during the final local search phase is generally lower compared to the initial global search phase.

3.3 EAGPSO

The EAGPSO algorithm categorizes all particles into four distinct groups, each adopting unique local and global search strategies, as detailed below.

Table 1. The methods for updating the acceleration coefficients in the AGPSO algorithm.

Group No.	Updating values of c_1	Updating values of c_2
Group (1)	$1.5 - (1.45k^{1/3}/k_{max}^{1/3})$	$(1.5k^{1/3}/k_{max}^{1/3}) + 0.05$
Group (2)	$(-1.5k^3/k_{max}^3) + 1.5$	$(1.5k^3/k_{max}^3) + 0.5$
Group (3)	$1.5 - (1.45k^{1/3}/k_{max}^{1/3})$	$(1.5k^3/k_{max}^3) + 0.5$
Group (4)	$(-1.5k^3/k_{max}^3) + 1.5$	$(1.5k^{1/3}/k_{max}^{1/3}) + 0.05$

4. PROPOSED MPPT ALGORITHM

4.1 Trisection Search method

In a graph with convex hull properties, we can determine the positions of the convex hull vertices by using a trisection search method. As an example, consider a convex hull with an opening facing downward to illustrate the principle. The principle is as follows.

Considering two trisection points, A and B within the interval, the subscripted letters represent the cases where the trisection points are on the same side or opposite sides of the extrema. For example, if the trisection points are A and B_1 in Figure 4, it indicates that the two trisection points are on the same side of the extrema.

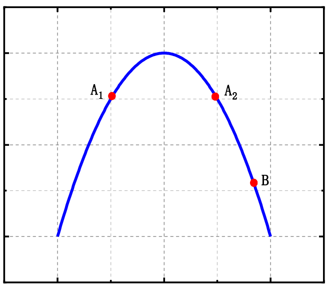


Fig. 4. Case1.

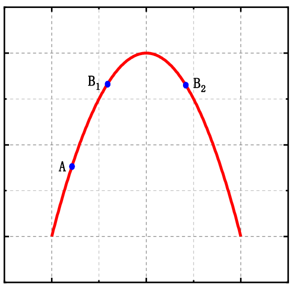


Fig. 5. Case2.

The overall situation of the trisection points is as follows:

$$\begin{cases} case1: A \le B_1, B_2 & \text{The maximum point is to the right of A} \\ case2: A_1, A_2 \ge B & \text{The maximum point is to the left of B} \end{cases}$$

Based on the above judgments, we can determine the left and right endpoints of the interval for the next iteration and continue using this method to reduce the search interval by one-third. When the difference between the two trisection points is less than a preset value, the trisection process is stopped.

In summary, when a curve is entirely within a convex hull, using the trisection search method can significantly reduce the complexity of the algorithm, decreasing its time complexity to O(log). This indicates that to narrow the search range to within 1e-6 in the interval [0,1], only 34 computations are needed. In contrast, traditional P&O and INC algorithms, along with their optimized versions, essentially remain O(n) algorithms. Thus, employing the trisection method can greatly reduce the time required to identify the maximum power point located within the boundaries of the convex hull.

4.2 IPSO-TS

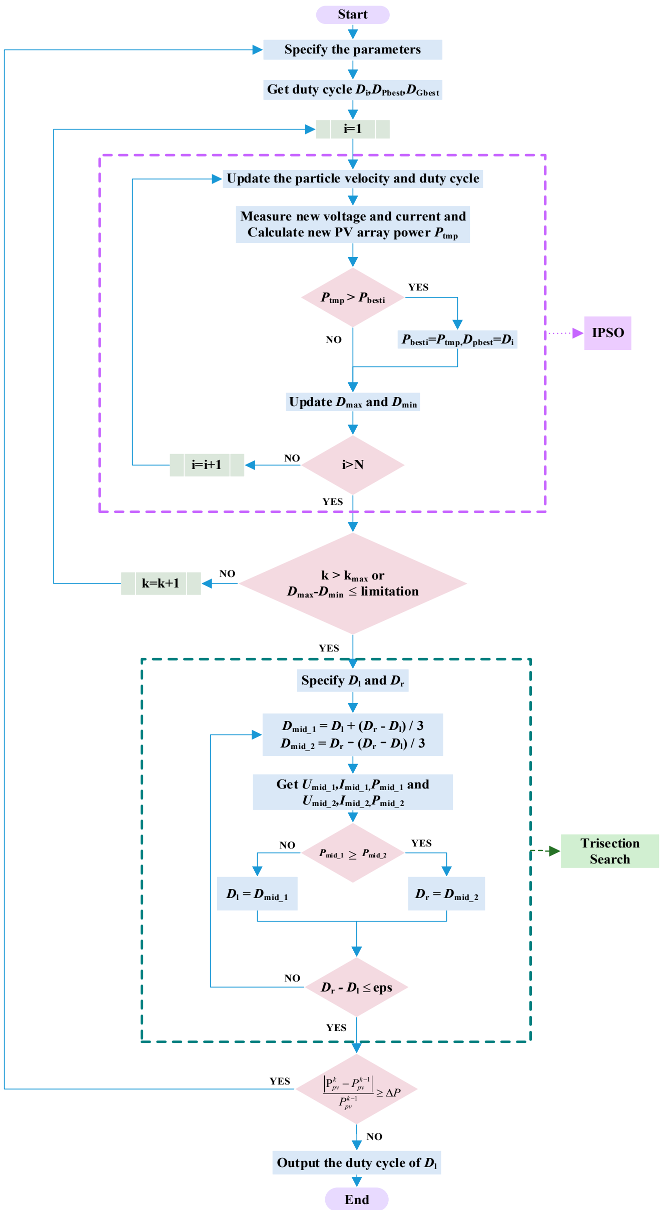


Fig. 6. The flowchart of the IPSO-TS MPPT technique.

The IPSO-TS algorithm introduced in this paper operates through two primary phases. The first phase involves the global search process of the IPSO algorithm, aiming to rapidly converge particles to the convex hull region containing the GMPP. To determine if the particles have successfully converged to the convex hull containing the GMPP, the algorithm uses the iteration count k and the maximum difference between particle positions D_{max}-D_{min} as convergence criteria. When the iteration count reaches a preset maximum value or D_{max}-D_{min} falls below a predefined threshold, which indicates the particles have converged to the convex hull containing the GMPP, and the algorithm proceeds to the trisection method for rapid convergence.

During the second phase, the trisection search technique is applied to progressively divide the upper and lower thresholds D_r and D_l of the duty cycle into thirds and updating these thresholds to approach the extrema of the convex hull. When the trisection interval D_r-D_l becomes smaller than a preset accuracy eps, the algorithm is considered to have successfully tracked the overall maximum power point across the entire power curve.

Upon successful tracking of the maximum power point, the algorithm dynamically monitors the real-time power P of the circuit. If the power variation exceeds a preset threshold ΔP, the algorithm restarts to keep tracking of the new global maximum power point.

5. SIMULATION AND DISCUSSION

5.1 Simulation Model

A solar photovoltaic power generation system, incorporating a Boost converter, was developed and simulated using the MATLAB 2024a/Simulink platform. The system features a dedicated subsystem that regulates the duty cycle of the Boost converter's switch, enabling precise control over the output voltage. The MPPT algorithm is simulated using a Function module. The primary model constructed is shown in Figure 7.

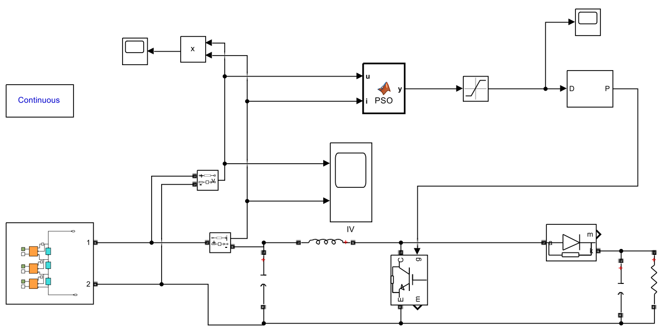


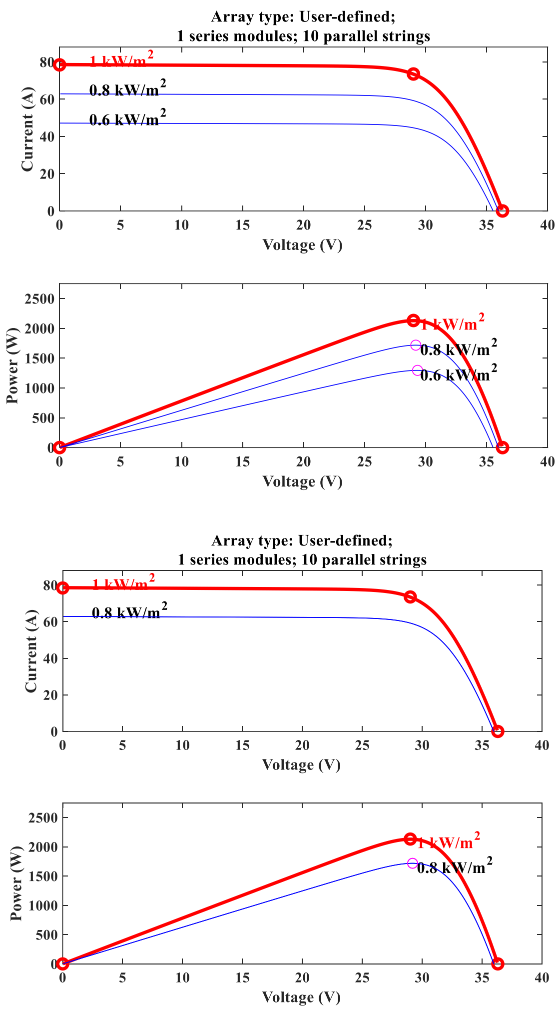
Fig. 7. Simulink simulation model.

The input to the Boost converter is provided by a built-in photovoltaic module in Simulink, while the battery module uses customized parameters. Each photovoltaic module consists of 10 battery modules connected in series, with a total of 30 photovoltaic modules connected in series. The corresponding battery parameters are shown in Table 2.

Table 2. PV module corresponding parameters.

Parameter	Value	Parameter	Value
Maximum power(P_{max})	213.15W	Maximum power point voltage (V_{mpp})	29V
Open-circuit voltage(V_{oc})	36.3V	Maximum power point current(I_m)	7.35A
Short-circuit current(I_{sc})	7.84A	Number of solar cells in each module (N_{cell})	60
Temperature coefficient of V_{oc}	-0.36099	Temperature coefficient of I_{sc}	0.102

In MATLAB 2024a/Simulink, the photovoltaic characteristic curves of the PV components are provided. The characteristic curves of the photovoltaic battery array utilized in the Boost circuit simulation are illustrated in Figure 8.



(a)

(b)

Fig. 8. Photovoltaic cell characteristic curve of (a) condition_1 and (b) condition_2.

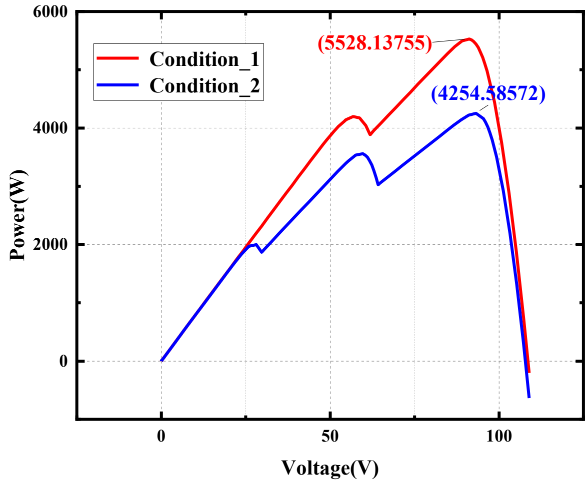


Fig. 9. P-V curve of condition_1 and condition_2.

The key parameters of the Boost converter are summarized in Table 3.

Table 3. Corresponding parameters of Boost circuit.

Parameter	Value
Input Filter Capacitor (C_1)	0.001F
Output Filter Capacitor (C_2)	0.001F
Inductor (L)	0.001H
PWM switching frequency (fs)	12000Hz

5.2 Evalution index

The proposal of several quantitative criteria can provide a more objective evaluation of the strengths and weaknesses of the algorithm in certain aspects. The proposed indexes are as follows:

5.2.1 GMPP tracking accuracy indicators η_1

$$\eta_1 = \frac{P_{avg}}{P_{GMPP}} \tag{8}$$

The tracking accuracy of the algorithm is determined by comparing the average steady-state power P_{avg} with the theoretical maximum power P_{GMPP}, and is measured by the index η_1. A higher η_1 value indicates better tracking accuracy. In addition, the degree of fluctuation is measured by η_2.

5.2.2 GMPP tracking stability indicators η_2

$$\eta_2 = \frac{\sum\left[P(k)-P_{avg}\right]^2}{\mathrm{n}} \tag{9}$$

The steady-state fluctuation of the algorithm is quantified using variance, where n represents the total number of sampling points is used to evaluate performance metrics. The lower the value of η_2, the greater the fluctuation of the algorithm.

5.2.3 Start Tracking Performance Index K_{st}

$$K_{st} = \frac{\int_0^{t_0} P_{MPPT}\,dt}{\int_0^{t_0} P_{GMPP}\,dt} \tag{10}$$

In the provided equation, t_0 denotes the time required by the MPPT algorithm to achieve tracking of the maximum power point.

5.3 Analysis and Comparison

For the simulation, Condition_1 was defined with irradiance levels of 1000 W/m², 1000 W/m², and 600 W/m² for the three PV cells, respectively, at a constant temperature of 25°C. The IPSO-TS algorithm was evaluated under these conditions, with the results presented in Figure 10.

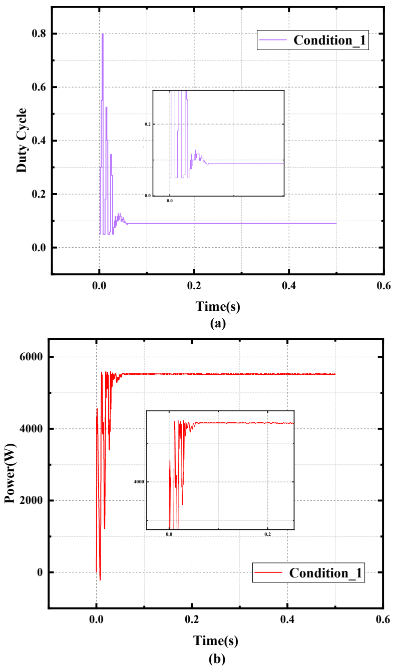


Fig. 10. IPSO-TS algorithm (a) Output duty cycle graph (b) Output power graph.

Figure 10 (b) shows that the maximum output power of the circuit reached 5528.138 W, with the duty cycle stabilizing at 0.901. The MPPT tracking was completed in 0.056 seconds, and the algorithm demonstrated minimal steady-state oscillations and high stability.

To assess the algorithm's dynamic tracking capability, a variation was introduced at 0.75 seconds by altering the irradiance to 1000 W/m², 800 W/m², and 600 W/m², respectively, while keeping the temperature unchanged. Comparative simulations were performed for the IPSO, EAGPSO, and IPSO-TS algorithms. The results, depicted in Figure 11, reveal that IPSO-TS exhibited superior tracking speed and stability.

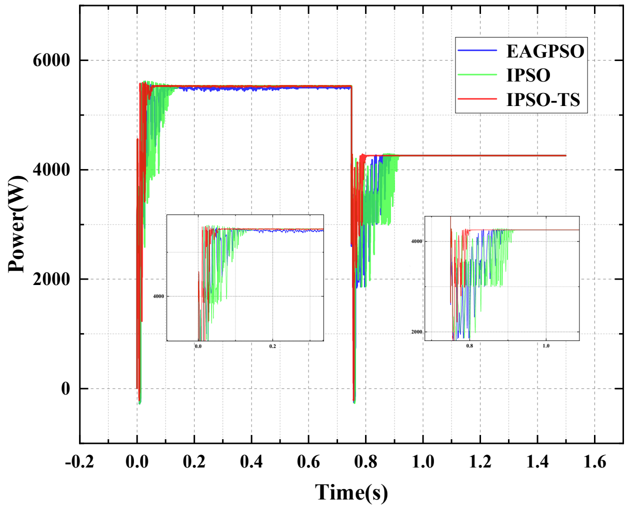
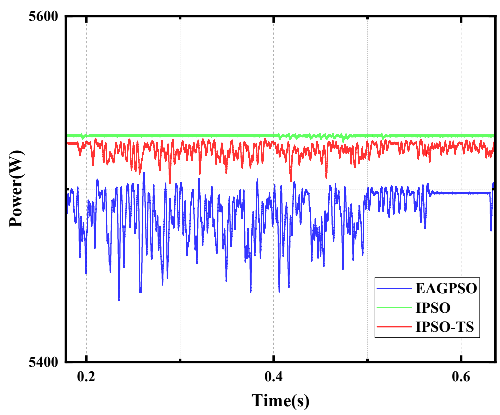


Fig. 11. Output power of the three algorithms.

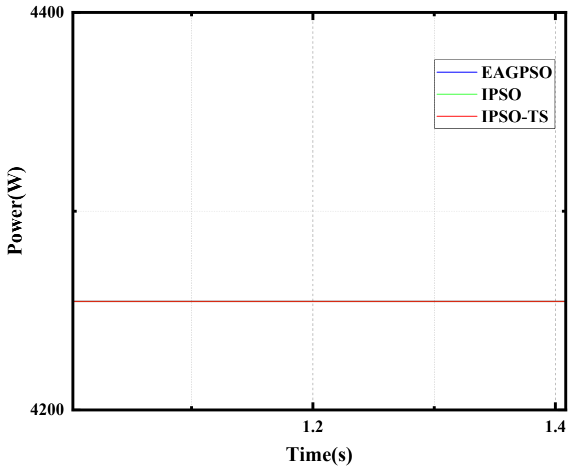
Figure 11 shows that before the condition change, the convergence speeds of the three algorithms in the first phase are relatively close, but as they enter the second phase, the differences in speed become more apparent. EAGPSO's group convergence gives it faster speed and smaller fluctuations than IPSO. EAGPSO converges to the GMPP at 0.135 seconds, while IPSO converges at 0.155 seconds. Nevertheless, in the second phase, IPSO-TS demonstrates a markedly faster convergence rate compared to the other two algorithms. This improvement can be largely attributed to differences in the complexity levels of the three methods. Under Condition_1, IPSO-TS tracks GMPP in 0.056 seconds, minimizing power loss.

Under Condition_2, the differences between the three algorithms become even more pronounced. The figure shows that after the condition change, EAGPSO experiences more fluctuations than in Condition_1, but still less than IPSO in terms of oscillation duration. IPSO-TS, on the other hand, remains largely unaffected, maintaining a fast convergence speed with minimal fluctuations.

Regarding the steady-state performance, Figure 11 illustrates the fluctuation behavior of each algorithm during the steady state.



(a) condition_1.



(b) condition_2.

Fig. 12. Steady-state output of the three algorithms under the two conditions.

Figure 12 (a) shows that after tracking the GMPP under Condition_1, both IPSO and IPSO-TS exhibit better steady-state performance, while EAGPSO experiences larger fluctuations, resulting in greater power loss. Under Condition_2, the steady-state performance of all three algorithms is consistent.

The above descriptions mostly provide a qualitative evaluation of the algorithms. The simulation results from the first phase of the three algorithms will be substituted into the three evaluation metrics proposed in Section 5.2, yielding the following results:

Table 4. Evaluation Results of the three Algorithms.

Index / Algorithm	η_1	η_2	K_{st}	Tracking loss
IPSO-TS	99.914%	12.366	88.492%	60.038J
IPSO	99.987%	1.201	84.452%	127.452J
EAGPSO	99.280%	163.848	87.198%	95.774J

Combining the analysis above with the data in Table 4, a comprehensive evaluation of the four algorithms can be obtained, as shown in Table 5.

Table 5 Synthesis of Four Algorithms.

Algorithm / Index	IPSO-TS	IPSO	EAGPSO
Steady-state suppression	medium	high	low
Fast tracking efficiency	excellent	low	medium
Start tracking performance	excellent	general	high
algorithm complexity	medium	general	high

6. CONCLUSION

The IPSO-TS algorithm marks a significant breakthrough in maximum power point tracking (MPPT) for photovoltaic systems. The application of the trisection search concept to the MPPT domain, for the first time, reduces the time complexity to O(logn) in single-convex scenarios. This achievement establishes an optimal solution for single-convex cases. By integrating the global optimization capabilities of IPSO with the rapid convergence of the trisection search method, the proposed approach effectively minimizes tracking time and power loss. This combination ensures high precision and stability throughout the tracking process, even in scenarios with multiple local maximum power points (LMPPs).

Simulation results across four key performance metrics underscore the clear advantages of the IPSO-TS algorithm over both traditional MPPT methods and other heuristic approaches. The algorithm delivers faster tracking performance while maintaining stable and reliable power output. This makes it an optimal solution for enhancing photovoltaic system efficiency, even in dynamic and complex operating environments. By overcoming the limitations of conventional methods—which often fail to accurately track the global maximum power point (GMPP) under partial shading—this innovation provides a robust alternative.

The exceptional robustness and efficiency of the IPSO-TS algorithm make it a vital tool for improving energy output and the operational reliability of photovoltaic systems. Furthermore, this method contributes significantly to sustainable energy development by maximizing the energy extraction potential of PV systems. Though in practical applications, environmental noise and sensor inaccuracies may affect tracking accuracy. As the global focus on renewable energy intensifies, future work will address these issues to enhance robustness. Meanwhile, the IPSO-TS algorithm represents a promising step forward in optimizing solar energy utilization.

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