Efficiency Assessment of PSO-Based MPPT Methods: Review, Simulation, and Benchmarking Against Conventional Techniques

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Abstract— **Under dynamic operating conditions, maximizing energy yield from photovoltaic systems requires efficient Maximum Power Point Tracking (MPPT). Conventional techniques such as Perturbation and Observation (P&O) and Incremental Conductance (InC) are easy to implement but suffer from oscillations and poor performance under partial shading. To address these limitations, Particle Swarm Optimization (PSO) has emerged as a robust alternative capable of rapidly locating the global maximum power point.**

This paper reviews recent PSO-based MPPT strategies and evaluates their performance through MATLAB/Simulink simulations. Advanced PSO variants and hybrid approaches are compared with conventional P&O and InC methods across uniform, rapidly varying, and partially shaded conditions. Results show that PSO-based controllers significantly reduce oscillations and achieve higher tracking efficiency, especially under shading, but at the cost of increased computational effort. Overall, PSO-based MPPT offers a promising solution for modern PV systems, with further research recommended to reduce algorithmic complexity for real-time applications.

Keywords: photovoltaic systems, MPPT, Hybrids methods, Perturb and Observe (P&O), Incremental Conductance, Particle Swarm Optimization, Adaptive Particle Swarm Optimization.

I. INTRODUCTION

The global energy landscape is undergoing a profound transformation, driven by the imperative to mitigate climate change and ensure sustainability. In this context, solar photovoltaic (PV) energy has emerged as a cornerstone of the renewable energy transition, prized for its abundance, scalability, and rapidly declining costs [1]. Despite its potential, the efficient conversion of solar energy into electricity is hampered by the inherent non-linear characteristics of PV modules. Their maximum power output is contingent upon fluctuating environmental conditions, primarily solar irradiance and temperature [2], [3]. To counteract this variability and maximize energy yield, Maximum Power Point Tracking (MPPT) controllers have become an indispensable element of modern PV systems, dynamically adjusting the electrical operating point to extract the highest possible power [1], [4].

The challenge of MPPT is significantly compounded by real-world operating conditions. Partial shading, caused by obstacles such as passing clouds, building shadows, or dust accumulation, presents a particularly complex problem [5], [6]. Under such conditions, the system's power-voltage (P-V) charact

eristic curve transforms from a single peak into a multimodal profile riddled with multiple local maxima (LMPPs) and a single global maximum (GMPP) [2], [5].

Conventional MPPT algorithms, most notably Perturb and Observe (P&O) and Incremental Conductance (InC), are fundamentally ill-suited for this scenario. While their simplicity and low computational cost make them popular for uniform irradiation [4], [7], their deterministic nature causes them to become trapped at the first LMPP they encounter, leading to substantial power losses [3], [4]. Furthermore, these methods exhibit a persistent trade-off between dynamic response speed and steady-state oscillations, struggling to perform optimally under rapidly changing atmospheric conditions [8], [9].

In response to these limitations, the field has witnessed a paradigm shift towards intelligent, metaheuristic approaches. Bio-inspired algorithms, which excel at navigating complex, non-linear search spaces, have shown remarkable success in reliably locating the GMPP. Among these, Particle Swarm Optimization (PSO) has distinguished itself due to its conceptual elegance, simple implementation, and powerful global search capabilities [5], [10], [11]. By simulating the social foraging behavior of a bird flock, the PSO algorithm employs a population of particles to collectively explore the solution space, demonstrating a consistent ability to avoid local optima and converge on the global peak [5], [12].

However, the standard PSO algorithm is not a panacea. Its performance is often sensitive to the selection of control parameters, such as inertia weight and acceleration coefficients. Poorly tuned parameters can result in slow convergence, premature convergence to a local peak, or significant transient power oscillations, rendering it less ideal for real-time MPPT applications [12], [13], [14]. This has catalyzed a vibrant area of research dedicated to enhancing the core PSO algorithm. These enhancements can be broadly classified into three streams:

Adaptive PSO (APSO): Techniques that dynamically adjust algorithm parameters during the search process to improve robustness and convergence speed under varying environmental conditions [1], [3], [6].

Simplified PSO: Variants that reduce computational complexity and the number of tuning parameters, making them more suitable for implementation on low-cost microcontrollers without sacrificing performance [6], [11], [15].

Hybrid PSO Methods: Architectures that synergistically combine PSO with other algorithms. This includes hybridization with conventional methods (e.g., P&O, InC) for precise local refinement [7], [13], artificial intelligence techniques (e.g., Artificial Neural Networks) for predictive capability [2], [8], or advanced control theories (e.g., Sliding Mode Control) for robust and fast tracking [1], [8].

While the literature is rich with proposed PSO variants, a clear and comprehensive assessment of their efficiency (benchmarked directly against conventional techniques and each other under standardized operating conditions) is often lacking. Such a comparative analysis is crucial to guide future research and inform practical implementation choices.

To address this gap, this paper presents a systematic efficiency assessment of PSO-based MPPT methods. The main contributions of this work are threefold:

A structured review of state-of-the-art PSO-based MPPT techniques, categorizing them into adaptive, simplified, and hybrid families.

A rigorous simulation-based benchmarking of selected advanced PSO methods against the conventional P&O and InC algorithms, evaluating performance under uniform irradiance, rapid environmental changes, and complex partial shading scenarios.

A critical analysis of the inherent trade-offs, such as convergence speed versus steady-state oscillation and algorithmic complexity versus tracking efficiency, providing valuable insights for both researchers and practitioners.

This is how the rest of the paper is structured. The background information on MPPT and the PSO algorithm is given in Section 2. The simulation approach and performance indicators are described in depth in Section 3. The comparison results are presented and discussed in Section 4, and the article is concluded in Section 5.

II. Review of MPPT Techniques

The evolution of Maximum Power Point Tracking (MPPT) algorithms reflects a continuous effort to balance performance, complexity, and cost. This section reviews the prominent techniques, beginning with conventional methods and progressing to the more sophisticated Particle Swarm Optimization (PSO)-based approaches, highlighting their evolutionary trajectory and comparative merits.

A. Conventional Methods: Simplicity at the Cost of Robustness

Conventional algorithms form the bedrock of MPPT technology, prized for their straightforward implementation and low computational demands. Their operational principle hinges on a perturb-and-observe mechanism, which, while effective under uniform conditions, reveals significant limitations in more complex scenarios.

1) Perturb and Observe (P&O)

The (P&O) algorithm is arguably the most ubiquitous MPPT method due to its simplicity [4], [7]. It operates by applying a small perturbation to the PV array's operating voltage and observing the resultant change in power. A positive power change instructs the algorithm to continue perturbing the voltage in the same direction; otherwise, the direction is reversed. This creates an oscillatory behavior near the (MPP), resulting in inherent power loss even at steady state [7]. A more critical flaw emerges under rapidly changing irradiance, where the algorithm can misinterpret the cause of a power change, leading to a loss of tracking integrity [4].

2) Incremental Conductance (InC)

Seeking to improve upon P&O, the (InC) algorithm uses the slope of the P-V curve for guidance [4], [16]. It leverages the principle that at the MPP, the condition $dP/dV = 0$ translates to $dI/dV = -I/V$. By comparing the instantaneous conductance (I/V) to the incremental conductance (dI/dV), it can determine the operating point's relation to the MPP and adjust the voltage accordingly. This allows it to theoretically settle precisely at the MPP and perform more reliably under changing atmospheric conditions than P&O. However, its increased computational complexity offers no advantage under Partial Shading Conditions (PSCs), as it remains susceptible to convergence on local peaks, just like its P&O counterpart [3], [4].

3) Strengths, Weaknesses, and the Impetus for Change

The primary strength of these conventional methods is their unparalleled ease of implementation on low-cost hardware [12]. However, their collective failure under PSCs (a common real-world occurrence) represents a fundamental limitation [4], [5]. Furthermore, they are plagued by a perennial trade-off: a large perturbation step size improves dynamic response at the expense of increased steady-state oscillations, while a small step size minimizes oscillation but renders the system sluggish [17]. This inherent lack of robustness and adaptability provided the direct impetus for the exploration of intelligent, metaheuristic solutions.

B. PSO-Based MPPT Methods: Embracing Intelligence and Adaptation

Particle Swarm Optimization (PSO) emerged as a powerful paradigm shift, introducing a population-based, stochastic search strategy capable of navigating the multi-modal search spaces characteristic of partially shaded P-V curves. Its ability to distinguish between local and global optima directly addresses the core failing of conventional techniques.

1) Fundamentals of Particle Swarm Optimization

Inspired by the social dynamics of bird flocking, PSO employs a "swarm" of particles, each representing a candidate solution (e.g., a duty cycle) within the search space [5], [12]. Each particle iteratively adjusts its trajectory based on its own experience (the best position it has found, P_{best}) and the social influence of its neighbors (the best position found by the swarm, G_{best}). This collaborative mechanism allows the swarm to collectively explore the solution space and converge reliably on the global maximum power point (GMPP) [6].

2) Standard PSO-MPPT Algorithm

The movement of each particle is governed by its velocity and position, updated using the classic equations [5], [12]:

$$V_i(t+1) = w * V_i(t) + c_1 * r_1\big(Pbest_i(t) - x_i(t)\big) + c_2 * r_2\big(Gbest_i(t) - x_i(t)\big) \quad (1)$$

$$x_i(t+1) = x_i(t) + V_i(t+1) \quad (2)$$

where w is the inertia weight, c1 and c2 are acceleration coefficients, and r1 and r2 are random numbers. While this standard PSO reliably finds the GMPP, its performance is sensitive to the choice of parameters (w, c1, c2), which can lead to slow convergence or significant transient oscillations if not properly tuned [12], [13], [14]. These limitations sparked a wave of innovations aimed at refining the core PSO algorithm.

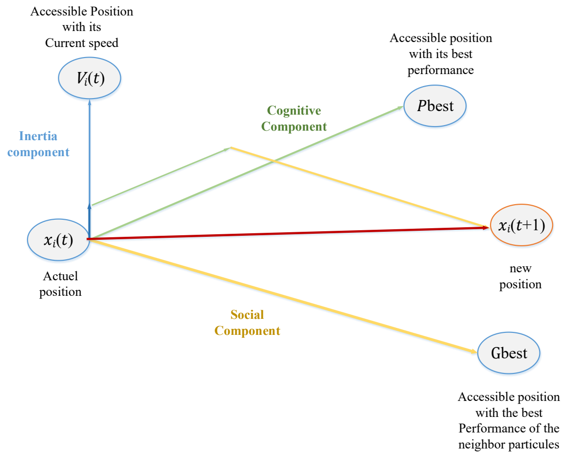

Figure 1: Particle dynamics inside the search space.[1]

3) Variants and Improvements: A Spectrum of Enhancements

The pursuit of higher performance and practicality has led to three dominant strands of PSO enhancements:

Adaptive PSO (APSO): To mitigate parameter sensitivity, APSO variants dynamically adjust parameters like the inertia weight during the search process. Typically, the inertia starts with a high value for global exploration and is gradually reduced for local refinement, leading to faster and more robust convergence under varying environmental conditions [1], [6].

Hybrid PSO Models: Arguably the most powerful trend involves creating hybrid controllers that leverage the strengths of complementary techniques. These hybrids often follow a hierarchical structure:

* Global/Local Search Hybrids (e.g., PSO-P&O): PSO performs the global exploration to locate the GMPP region, after which a fast local search algorithm like P&O takes over for precise, low-oscillation tracking [7], [13].

* AI-Enhanced Hybrids (e.g., PSO-ANN): Here, PSO acts as a powerful meta-optimizer to train Artificial Neural Networks (ANN) or other AI models. The AI model then provides predictive capabilities, while PSO ensures it is optimally tuned for accuracy [2], [8].

* Control-Theoretic Hybrids (e.g., PSO-SMC, PSO-MPC): These architectures use PSO to optimally tune the parameters of advanced nonlinear controllers like Sliding Mode Control (SMC) or Model Predictive Control (MPC). This combines PSO's global search prowess with the superior dynamic response and robustness of these controllers [1], [9], [16].

C. Comparative Summary of MPPT Methods

The progression from conventional to advanced PSO-based methods represents a clear trade-off between simplicity and performance. The following table provides a consolidated comparison to delineate the operational domains of these different algorithmic families.

TABLE 1: COMPARATIVE SUMMARY OF MPPT TECHNIQUES

Method Category	Example Algorithms	Strengths	Weaknesses	Primary Suitability
Conventional	P&O, InC [4, 12]	Simple, low cost, easy to implement.	Fails under PSCs, steady-state oscillations.	Uniform irradiance, cost-sensitive applications.
Standard PSO	Basic PSO [7, 20]	Robust GMPP tracking under PSCs.	Parameter tuning sensitive, transient oscillations.	Systems where conventional methods fail.
Adaptive PSO	APSO [5, 19]	Faster convergence, robust to changing conditions.	Slightly increased complexity.	Dynamic environments with changing shading.
Hybrid PSO	PSO-SMC , PSO-ANN [1]	High accuracy, minimal oscillation, robust.	High complexity, difficult implementation/tuning.	High-performance systems requiring maximum efficiency.

This review establishes that while no single algorithm is universally superior, the choice depends critically on the specific application requirements, including the prevalence of partial shading, the available computational resources, and the desired balance between tracking speed and steady-state accuracy. The following section will detail the simulation framework designed to quantitatively benchmark these trade-offs.

III. SIMULATION FRAMEWORK AND METHODOLOGY

To conduct a fair and rigorous efficiency assessment, a standardized simulation framework was established in MATLAB/Simulink. This section details the components of the modeled PV system, the definition of the test scenarios designed to evaluate MPPT performance under various conditions, and the key performance metrics used for quantitative comparison.

A. PV System and Power Converter Modeling

The core of the simulation model consists of a PV array, a DC-DC converter, and the MPPT controller, reflecting a typical stand-alone PV system configuration [13], [18].

1) PV Array Model

The PV array was modeled using the single-diode equivalent circuit, which offers a suitable balance between accuracy and computational efficiency for system-level studies [3], [4]. The model accounts for the effects of solar irradiance (G) and cell temperature (T) on the output characteristics. To simulate partial shading conditions (PSCs), the array was subdivided into strings protected by bypass diodes. The activation of these diodes under non-uniform irradiance is what generates the characteristic multi-peaked P-V curves, creating the challenging environment for MPPT algorithms [5], [6]. The specific parameters of the PV modules used in the simulation are based on commercially available models to ensure realistic behavior.

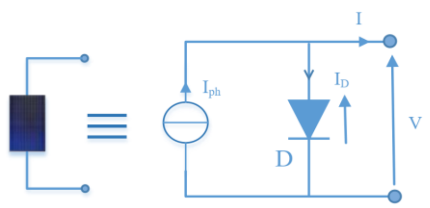

Figure 2. Simplified equivalent circuit of a PV cell.[4]

$$I = I_{Ph} - I_D = \ I_{Ph} - \ I_S.\left(e^{\frac{V}{m.V_T}} - 1 \right) \tag{3}$$

With, I_{Ph}: photo-current of the cell generated by the illumination; I_S: saturation current of the diode (very low); V_T: thermal voltage of the cell [V_T = kT/q = 26 mV at 300 K (27°C) for silicon]; k: Boltzmann constant [1.38 10^{-23} J.K^{-1}]; T: temperature in Kelvin [K], q: charge of an electron [1.602 10^{-19} C] and m: the ideal factor of a diode, it is often between 1 and 2.[4]

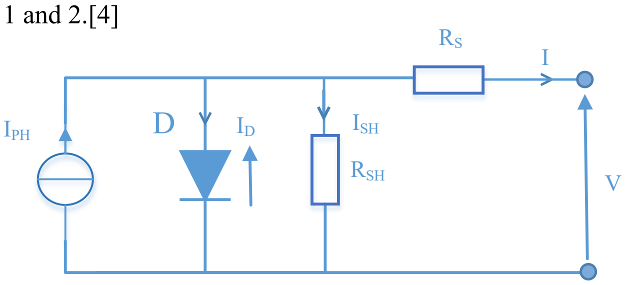

Figure 3: Equivalent model of a PV cell

$$I = I_{Ph} - I_s \cdot \left(e^{\frac{v+I.Rs}{m \cdot V_T}} - 1 \right) - \frac{v + I \cdot R_s}{R_{sh}} \tag{4}$$

I_{SH} : Current flowing through the parallel resistor.

R_S: serie resistor, R_{Sh}: shunt resistor a few ohms.

2) DC-DC Converter

A boost (step-up) converter was selected as the MPPT interface for this study [3], [10]. In order to reduce input current ripple, which is advantageous for the PV source, the converter was built to function in Continuous Conduction Mode (CCM). The key components were sized using standard design equations to ensure stable operation under the expected range of PV voltages and power levels[18]. The output voltage relationship is governed by the equation below:

$$V_{out} = \frac{V_{in}}{1 - D} \tag{5}$$

Where D is the duty cycle controlled by the MPPT algorithm. The minimum inductance to maintain CCM was calculated as:

$$L > \frac{D * (1 - D)^2 * R_{Load}}{2 * f_{sw}} \tag{6}$$

And the output capacitor was sized to limit voltage ripple to less than 5% using:

$$C \geq \frac{D}{R_{Load} * f_{sw} * \left(\frac{\Delta V_{out}}{V_{out}} \right)} \tag{7}$$

The switching frequency f_{sw} was set to 20 kHz to balance switching losses and dynamic response.

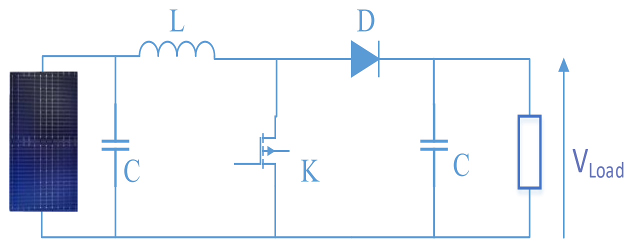

Figure 4 : Equivalent circuits of boost converter.

IV. Simulation Results and Analysis

The outcomes of the MATLAB/Simulink simulations, which were carried out to assess and contrast the performance of the developed MPPT algorithms, are shown in this part. To ensure a fair and consistent foundation for comparison, all simulations were run using the same DC-DC boost converter setup (explained in Section 3) and the same PV module (supplied in Table 2). Conventional (P&O) and (InC) algorithms, as well as standard (PSO) and its improved versions, Adaptive PSO (APSO) and a Hybrid PSO-P&O, are all assessed.

TABLE 2: PV ARRAY SPECIFICATIONS

Model No.	PLM-290M-72
(Pmax)	290,39 Wp
(Vmpp)	35,37 V
(Impp)	8.21 A
(Voc)	44,82 V
(Isc)	8,76 A
Temperature Coefficient of Pmax	-0,45 %/°C
Temperature Coefficient of Voc	-0,43 %/°C
Temperature Coefficient of Isc	0.06 %/°C
cell Type	Monocrystalline
Cell Size	156×156 mm
Cell Number	72

A. Simulation Results and Discution

Five MPPT algorithms (P&O, INC, regular PSO, APSO, and the suggested PSO-SMC) are compared in this section under various irradiation scenarios. Performance is evaluated in terms of convergence speed, tracking accuracy, steady-state oscillations, and robustness. Figures 5, 6, and 7 show the voltage, current, and power responses, respectively.

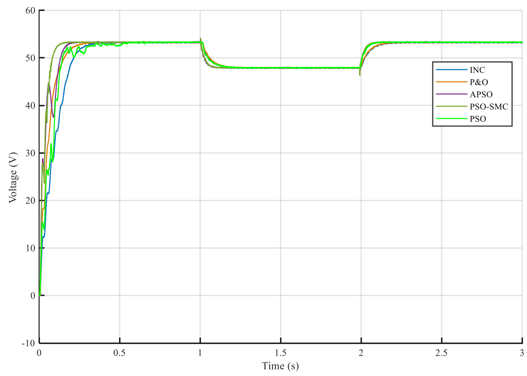

Figure 5: PV Voltage Response

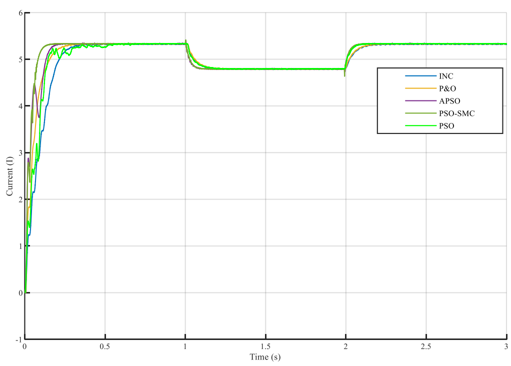

Figure 6: PV Current Response

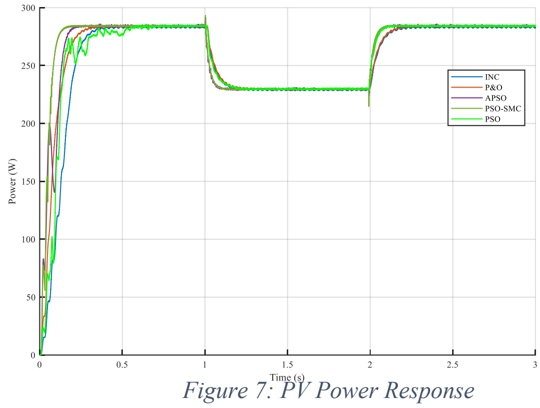

Figure 7: PV Power Response

The dynamic performance of five MPPT algorithms (INC, P&O, standard PSO, APSO, and PSO-SMC) is evaluated under varying irradiation conditions. Figures 5, 6, and 7 illustrate the voltage, current, and power responses, respectively.

Voltage Response (Fig. 5): All algorithms track the MPP under steady-state conditions, but differences appear during transients. At startup, PSO-SMC achieves the fastest convergence with minimal overshoot, whereas INC and P&O exhibit slower responses and pronounced oscillations. Standard PSO improves classical behavior yet remains slow. APSO enhances speed via its adaptive mechanism, though minor oscillations persist. PSO-SMC ensures rapid, smooth, and stable convergence.

Current Response (Fig. 6): Following irradiation changes at t≈1 s and t≈2 s, PSO-SMC demonstrates rapid, stable adjustment with minimal fluctuations. APSO and standard PSO show moderate performance with reduced oscillations versus INC and P&O, yet remain inferior to PSO-SMC. Conventional methods exhibit the largest oscillations and longest settling times, indicating weaker dynamic tracking.

Power Response (Fig. 7): At each irradiation transition, PSO-SMC rapidly converges to the Global Maximum Power Point (GMPP) with minimal loss and negligible oscillations. INC and P&O suffer from slower tracking and significant MPP oscillations, reducing efficiency. Standard PSO improves but remains slower; APSO balances speed and stability. PSO-SMC achieves the best overall tracking accuracy, dynamic response, and oscillation reduction.

Overall, integrating sliding mode control with PSO significantly enhances MPPT performance under rapidly changing conditions. The proposed PSO-SMC provides superior robustness, faster convergence, and improved steady-state behavior compared to conventional and standalone PSO methods, making it highly effective for PV systems under dynamic partial shading.

V. CONCLUSION

This paper compared five MPPT algorithms (INC, P&O, standard PSO, APSO, and the proposed hybrid PSO-SMC) for photovoltaic systems under dynamically varying irradiation conditions. Performance was evaluated in terms of convergence speed, tracking accuracy, steady-state oscillations, and robustness.

Results demonstrate that conventional methods (INC and P&O) suffer from slow convergence, pronounced oscillations, and poor dynamic response. Standard PSO improves performance but remains limited in transient conditions. APSO offers enhanced speed via adaptive mechanisms, yet minor oscillations persist.

The proposed PSO-SMC hybrid consistently outperforms all other algorithms across voltage, current, and power responses. It achieves the fastest convergence, minimal overshoot, negligible steady-state oscillations, and superior robustness under rapid irradiance changes.

Integrating sliding mode control with PSO significantly enhances MPPT performance, making PSO-SMC a highly effective solution for photovoltaic systems operating under dynamic partial shading conditions. Future work will focus on experimental validation and hardware implementation of the proposed controller.

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