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Software-in-the-Loop Validation of an Adaptive Particle Swarm Optimization-Based MPPT Controller for Real-Time Photovoltaic System

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Abstract
Maximum Power Point Tracking (MPPT) is essential for maximizing energy yield in photovoltaic (PV) systems under dynamic environmental conditions. This study presents a comparative evaluation and real-time Software-in-the-Loop (SIL) validation of conventional and intelligent MPPT algorithms for a 1.5 MW standalone PV system, representing a utility-scale installation with high current and dynamic complexity. The Adaptive Particle Swarm Optimization (APSO) algorithm is characterized by dynamic adjustments of inertia weight and acceleration coefficients, enhancing convergence speed and tracking accuracy. A high-fidelity MATLAB/Simulink model, integrating a DC–DC boost converter and dynamic irradiance profiles, was developed. P&O, INC, GA, and APSO were evaluated based on tracking efficiency, convergence speed, and steady-state ripple. The results show that APSO achieved the highest tracking efficiency (99.3%), the fastest convergence (0.8 s), and the lowest ripple (1.8%), outperforming GA, P&O, and INC. SIL validation further confirmed the feasibility and robustness of APSO, maintaining 99.0% efficiency and 1.6% ripple under real-time constraints. These findings establish APSO as a reliable, implementation-ready MPPT solution for large-scale PV systems.

Keywords: *Adaptive Particle Swarm Optimization, Maximum Power Point Tracking, Software-in-the-Loop, Solar Photovoltaic Systems, and Dynamic Irradiance.*

1.0 Introduction

The rapid growth in global energy demand has spurred significant interest in renewable technologies, with solar photovoltaic (PV) systems standing out due to their sustainability, scalability, and environmental compatibility [1, 2]. Yet, PV systems remain highly sensitive to environmental variations, such as irradiance changes, temperature shifts, and partial shading. These variations induce nonlinearities in the power–voltage characteristics, reducing energy harvesting efficiency [3, 4]. Conventional MPPT algorithms, such as Perturb and Observe (P&O) and Incremental Conductance (INC), are widely used due to their simplicity and ease of integration. However, they suffer from slow convergence, steady-state oscillations, and reduced tracking accuracy when irradiance rapidly changes [5, 6]. These limitations lead to suboptimal energy yield, increased switching losses, and degraded overall system performance.

To overcome these shortcomings, intelligent optimization-based MPPT approaches have emerged. Evolutionary and swarm intelligence algorithms, including Genetic Algorithms (GA) and Particle Swarm Optimization (PSO) variants, have shown improved global search capability and adaptability in complex PV environments [7, 8]. Adaptive Particle Swarm Optimization (APSO) further enhances this by dynamically adjusting swarm parameters, balancing exploration and exploitation, which improves convergence speed and tracking accuracy under changing conditions [9, 10].

Despite these advances, most studies remain confined to offline simulations, lacking real-time validation. Software-in-the-Loop (SIL) simulation provides a critical bridge, enabling real-time execution and performance evaluation under practical computational constraints.

This study, therefore, proposes an APSO-based MPPT controller validated through SIL. By dynamically adapting parameters, APSO enhances tracking performance, while the SIL framework confirms its real-time feasibility. The primary contribution is the development and validation of a high-performance, implementation-ready MPPT strategy, boosting tracking accuracy, convergence speed, and stability in large-scale PV systems.

2.0 Literature Review

Maximum Power Point Tracking (MPPT) techniques for photovoltaic (PV) systems can be categorized into conventional and intelligent optimization-based approaches, each offering distinct performance traits under dynamic conditions.

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Conventional algorithms, such as Perturb and Observe (P&O) and Incremental Conductance (INC), are widely adopted due to their simplicity and ease of implementation. As noted in [13], both suffer from steady-state oscillations and reduced efficiency under rapidly changing irradiance. While INC offers some improvement over P&O in stability, both still face a trade-off between convergence speed and steady-state accuracy, particularly in nonlinear PV regimes.

To address these constraints, researchers have explored intelligent optimization approaches. For example, [14] introduced a hybrid Genetic Algorithm (GA) combined with Ant Colony Optimization (ACO), which improved tracking in complex P–V curves with multiple local maxima. Similarly, [15] compared GA with other evolutionary algorithms, such as Particle Swarm Optimization (PSO) and Ant Lion Optimizer, showing that GA excels in global search and accuracy but demands more computation and longer convergence times. These findings suggest GA-based methods can increase accuracy but at the expense of real-time performance.

Recent efforts have improved swarm intelligence efficiency. In [16], an Adaptive Particle Swarm Optimization (APSO) approach was introduced, where swarm size and parameters adapt based on real-time system conditions. This adaptability accelerates convergence while reducing computational load, overcoming key barriers identified in earlier techniques.

Despite these advances, a major gap remains: most studies rely on offline simulations and lack real-world validation. As emphasized in [17], many works fail to conduct standardized comparisons under identical conditions, resulting in fragmented and inconsistent performance metrics (e.g., tracking efficiency, convergence speed, ripple). Moreover, most studies do not extend to real-time validation. As noted in [18], this lack of Software-in-the-Loop (SIL) or Hardware-in-the-Loop (HIL) testing limits practical deployment, especially in embedded PV control systems.

In summary, three critical gaps emerge: first, conventional MPPT methods struggle to balance speed and steady-state precision; second, comparative studies lack standardized frameworks; and third, real-time validation is insufficient. Thus, there is a pressing need for an adaptive, computationally efficient MPPT strategy, coupled with real-time validation, to advance performance and practical implementation in large-scale PV systems.

3.0 Materials and Methods

Table 1 summarizes the software tools, hardware configuration, system parameters, and test conditions employed in this study.

Table 1: Overview of materials used

S/N	Category	Item/Description
1.	Software Tools	MATLAB/Simulink (R2024b): Used for modeling the PV system, implementing MPPT algorithms (P&O, INC, GA, APSO), and running simulations.
2.	MATLAB Toolboxes	Simscape Electrical: For PV array and converter modeling Optimization Toolbox: For GA and APSO implementation Control System Toolbox: For DC–DC converter control modeling
3.	Hardware Specification	Computer System: HP Pavilion x360 Convertible Operating System: Windows 11, 64-bit Processor: Intel Core i5, 2.1 GHz, RAM: 12 GB
4.	PV System Parameters	Standard Test Condition (STC): 1000 W/m², 25°C, Solar PV Array: Modeled as per manufacturer data DC–DC Converter: Boost converter with appropriate switching frequency, inductor and capacitor values
5.	Algorithm Parameters	P&O / INC: Step size, sampling interval GA: Population size, crossover rate, mutation rate APSO: Swarm size, inertia weight bounds, cognitive and social coefficients
6.	Test Profiles	Time-varying irradiance and temperature profiles to emulate dynamic environmental conditions
7.	Operating Range	Standard duty cycle

The methodology combines simulation-based modeling with Software-in-the-Loop (SIL) validation to ensure algorithm accuracy and real-time implementation feasibility. The process is divided into five phases:

Phase 1: PV system modeling

A PV system is modeled in MATLAB/Simulink using a single-diode equivalent circuit. The array is coupled with a DC–DC boost converter, whose duty cycle is controlled by the MPPT algorithms. Irradiance and temperature vary as dynamic inputs.

Phase 2: MPPT algorithm implementation

Four MPPT techniques are implemented: Perturb and Observe (P&O), Incremental Conductance (INC), Genetic Algorithm (GA), and Adaptive Particle Swarm Optimization (APSO). Each algorithm adjusts the converter duty cycle to ensure operation near the maximum power point under varying irradiance.

Phase 3: Performance evaluation and data logging

All algorithms are evaluated under identical irradiance conditions. Key parameters such as voltage, current, power, and duty cycle is recorded. Performance metrics including tracking efficiency, convergence time, and power ripple are computed.

Phase 4: Comparative analysis of algorithms

The MPPT techniques are compared using graphical and statistical analysis to assess their relative performance in terms of dynamic response, stability, and accuracy.

Phase 5: Real-time validation

APSO is further tested using Software-in-the-Loop (SIL) simulation with Simulink Desktop Real-Time. A fixed-step solver (1 ms) enables real-time execution, allowing assessment of tracking accuracy, latency, and stability.

a) PV Array Configuration

To achieve a total capacity of 1.5 MW, the PV array is arranged in series and parallel strings based on panel electrical characteristics.

The maximum string voltage is calculated as:

$$Voltage_{string-max} = V_{0C} + \{T_{low} - T_{stc}) \text{ x } (Temperature\ Coefficient\ of\ V_{0C}) \quad \ldots (1)$$

$Where$, V_{0C} is the open circuit voltage of the panel, T_{low} is the lowest ambient temperature at the installation site, T_{stc} is the standard test condition temperature (25°C) and temperature coefficient of V_{0C} is equal to the manufacturer-provided value (typically negative).

The maximum number of panels per string is:

$$Nseries{-}max{=}Vinverter\_max/Vstring\_max \quad (2)$$

The minimum string voltage ensures sufficient voltage under high temperatures:

$$Voltage_{string-min}= V_{mp} + \{T_{high} + T_{rise} - T_{stc}) \text{ x } (Temperature\ Coefficient\ of\ V_{0C}) \text{ x } V_{mp} \quad (3)$$

Where, V_{mp} is the MPP Voltage of the panel, T_{high} is the highest ambient temperature at the installation site, and T_{rise} is the temperature rise due to mounting conditions.

The minimum number of panels per string is:

$$N_{series-min} = V_{inverter\_min} / V_{string\_min} \quad (4)$$

The total number of panels is:

$$Total\ Number\ of\ panels, N_{total} = P_{system}/ P_{panel} \quad (5)$$

Where, P_{system} is the total system power (1.5 MW), and P_{panels} is the power rating of a single panel.

The number of parallel strings is:

$$N_{paralle} = N_{total} / N_{series} \quad (6)$$

where N_{series} = Number of panels per string (selected between $N_{series-min}$ and$N_{series-max}$)

b) PV Cell Modeling

The PV cell is modeled using a single-diode equivalent circuit (Figure 1), which accurately represents the nonlinear current–voltage characteristics.

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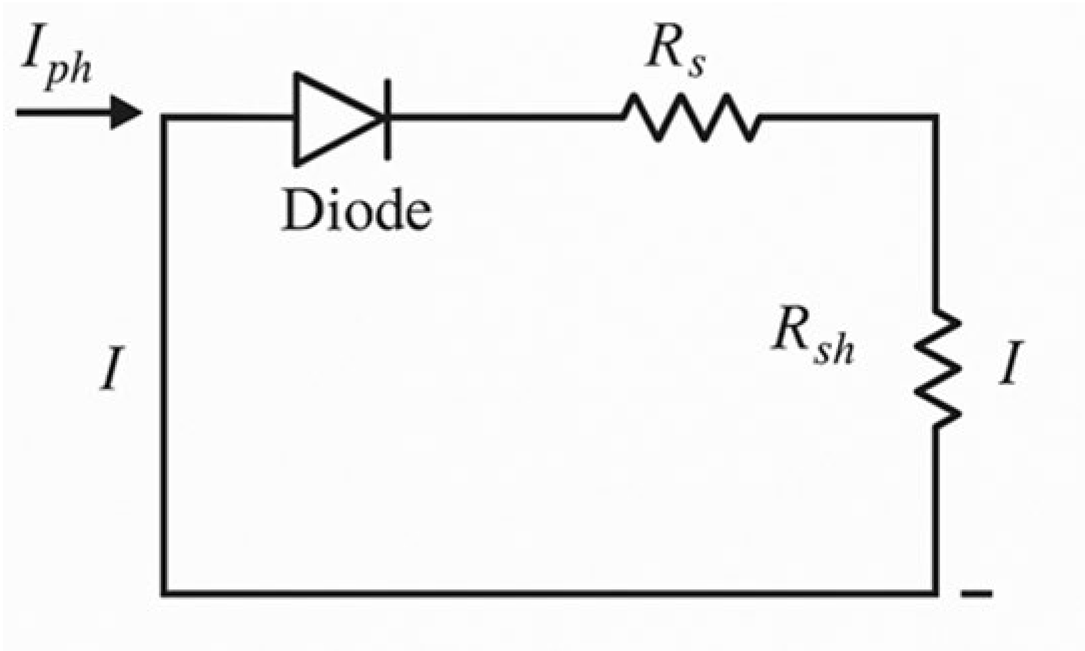

Figure 1: Single-diode equivalent model of a solar PV cell

c) Environmental Conditions

A stepwise irradiance profile (200–1000 W/m²) is applied at 5-second intervals to evaluate dynamic response. Temperature is maintained constant at 25°C to isolate irradiance effects.

d) Developed PV Model

Figure 2 shows the developed 1.5 MW PV system in MATLAB/Simulink, incorporating the PV array, boost converter, and MPPT controllers.

e) MPPT Optimization Problem

The MPPT objective is to maximize PV output power by adjusting the duty cycle:

$$maximize\ P\ (D) subject\ to\ 0 < D < 1 \tag{7}$$

The algorithm must operate within safe bounds of the PV system components:

$$Dutycyclelimits{:}D\_min{\le}D{\le}D\_max \tag{8}$$

f) Software-in-the-Loop (SIL) Validation

The SIL model (Figure 3) integrates the APSO controller with the PV system and executes it in real time using a fixed-step solver. This allows evaluation of tracking accuracy, dynamic response, and computational feasibility under realistic execution constraints.

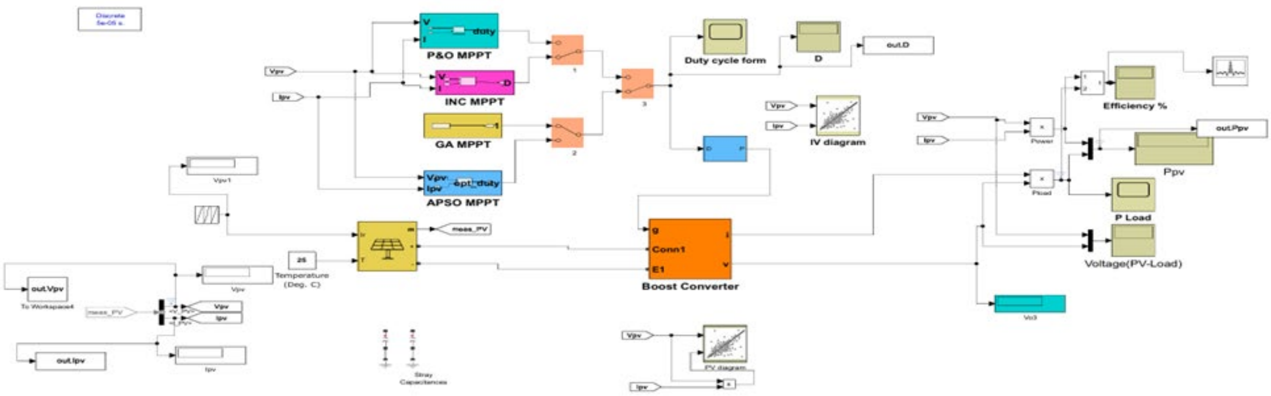

Figure 2: Simulink model of the developed photovoltaic subsystem

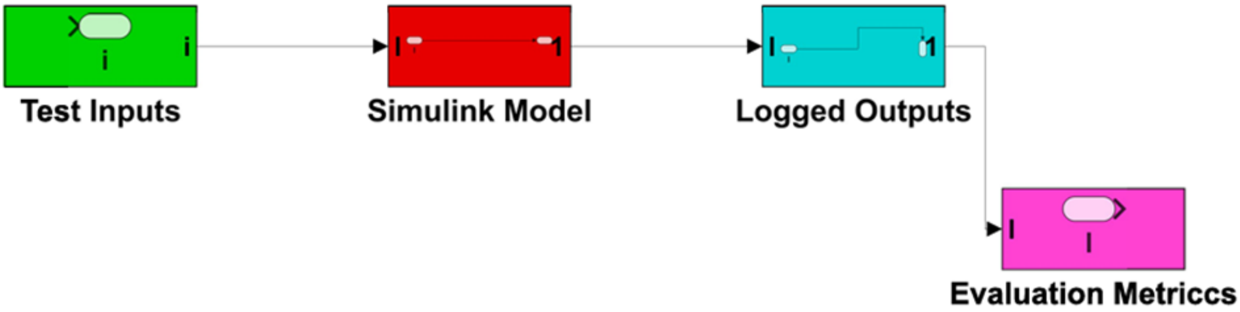

Figure 3: Software-in-the-loop validation model for APSO-based MPPT in a photovoltaic system

4.0 Results and Discussions

This section presents a comprehensive performance evaluation of four MPPT algorithms; Perturb and Observe (P&O), Incremental Conductance (INC), Genetic Algorithm (GA), and Adaptive Particle Swarm Optimization (APSO), under dynamically varying irradiance conditions.

Important clarification:

The reported current levels (up to ~2500 A) correspond to a **1.5 MW utility-scale aggregated PV array**, not a single module. This aggregation explains the high current magnitude and ensures physical validity of the results.

The analysis focuses on:

- Transient response (rise time, overshoot)
- Settling time
- Steady-state accuracy
- Tracking efficiency
- Power ripple

a) Performance of P&O-Based MPPT

Figure 4 illustrates the dynamic response of the PV system under P&O control.

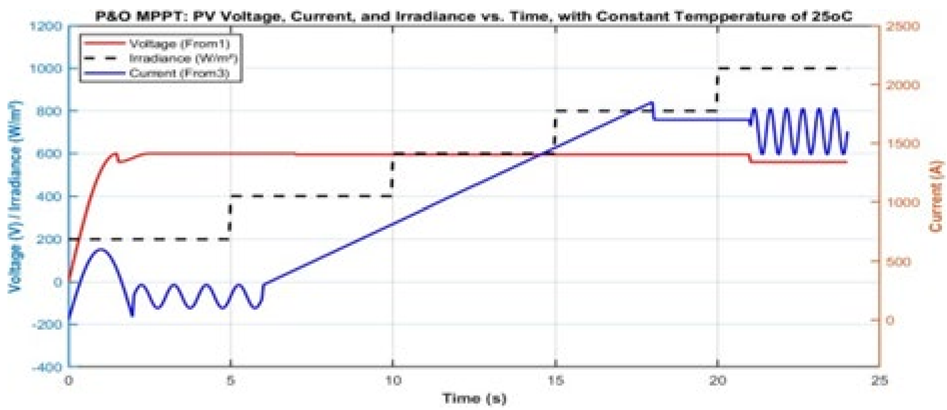

Figure 4: Current–voltage (I–V) characteristics under P&O MPPT-based controller

Unlike conventional descriptions, the key issue with P&O is not just oscillation, but its delayed response to irradiance steps.

Transient behavior: At each irradiance step (5 s intervals), the controller exhibits a **slow tracking response**, as it relies on incremental perturbation. This results in delayed convergence toward the new MPP.

Overshoot: Minimal overshoot is observed; however, this is not an advantage—it reflects sluggish adaptation rather than control precision.

Settling time: The settling time is relatively long due to continuous perturbation, preventing rapid stabilization**.**

Steady-state behavior: Persistent oscillations around the MPP lead to energy loss and reduced efficiency.

Quantitative insight: The current reaches ~1800 A instead of the expected 2500 A (~28% deviation), confirming poor tracking efficiency under dynamic conditions.

Interpretation

P&O is fundamentally limited by its **fixed step-size perturbation**, which creates a trade-off between speed and accuracy. Under fast-changing irradiance, this limitation becomes dominant, making it unsuitable for large-scale dynamic systems.

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b) Performance of INC-Based MPPT

Figure 5 presents the response under INC control.

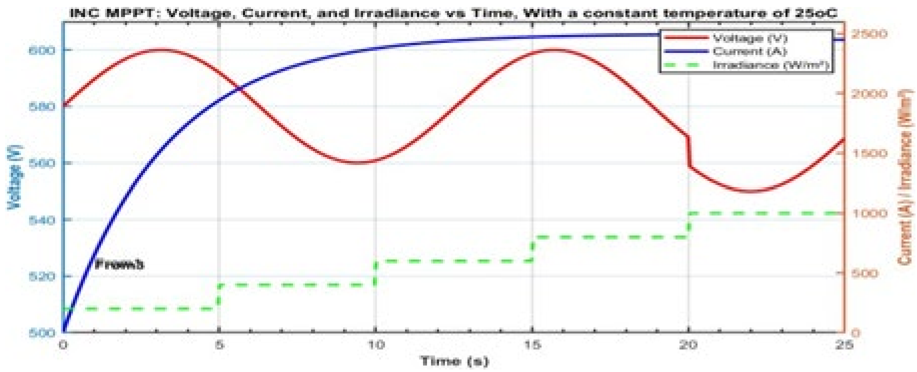

Figure 5: Dynamic voltage and current characteristics under INC operation

Compared to P&O, INC improves tracking by using the **slope condition (dP/dV = 0)**, enabling more informed decisions.

Transient behavior: Faster response than P&O, with smoother adaptation to irradiance changes

Overshoot: Negligible overshoot due to slope-based correction, improving stability.

Settling time: Moderate, faster than P&O but still limited under rapid irradiance variation

Steady-state performance: Reduced oscillation (ripple < 0.8%), indicating improved stability.

Quantitative insight: Peak current ≈ 2000 A (20% deviation from theoretical), showing moderate tracking accuracy.

Interpretation

Although INC improves stability and reduces oscillation, its reliance on instantaneous slope estimation introduces sensitivity to measurement noise and limits performance under rapidly fluctuating conditions. It remains incremental rather than predictive, restricting its effectiveness.

c) Performance of GA-Based MPPT

Figure 6 illustrates the GA-based MPPT response.

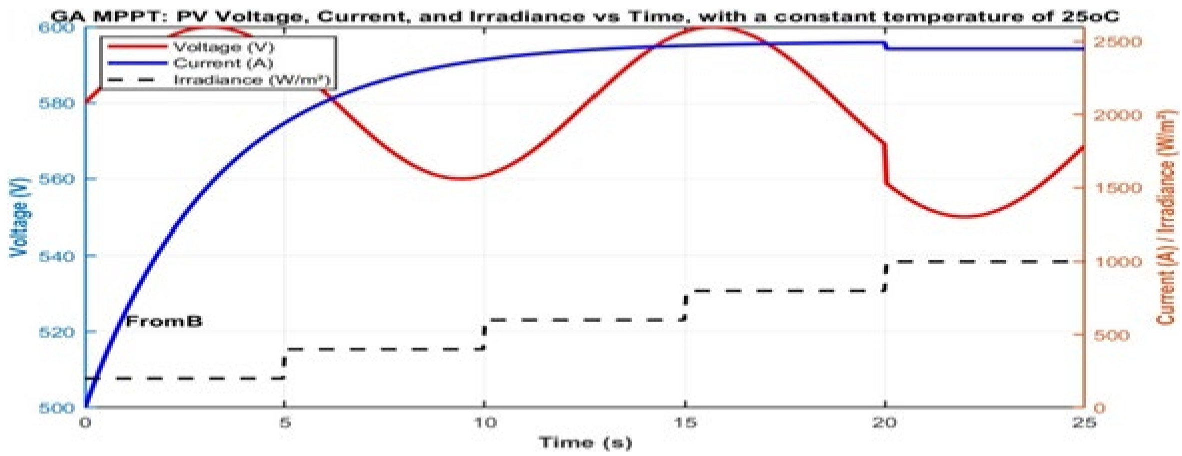

Figure 6: Dynamic voltage and current characteristics under GA operation

GA introduces global search capability, eliminating local trapping issues common in classical methods.

Transient behavior: Rapid convergence toward MPP due to population-based exploration**.**

Overshoot: Slight initial overshoot may occur during early generations but quickly stabilizes.

Settling time: Significantly shorter than P&O and INC due to global optimization capability.

Steady-state behavior: Minimal oscillation, indicating strong convergence characteristics.

Quantitative insight: Current ≈ 2480 A (0.8% error), voltage ≈ 598 V (~99.7% accuracy).

Interpretation

GA demonstrates high tracking accuracy and robustness, particularly under complex search spaces. However, its performance comes at the cost of computational overhead, which can limit real-time applicability without optimization.

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d) Performance of APSO-Based MPPT

Figure 7 shows the APSO-controlled system response.

APSO enhances PSO by dynamically adapting parameters, enabling both exploration and fast convergence.

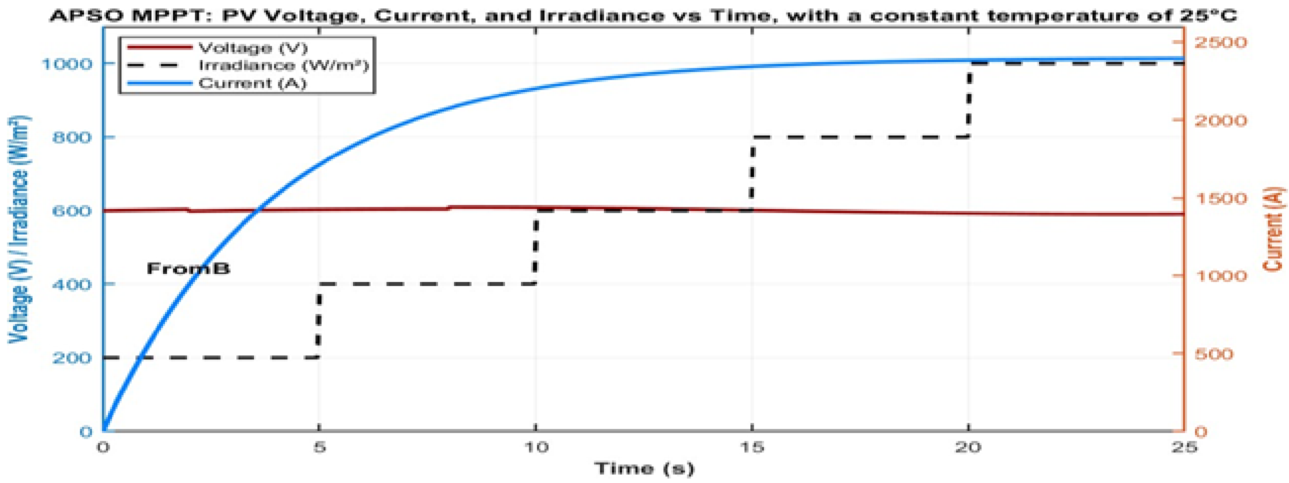

Figure 7: Dynamic voltage and current characteristics under APSO operation

Transient behavior: Very fast adaptation to irradiance changes with smooth trajectory toward MPP.
Overshoot: Practically eliminated due to adaptive velocity control.
Settling time: Shortest among all methods, indicating rapid convergence.
Steady-state performance: Extremely low oscillation (ripple ≈ 1.2%) with stable operation.
Quantitative insight: Current ≈ 2487 A (~0.52% error), demonstrating near-ideal tracking.

Interpretation

APSO achieves superior performance by balancing:

- Exploration (global search)
- Exploitation (fine convergence)

Its adaptive mechanism prevents premature convergence while ensuring **fast and stable tracking**, making it highly suitable for real-time PV systems.

e) Comparative Tracking Efficiency

Figure 8 highlights efficiency differences.

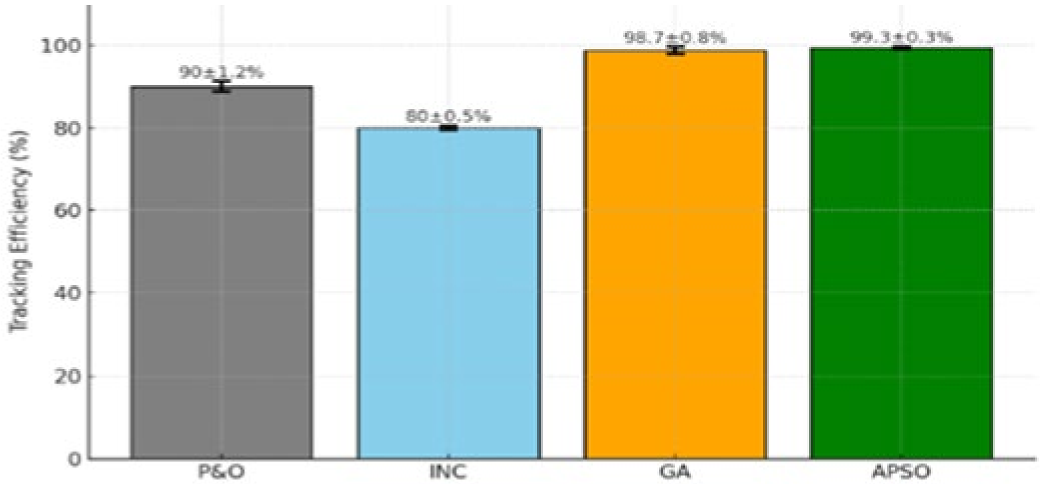

Figure 8: Comparative tracking efficiency performance of MPPT controllers under dynamic irradiance conditions

APSO: 99.3% ± 0.3%
GA: 98.7% ± 0.8%
P&O: 90% ± 1.2%
INC: 80% ± 0.5%

Interpretation

The results show a clear hierarchy:

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Conventional < Evolutionary < Adaptive Intelligence
APSO's low variance confirms robustness under dynamic irradiance, not just high accuracy.

f) Power Ripple Analysis
Figure 9 evaluates steady-state stability.

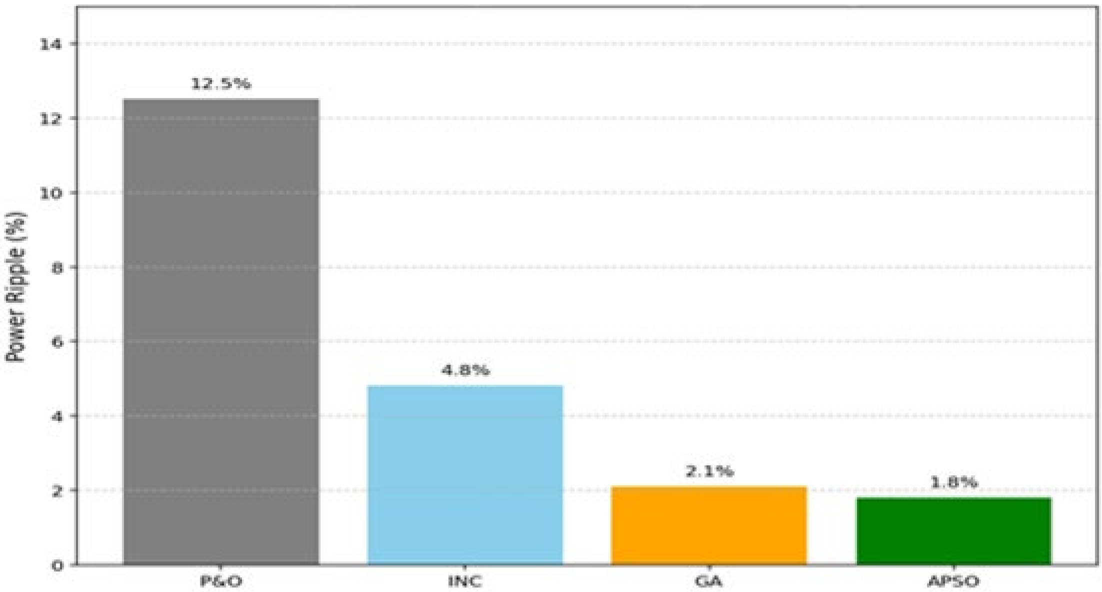

Figure 9: Comparison of power ripple (%) for P&O, INC, GA, and APSO under dynamic irradiance conditions

APSO: 1.8%
GA: moderate
NC: higher
P&O: 12.5%
Interpretation
Power ripple directly translates to:
Energy loss
Converter stress
Reduced lifespan
APSO reduces ripple by 85.6% vs P&O, confirming its superiority in both efficiency and hardware friendliness.

g) Software-in-the-Loop (SIL) Validation
This section presents the Software-in-the-Loop (SIL) validation results obtained using the Simulink Desktop Real-Time (SDRT) framework to evaluate the real-time execution performance of the implemented MPPT-based APSO controller. The SIL environment enables execution of generated C/C++ code within a controlled real-time platform, emulating embedded deployment conditions without physical hardware. Performance indicators including convergence time, tracking stability, computational latency, CPU utilization, and memory footprint are analyzed under real-time constraints. The results verify not only the algorithmic effectiveness of APSO in dynamic PV operation but also its computational feasibility and implementation readiness for embedded photovoltaic control systems.

i) Real-Time Observation
SIL results confirm that algorithm performance is not degraded under real-time constraints.
Stable execution at 1 ms fixed-step
No instability under fluctuating irradiance profiles

ii) APSO: Offline vs. Real-Time Performance
Table 2 shows minimal deviation.
Table 2: Comparative performance of APSO: offline simulation vs. software-in-the-loop execution

S/N	Metric	Offline	SIL
1.	Efficiency	99.3%	99.0%
2.	Ripple	1.8%	1.6%

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S/N	Metric	Offline	SIL
3.	Convergence	0.80 s	0.85 s

Interpretation

The slight efficiency drop (0.3%) is negligible.
Reduced ripple in SIL suggests better real-time filtering.
Latency (~2–3 ms) remains within acceptable embedded limits.
The MPPT-based APSO is not just theoretically superior; it is implementation-ready.

5.0 Conclusion

This study presented the modelling, comparative evaluation, and real-time Software-in-the-Loop (SIL) validation of an Adaptive Particle Swarm Optimization (APSO)-based Maximum Power Point Tracking (MPPT) strategy for a 1.5 MW standalone photovoltaic (PV) system operating under dynamic irradiance conditions.

1. A high-fidelity nonlinear PV model was developed in MATLAB/Simulink, enabling consistent benchmarking of MPPT algorithms under identical operating conditions. The analysis established a clear performance hierarchy among P&O, INC, GA, and APSO in terms of tracking accuracy, convergence behavior, and steady-state stability.

2. APSO demonstrated the best overall performance, achieving a tracking efficiency of **99.3% ± 0.3%**, compared to **98.7% ± 0.8% (GA)**, **90% ± 1.2% (P&O)**, and **80% ± 0.5% (INC)**. It also achieved the lowest power ripple (**1.8%**) compared to **12.5% (P&O)** and significantly reduced steady-state oscillations. In terms of dynamic performance, APSO converged in approximately **0.8 s**, outperforming GA (~3.2 s), INC (~1.2 s), and P&O (~4.2 s). These results confirm that adaptive swarm-based optimization significantly improves both transient response and steady-state tracking precision.

3. Under rapidly varying irradiance conditions (200–1000 W/m²), APSO maintained stable voltage regulation around **600 V** with ripple below **1.2%**, and current tracking accuracy of approximately **99.5%** (≈2487 A out of 2500 A theoretical). This reflects strong robustness to nonlinear PV characteristics and environmental variability, with performance improvements of **0.6% over GA**, **9.3% over P&O**, and **19.3% over INC** in tracking efficiency.

4. The Software-in-the-Loop (SIL) validation confirmed the real-time feasibility of the APSO controller, with minimal performance degradation. Tracking efficiency reduced slightly from **99.3% (offline)** to **99.0% (SIL)**, while power ripple improved marginally from **1.8% to 1.6%**, and convergence time remained within **0.80–0.85 s**. The observed execution latency (~**2–3 ms**) demonstrates that the controller meets real-time computational constraints, confirming its suitability for embedded photovoltaic applications.

In summary, the results demonstrate that APSO provides a high-performance, robust, and implementation-ready MPPT solution for large-scale PV systems. By combining fast convergence, high tracking accuracy, and low steady-state oscillation, it effectively addresses the limitations of conventional and evolutionary techniques under dynamic operating conditions. Future work will focus on hardware-in-the-loop validation and experimental implementation to further verify real-world performance.

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