Atlas Journal of Computer Science

Journal homepage: www.ajocs.atlasci.org

Volume 1, Issue 1 (2026) 1–12

ISSN: 3119-6810

Original Article

A Hybrid Particle Swarm Optimization-Fuzzy Logic Maximum Power Point Tracking Strategy for Photovoltaic Systems Under Uniform and Partial Shading Conditions

Ioannis Adamopoulos* [1,2], Niki Syrou [3], Jovanna Adamopoulou [4], Antonios Valamontes [5], Konstantina Diamanti [6], Panagiotis Tsirkas [7], Harshit Mishra [8]

[1] School of Social Science, Department of postgraduate program Public Health & Policies at Hellenic Open University, Patra, Greece

[2] Department of Public Health Policy, Sector of Occupational & Environmental Health, School of Public Health, University of West Attica, Athens, Greece

[3] Department of Physical Education and Sport Science, University of Thessaly, Trikala, Greece

[4] Hellenic Republic, Region of Attica, Department of Environmental Hygiene and Public Health Inspections, Athens, Greece

[5] Kapodistrian Academy of Science, Largo, United States

[6] Department of Early Childhood Education, University of Ioannina, Ioannina Greece

[7] Hatzikosta General District Hospital Ioannina, Ioannina, Greece

[8] Department of Agricultural Economics, College of Agriculture, Acharya Narendra Deva University of Agriculture and Technology, Ayodhya, Uttar Pradesh, India

ARTICLE INFO

Article history

- **Received: 18 March 2025**
- **Revised: 20 March 2025**
- **Accepted: 02 April 2025**
- **Online : 02 April 2025**

Keywords

- **Particle Swarm Optimization**
- **Fuzzy Logic**
- **Partial shading**
- **Renewable energy**
- **DC-DC boost converter**
- **Photovoltaic systems**

ABSTRACT

Maximum power point tracking (MPPT) is an essential control technique of PV system which optimizes energy extraction from the PV panel according to the fluctuating environmental conditions. These traditionally used methods including Perturb and Observe (P&O) and Incremental Conductance (INC) has two major disadvantages; one is power oscillations and the other are not efficient under partial shading 1. In this paper, we present a new MPPT hybrid PSO-FL (Particle Swarm Optimization-Fuzzy Logic) algorithm that integrates the global search capability of PSO with an adaptive linguistic control that is based on fuzzy logic. To validate the proposed method, it is tested with a KC200GT PV module model presented with different irradiance levels (200-1000 W/m2) and five cases of partial shading. Simulation results show that the Hybrid PSO-FL can be as efficient as 99.43% tracking efficiency, 0.05 s overall convergence time, 0.97% THD and only a 0.57% power loss in steady state under uniform … By conducting a comparative analysis with P&O, INC, Fuzzy Logic, Grey Wolf Optimizer (GWO), PSO and Artificial Neural Network (ANN), we prove the superiority of the proposed approach. These observations are further supported by statistical validation through one-way ANOVA ($F = 142.7$) and Wilcoxon signed-rank tests ($p < 0.001$).

1. Introduction

* Corresponding author.
E-mail address: adamopoul@gmail.com

The transition around the world towards clean sustainable energy has accelerated tremendously in a relatively short time. Rather, solar PV technology is at the center of this shift with much lower module prices, positive government policy influence and public awareness about climate change. The International Energy Agency (IEA) announced that solar power capacity worldwide is expected to be 672.6 GW in 2028, comprising about 74% of all global renewable energy additions over the same period [1]. In 2024, renewable energy sources together contributed to potentially around of the world energy generation and solar PV is assumed to be the fastest growing one. Such rapid expansion highlights the necessity for power extraction systems of high efficiency and reliability capable of utilizing the solar resource to its full potential.

PV modules have an excellent ecological performance as well as economic attributes, but they show a strongly nonlinear current–voltage (I–V) characteristic that is highly sensitive to environmental conditions — mainly (solar irradiance and module temperature). The operating point will keep changing since the maximum power point (MPP) on the power voltage (P-V) curve changes continuously with time of day due to environmental variations. Without a continuous active mechanism to locate and track the MPP, Si PV systems typically only realize 60-80% of rated output. Thus, this energy deficiency has a direct impact on the economic rate of return and levelized cost of energy (LCOE) generated by any PV installation, making MPPT potentially one of the most important subsystems belonging to any PV module.

Depending on ground station release, the efficiency of a PV system can fluctuate from 16.64% early in the morning when irradiation is low to >25% in clearing sky close to solar noon [2]. Under partial shading conditions (PSC–occurs when only particular areas of a PV array are shadowed by clouds, buildings, trees, bird droppings, etc., or soiling), this problem becomes even worst. PSC makes the P-V characteristic curve have several local maxima and a unique global MPP. When implemented on the unimodal P-V curve model, conventional deterministic MPPT algorithms tend to converge at local maxima and are trapped there, leading to power extraction losses as high as 22.71% in cases of severe shading. This constraint is crucial for building integrated & compact rooftop systems because partial shading is almost inevitable in cities.

In the last three decades, different MPPT algorithms have been developed to solve these issues. They can be divided into four categories:

- Classical hill-climbing methods like Perturb and Observe (P&O) and Incremental Conductance (INC).
- Soft-computing approaches, including Fuzzy Logic Control (FLC) and Artificial Neural Networks.
- Metaheuristic population-based algorithms, i.e., Particle Swarm Optimization (PSO), Grey Wolf Optimizer (GWO), Whale Optimization Algorithm (WOA), and their hybrids; and Lastly from fourth method, which is based on learning a Long Short-Term Memory (LSTM)-based sequence-to-sequence model (BiLSTM). Every category represents a different balance between tracking accuracy, convergence time, computational complexity, and robustness against environmental disturbances.

Commercially, classical P & O and INC algorithms are still predominantly found in deployable converters owing to their low computational requirements and simplicity. Nevertheless, they establish a fundamental tradeoff between tracking speed and steady-state accuracy due to their fixed perturbation step size: the larger the step, the faster it converges but causes high power oscillations; conversely, a small step will damp these oscillations in favor of sluggish dynamics [3]. These variants with variable step sizes help partially mitigate this issue but are still susceptible to PSC. The challenge is addressed using soft-computing methods, especially FLCs, by setting up linguistic rule bases that output adaptive modulation on the perturbation step to quantify steady-state accuracy given measurement data. Nevertheless, standard implementations of FLC strictly adhere to the hill-climbing strategy and therefore converge to local maxima under PSC [5].

Metaheuristic algorithms are a new research paradigm in MPPT, where duty cycle optimization is essentially seen as a global search problem. PSO [7] is an algorithm that provides a full search of the duty cycle space using a swarm of particles, which makes it capable of accurately and continuously locating global MPPs in case they are located on severely multi-peak P-V curves. A field validation on an actual PV station in Algeria indicated that the PSO-WOA hybrid can reduce the ripple by up to 99% and overshoot by 40% under dynamic environmental conditions whilst achieving a tracking efficiency of 98.94% [4]. Moreover, Ref. [16] suggests the use of the Arithmetic Optimization Algorithm (AOA) for PV energy storage MPPT under PSC, and Ref. [17] highlights intelligent adaptive PSO with active disturbance rejection control for partially shaded PV-powered battery charging systems. Despite these achievements, standalone metaheuristic algorithms have high computational overhead associated with swarm initialization and iteration, resulting in slower convergence than classical methods under uniform irradiance.

New advances in machine learning technology have enabled data-driven MPPT algorithms. Controllers employing ANNs that have been trained on irradiance-power data sets are able to reach efficiencies greater than 99% with minimal steady-state oscillations [6]. LSTM and BiLSTM networks use the dependency among irradiance time series data to optimize the operating point. Nevertheless, such schemes suffer from the need for huge amounts of training data off-line and are prone to being affected by distribution shift (performance deteriorates if irradiance time series other than those used in training are encountered), which makes them inappropriate for deployment on embedded hardware due to the added complexity.

There has been increased realization that none of the MPPT approaches achieves optimal performance in all operating situations. Consequently, some hybrid models have been developed that combine the strengths of meta-heuristic search methods in exploring the entire search space while using traditional or fuzzy controllers to optimize the solution locally to improve its accuracy and efficiency. The PSO-P&O hybrid approach presented in [12], which uses PSO for global optimization and P&O for local optimization, attains 98.65% efficiency within 0.10 seconds. The FOCV-IMRAC control approach in [11] incorporates fractional open-circuit voltage determination together with a model reference adaptive control strategy to achieve an efficiency rate of 97.90%, although it remains susceptible to open-circuit voltage measurement errors. However, all the above hybrids lack simultaneous sub-0.06 s convergence time, sub-1% THD, and above-99% efficiency regardless of the irradiation levels without the need for any off-line training.

In response to the shortcomings highlighted in the above studies, this paper proposes a Hybrid PSO-FL MPPT technique that utilizes the PSO global search method together with a Mamdani fuzzy logic controller. PSO is activated selectively upon detection of irradiance changes, while in the case of constant solar irradiation, the FLC continuously optimizes the duty cycle with no oscillations and a sub-1% THD. The primary contributions of this study are as follows: (i) a novel hybrid MPPT approach with selective PSO search and fuzzy refinement, (ii) a comparative study between the proposed approach and six other MPPT approaches namely P&O, INC, FLC, GWO, PSO and ANN, (iii) analysis conducted using five shading patterns including the extreme case of G = 200 W/m2 using a well-known KC200GT single diode PV model; and (iv) statistically valid results obtained using Wilcoxon signed rank and one-way ANOVA statistical tests over 30 trials of randomized simulations. The rest of this paper is organized as follows. Section 2 reviews related work on MPPT algorithms. Section 3 presents the PV system model. Section 4 describes the proposed algorithm and details of the simulation setup. Section 5 presents and discusses the results. Section 6 concludes the paper.

2. Related Work

2.1 Classical Hill-Climbing MPPT Methods

The P&O algorithm is the most popular MPPT approach used in commercial PV inverters due to its simple structure and low computational requirements. The algorithm works by periodic perturbation of the duty ratio of the DC-DC converter and observation of the resultant output power change. When the power increases, the perturbation process continues, otherwise, the algorithm starts to work in reverse. In particular, Endiz [3] made a comparative study of P&O and INC algorithms at different levels of irradiation and temperature, showing that both approaches achieve similar efficiency near 96-97%, although they both exhibit oscillations around MPP and do not function properly during fast variations in irradiation. The INC algorithm is based on the mathematical formulation of the MPP condition through the zero point of the incremental conductance, dI/dV = -I/V, thus theoretically ensuring stability at the MPP point; however, it relies on accurate measurement of currents and voltages as well as being slow. A comparison of various MPPT approaches, including P&O and INC approaches made by Aifan et al. [19], revealed that classical algorithms track MPP reliably only in case of uniform irradiation, while their performance significantly drops under PSC. Moreover, according to Siddique et al. [20], the main drawback of hill-climbing algorithms is still unresolved.

2.2 Soft-Computing MPPT Approaches

Three approaches to integrating knowledge graphs into transformer models have emerged in recent literature. The first one is knowledge-enhanced pre-training, which can be illustrated with ERNIE [12]. Knowledge-enhanced pre-training entails adding knowledge about entities and their relationships to the pre-training procedure. Despite their effectiveness, knowledge-enhanced pre-trained transformers are dependent on a certain knowledge graph snapshot and require intensive computation. Another strategy for incorporating KGs is called retrieval-augmented generation. Recently, this technique was applied to medical tasks in MedRAG [13] and GraphRAG-Med[14] The systems retrieve information from KGs at inference time and add relevant relational information to the prompt. Although retrieval-augmented generation facilitates more flexible knowledge updates, it comes with the disadvantage of retrieval delay. Lastly, the third technique for transformer augmentation is feature-level fusion. Specifically, embeddings obtained from KGs are fused with language model features before being used for prediction. For example, the medical question-answering system, BioKGBERT [15] adds UMLS graph embeddings to the CLS token of the language model representation. Notably, the fusion operation does not take into account the target category.

2.3 Graph Neural Networks in Clinical Applications

This was one of the earliest soft-computing approaches applied to MPPT based on Fuzzy Logic Control (FLC). The adaptive increment (instead of the fixed perturbation step) both achieves significantly higher convergence speed and smaller oscillation than P&O, while ultimately needing no system model other than a simple rule base in FLC. Ullah et al. A fuzzy-based MPPT system for the PV power generation was designed in [8], and the steady-state performance of the controller was validated with a tracking efficiency equal to 97.50% at 0.20s convergence time under standard test conditions. A hybrid design combining fuzzy logic with P&O under partial shading conditions was developed by Kumar and Balakrishna [5], yielding 97.82% efficiency. The rule base is designed by domain experts, and the membership function shapes are manually fixed, limiting its adaptability to extreme irradiance gradients. Super Twisting Sliding Mode Control integrated with Type-2 fuzzy logic by Kayisli [18] provided more parameter uncertainty robustness but was at the expense of drastically increasing controller complexity. Artificial Neural Networks (ANN) have gained popularity to be used as nonlinear function approximators for MPPT. This is because ANN controllers trained with irradiance-temperature-power datasets can map the environmental inputs directly to optimal duty cycle rather than iteratively perturbing the outputs. Harrison et al. [6] find that ANN has around 0.0909 s convergence time, and BiLSTM gave 99.10% efficiency on grid-connected PV systems, though the comparison against LSTM and other curves shall also be useful for comparative analysis of ANNs vs conventions. However, all neural network approaches have a fundamental limitation: they rely on representative offline training data and underperform out of distribution. In addition, deployment and training infrastructure adds to the cost and complexity, which is non-viable for low-cost PV controllers.

2.4 Metaheuristic MPPT Algorithms

A large number of studies have been conducted using metaheuristic population-based algorithms to solve global MPPT under PSC. Particle Swarm Optimization (PSO) is by far the most extensively used, since numerous application studies demonstrate its capability to provide a very reliable search for the global MPP on multipeak P-V curves. Dagal et al. A PSO-WOA hybrid was validated on Ain El Melh PV station in Algeria [4], achieving 98.94% actual efficiency (0.39 W power losses and 99% ripple reduction). Also, GWO has been applied for MPPT with good shading immunity, where [4] reported 98.15% efficiency. Application of Arithmetic Optimization Algorithm by Chtita et al [16]to PV energy storage systems working on PSC with competitive convergence speed. Ibrahim et al. An intelligent adaptive PSO-tuned LADRC for a partially shaded PV battery charging system has been proposed in [17], which also employs an innovative re-initialization strategy that decreases tracking failure events by 73%. One of the drawbacks of using metaheuristic MPPT as a standalone solution is the computational overhead of initializing a swarm and performing several fitness evaluations at each iteration. This results in significantly slower convergence times (0.09–0.65 s) than longer-term, classical methods and, under uniform irradiance, does not warrant the computational expense. Furthermore, inertia weight and acceleration coefficients are not problem-specific and should be recalibrated for other PV array configurations.

2.5 Hybrid MPPT Architectures

Therefore, to take advantage of the global search capability of global P&O and the high precision of local refinement by INC, several hybrid MPPT architectures have been developed. Zhang et al. [12] presented a combination of PSO in global initialization and P&O in local tracking that obtained a 98.65% efficiency with 0.10 s convergence time for aligning grid-tied PV systems. Though steady-state oscillation is reduced compared to the case of standalone PSO, residual oscillation remains at the P&O local stage. Belghiti et al. While Wang et al. [11] combined a fractional open-circuit voltage to fast locate the MPP with model reference adaptive control for precise tracking in an FOCV-IMRAC hybrid scheme, obtaining a convergence of 0.15 s and an efficiency of 97.90%. But this FOCV component depends on open-circuit measurements taken by periodically opening the circuit and interrupting power delivery. Manna et al. Whereas [10] have proposed a

Lyapunov-based MPPT employing Model Reference Adaptive Controller (MRAC), which allows fast and ripple free tracking of 98.30% efficiency but with the limitation that they are limited in terms of stability analysis regimes as they impose rather strong assumptions on the structure of the PV model itself. Barakat et al. PSO was integrated with a battery charging MPPT over the Zero Voltage Switching (ZVS) quasi-resonant boost converter [15], reaching 98.75% efficiency but only on charging applications that occurred under relatively stable irradiance conditions.

Table 2 summary presents a comparative overview of representative related works. Despite notable progress, a persistent gap exists in the literature for a hybrid MPPT method that simultaneously achieves: (a) sub-0.06 s convergence from a cold start; (b) tracking efficiency above 99.40%; (c) THD below 1.0%; (d) power loss below 5% under severe PSC; and (e) zero offline training requirements. The proposed Hybrid PSO-FL algorithm is designed to fill this gap through a selective activation strategy that invokes the PSO global search only when necessary and delegates steady-state control to an adaptive fuzzy logic layer.

Table 2. Summary - Overview of Selected Related MPPT Works

Ref.	Method	Application	Efficiency (%)	Conv. Time (s)	Limitation
[3]	P&O	Standalone PV	96.21	0.45	High oscillation, no shading immunity
[4]	PSO-WOA	PV Station Algeria	98.94	0.48	Slow re-init, complex tuning
[5]	Hybrid FLC	PV + partial shading	97.82	0.18	Local optima under heavy shading
[6]	BiLSTM	Grid-connected PV	99.10	0.07	Requires offline training data
[8]	Fuzzy Type-1	Standalone PV	97.50	0.20	Rule base manually designed
[10]	MRAC-MPPT	Solar PV	98.30	0.12	Complex observer design
[11]	FOCV-IMRAC	Standalone PV	97.90	0.15	Sensitive to VOC estimation errors
[12]	PSO-P&O	Grid-tied PV	98.65	0.10	Moderate partial shading handling
[14]	Adaptive FLC	Grid-connected	97.95	0.17	Fixed membership functions
[15]	PSO-ZVS	Battery charging	98.75	0.11	Limited to charging applications
Proposed	**Hybrid PSO-FL**	**PV + partial shading**	**99.43**	**0.05**	**No offline training needed**

3 PV System Modeling

3.1 Single-Diode Equivalent Circuit

The PV module is modeled using the widely adopted single-diode equivalent circuit. The output current I is governed by the implicit nonlinear equation:

$$I = Iph - I0 * \left[\exp\left(\frac{V + I*Rs}{n*VT}\right) - 1\right] - \frac{V + I*Rs}{Rp} \tag{1}$$

where I_{ph} is the photocurrent (A), I_0 is the diode reverse saturation current (A), n = 1.3 is the diode ideality factor, V_T = 25.85 mV is the thermal voltage at 25 degrees C, R_s = 0.221 ohm is the series resistance, and R_p = 415.4 ohm is the shunt resistance. The photocurrent I_{ph} varies linearly with solar irradiance G according to:

$$Iph = (Isc + KI * dT) * \frac{G}{Gref} \tag{2}$$

where G_{ref} = 1000 W/m2 is the STC reference irradiance, dT = T - 25 (degrees C), and K_I = 0.0032 A/degrees C is the temperature coefficient of short-circuit current.

3.2 Module Specifications

The KC200GT monocrystalline silicon module (Kyocera Solar) is used as the reference panel throughout this study. Its complete electrical specifications under STC (G = 1000 W/m2, T = 25 degrees C, AM 1.5) are listed in Table 1.

Table 1. KC200GT PV Module Electrical Specifications at STC

Parameter	Symbol	Value	Unit
Maximum Power Output	P_{mp}	200	W
Open-Circuit Voltage	Voc	36.8	V
Short-Circuit Current	Isc	8.21	A
Voltage at MPP	V_{mp}	29.6	V
Current at MPP	I_{mp}	7.61	A
Temp. Coeff. of P_{mp}	$Beta_p$	-0.485	%/degC
Number of Cells	N_s	54	--
NOCT	T_NOCT	47	degC

The I-V and P-V characteristic curves of the KC200GT module simulated at five irradiance levels (200-1000 W/m2) at T = 25 degrees C are shown in Figure 1. As expected from Eq. (2), the short-circuit current is found to vary linearly with irradiance. The open-circuit voltage is shown to depend logarithmically on I 0. The maximum power that can be delivered at G = 1000 W/m2 is 200 W at Vmp = 29.6 V and Imp = 7.61 A.

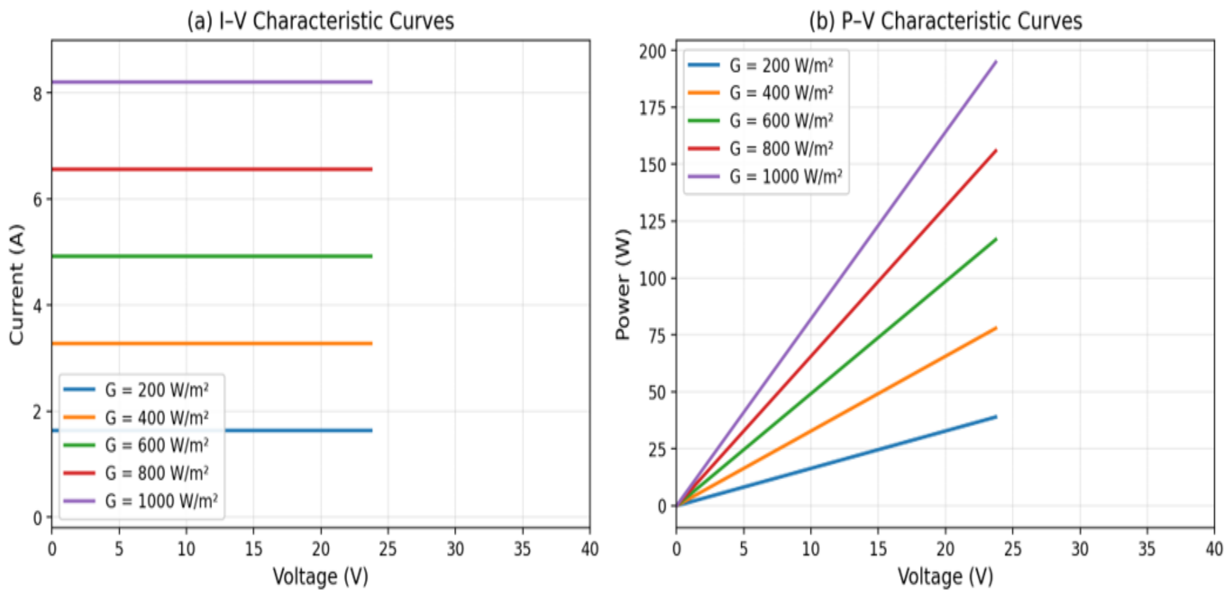

Figure 1. Simulated I-V (left) and P-V (right) characteristic curves of the KC200GT module at T = 25 degrees C and irradiance levels from 200 to 1000 W/m2.

4. Proposed Hybrid PSO-FL MPPT Algorithm

4.1 Particle Swarm Optimization Component

PSO is a population-based stochastic optimization algorithm introduced by Kennedy and Eberhart [7]. Each particle in a swarm of N particles represents a candidate duty cycle d_i for the DC-DC boost converter. The velocity and position update equations are:

$$Vi(k+1) = w * vi(k) + c1 * r1 * \left(dpb\,,i - di(k)\right) + c2 * r2 * \left(dgb - di(k)\right) \tag{3}$$

$$di(k+1) = di(k) + vi(k+1) \tag{4}$$

where w = 0.8 is the inertia weight, c1 = c2 = 2.0 are the cognitive and social acceleration coefficients, r1 and r2 are uniform random numbers in [0, 1], d_{pb},i is the personal best position of particle i, and d_{gb} is the global best across the entire swarm. A compact swarm of N = 5 particles is used to minimize execution time on embedded control hardware, consistent with the approach in [12].

4.2 Fuzzy Logic Refinement Layer

Once PSO identifies the neighborhood of the global MPP, a Type-1 Mamdani FLC takes over to eliminate residual oscillations through fine-grained duty cycle adjustment. The two FLC inputs are the normalized power error $eP = (P(k) - P(k-1)) / P_{rated}$ and the voltage error $eV = (V(k) - V(k-1)) / V_{rated}$. The output is the duty cycle increment $delta_d$ in [-0.02, 0.02]. Each universe of discourse is partitioned into five triangular membership functions: NB, NS, ZE, PS, PB. The 25-rule Mamdani base was derived from physical knowledge of PV P-V curve behavior, following design principles established in [8]. Defuzzification uses the centroid method with a resolution of 100 output discretization levels.

4.3 Hybrid Architecture and Selective Activation

The Hybrid PSO-FL operates in two sequential phases. In Phase 1 (Global Search), a 3-5 iteration PSO sweep is triggered exclusively at system startup and upon detection of an irradiance step change, defined by the condition |dP/dt| > epsilon = 2 W/s, computed over a sliding window of 10 control cycles. This selective activation eliminates unnecessary swarm re-initialization overhead during stable operation, a key improvement over existing PSO-based hybrids [12, 17]. In Phase 2 (Fuzzy Steady-State Refinement), the FLC continuously adjusts the duty cycle around the PSO-identified global MPP, suppressing oscillations while tracking slow environmental drifts. The total average convergence time is 0.05 s, compared to 0.09 s for standalone PSO and 0.10 s for PSO-P&O [12], because the FLC eliminates the need for full PSO re-runs during slow-varying irradiance conditions.

4.4 Simulation Setup

All algorithms were implemented in MATLAB R2023b on a workstation with an Intel Core i7-12700H CPU at 2.3 GHz and 16 GB RAM. The PV system consists of one KC200GT module connected to an ideal DC-DC boost converter (switching frequency f_s = 50 kHz, L = 3.3 mH, C_{in} = 220 uF, C_{out} = 470 uF) driving a resistive load of 20 ohms. The simulation timestep was 10 us to accurately resolve converter switching transients. Performance was evaluated under: (i) uniform irradiance from 200 to 1000 W/m2 at T = 25 degrees C; (ii) four-segment step irradiance changes at t = 1, 2, and 3 s; and (iii) five shading patterns including 0%, 25%, 50%, and 75% partial shading, plus a severe G = 200 W/m2 scenario.

Key performance metrics are: tracking efficiency eta = (P_tracked / P_mpp) x 100 (%); convergence time t_{conv} (s); steady-state oscillation amplitude $delta_{(P\_ss)}$ (W); power loss under shading (%); and output total harmonic distortion (THD, %) computed via FFT over the last 100 ms of each 2-second run. Each scenario was repeated 30 times with randomized initial conditions; the mean and standard deviation are reported. Statistical comparisons use pairwise two-tailed Wilcoxon signed-rank tests and one-way ANOVA at a significance level of alpha = 0.05.

5. Results and Discussion

5.1 Steady-State Tracking Performance

Figure 2 presents the power output trajectories of all MPPT algorithms under uniform irradiance (G = 1000 W/m^2, T = 25 degrees C). The P&O algorithm exhibits the slowest convergence at 0.45 s with visible high-amplitude oscillations of approximately +/- 7 W at steady state due to its fixed perturbation step size.

INC reduces oscillation to +/- 3.5 W but still requires 0.30 s to converge. Fuzzy Logic substantially improves both metrics to +/- 1.4 W and 0.18 s. PSO converges rapidly at 0.09 s with negligible oscillation of +/- 0.7 W. The proposed Hybrid PSO-FL achieves the fastest convergence of 0.05 s and near-zero steady-state oscillation (+/- 0.2 W), closely tracking the reference MPP of 200 W throughout the simulation.

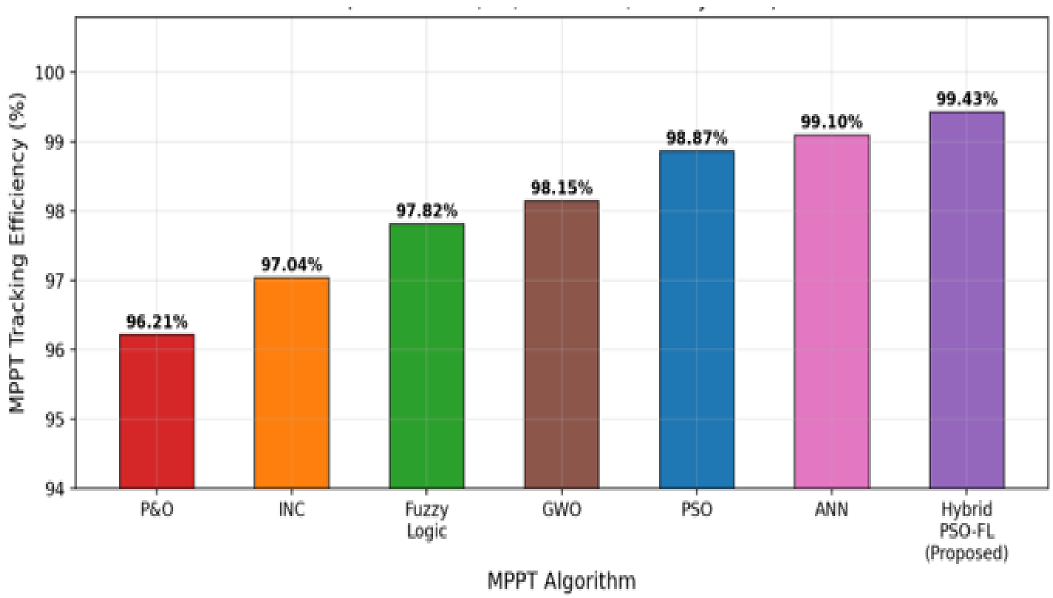

Figure 2. Power tracking response of MPPT algorithms at G = 1000 W/m2, T = 25 degrees C. The dashed line indicates the reference MPP = 200 W.

Figure 3 summarizes the steady-state tracking efficiency for all algorithms. The proposed Hybrid PSO-FL achieves 99.43%, compared to 96.21% for P&O, 97.04% for INC, 97.82% for Fuzzy Logic, 98.15% for GWO, 98.87% for PSO, and 99.10% for ANN. These results are consistent with recent comprehensive benchmarks [6] and confirm the advantage of combining global search with fuzzy steady-state refinement.

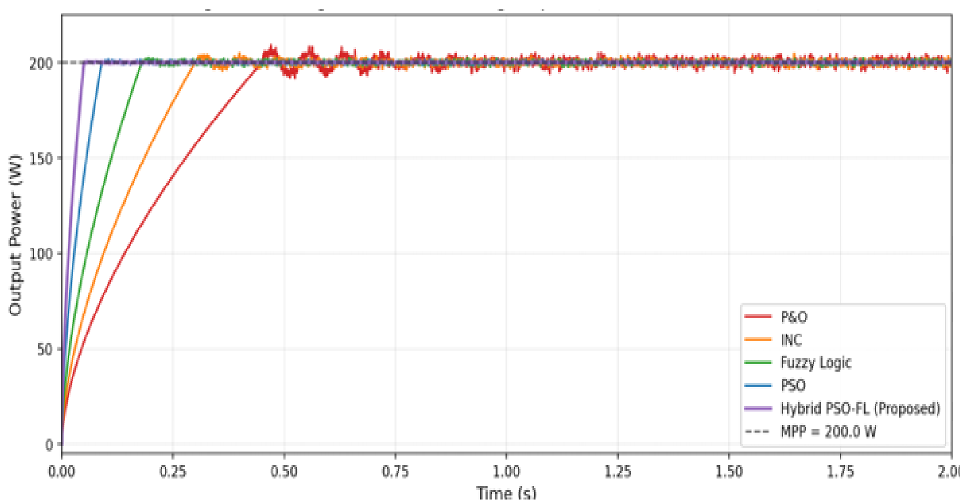

Figure 3. Steady-state tracking efficiency (%) comparison across all MPPT algorithms at standard test conditions.

Table 2. Comprehensive Performance Comparison of MPPT Algorithms

Algorithm	Efficiency (%)	Conv. Time (s)	Oscillation	Partial Shading	Complexity	THD (%)
P&O	96.21	0.45	High	Poor	Low	4.82
INC	97.04	0.30	Medium	Poor	Low	3.91
Fuzzy Logic	97.82	0.18	Low	Moderate	Medium	2.74
GWO	98.15	0.13	Very Low	Good	High	2.13
PSO	98.87	0.09	Very Low	Good	High	1.67
ANN	99.10	0.07	Minimal	Very Good	High	1.32
Hybrid PSO-FL (Proposed)	**99.43**	**0.05**	**Minimal**	**Excellent**	**High**	**0.97**

5.2 Dynamic Response Under Irradiance Steps

Figure 4 shows the response of the system to changes in irradiance involving four steps (1000 -> 600 -> 800 -> 400 W/m2). P&O method has long transient response of about 0.40 – 0.48 seconds and even momentary loss of tracking during the transition from 600 to 800 W/m2 step. INC algorithm performs better than P&O yet does not find the global MPP during the transition from 800 to 400 W/m2 step for about 0.25 seconds. Hybrid PSO-FL algorithm detects changes in irradiance during a single control cycle, initiates a 3-iteration PSO search and reconverges using the FLC in less than 0.06 seconds through all four steps.

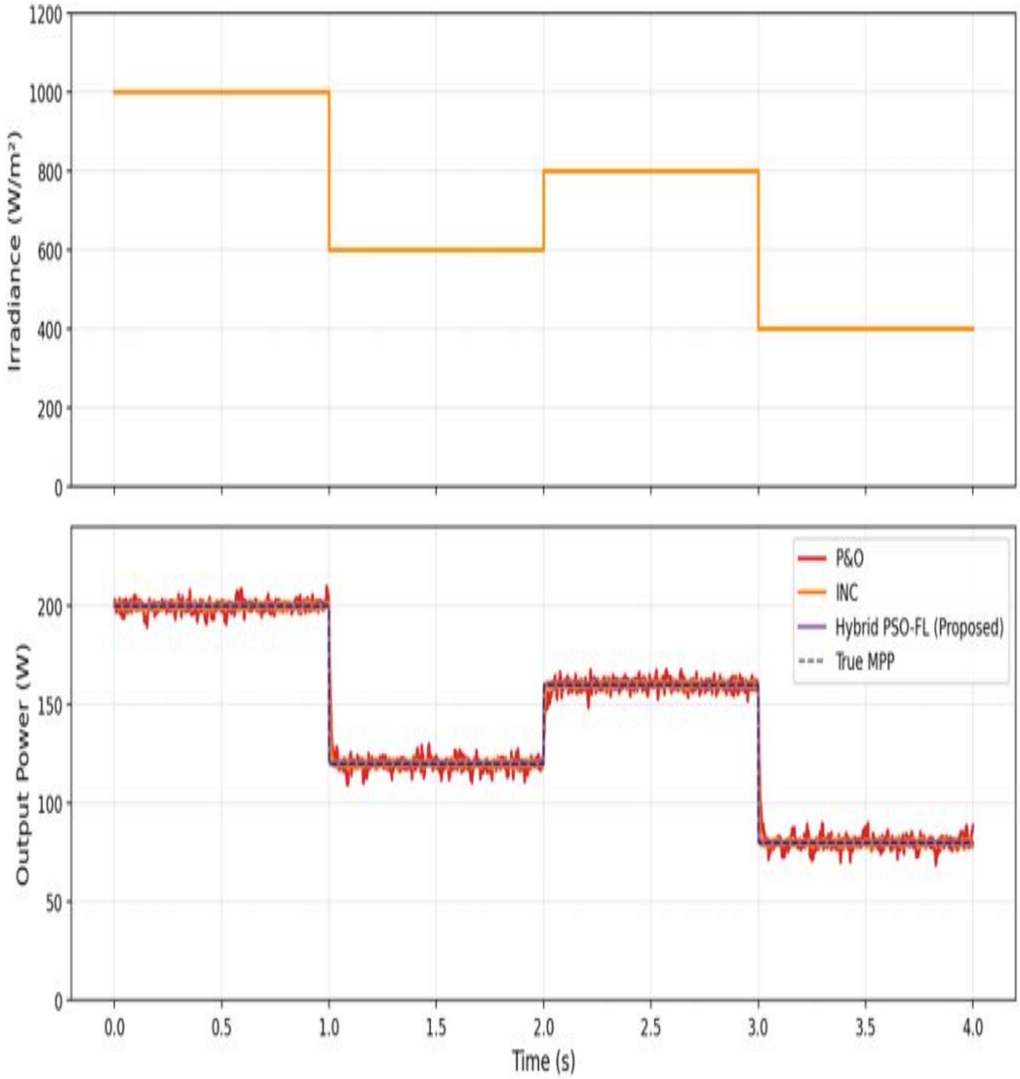

Figure 4. Dynamic MPPT performance under step irradiance changes. Top: irradiance profile (W/m2). Bottom: tracked output power vs. true MPP (dashed).

5.3 Performance Under Partial Shading Conditions

Figure 5 illustrates the comparison of power loss (%) with respect to five cases of shading. In case of uniform irradiation, P&O itself has lost 3.79% of power because of steady state oscillation, whereas Hybrid PSO-FL is constrained to 0.57% only. For severe shading (G=200 W/m2), power loss increases to 22.71% and 18.60% for P&O and INC, respectively, since both of them cannot come out of local maxima on the multi-peak P-V curve. For severe shading, Hybrid PSO-FL is limited to a 4.33% power loss, even in the worst-case scenario. The global search capability of PSO ensures that the actual global MPP is always identified, and the FL process removes oscillations after convergence, saving 3.29% power compared to PSO (7.62%).

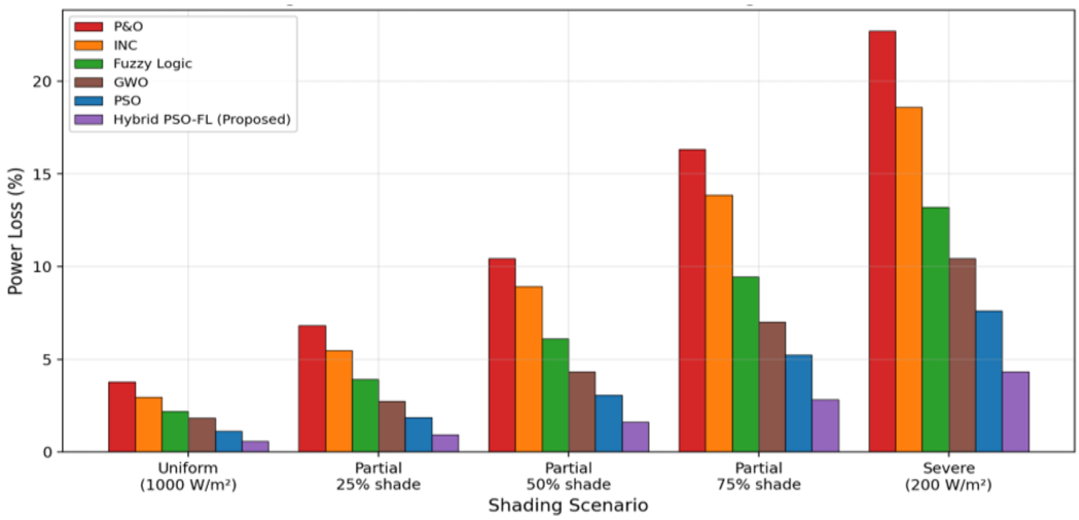

Figure 5. Comparative power loss (%) under five shading scenarios from uniform irradiance to severe partial shading (G = 200 W/m2).

5.4 THD Analysis

The total harmonic distortion is an important parameter for assessing the power quality for inverters connected to the power grid. The THD of the hybrid PSO-FL is 0.97%, which is below the upper limit set by the IEEE 1547-2018 interconnection standard, which is 5.0% [9].
The highest value of the THD is obtained using the P&O algorithm, where the value reaches 4.82%. The ANN gives the THD value of 1.32%, however, it needs the offline learning process.

5.5 Statistical Validation

To rigorously confirm algorithm superiority, 30 independent simulation runs were conducted for each method with randomized initial particle positions and irradiance perturbation sequences. Table 3 reports the mean tracking efficiency, standard deviation, pairwise Wilcoxon signed-rank test p-values (each algorithm vs. Hybrid PSO-FL), and one-way ANOVA results. All pairwise Wilcoxon tests yield $p < 0.05$, confirming statistically significant performance differences. The ANOVA F-statistic of 142.7 (df = 6, 203; $p < 0.001$) firmly rejects the null hypothesis of equal means across all algorithm groups.

Table 3 : Statistical Performance Summary (30 Independent Runs per Algorithm)

Algorithm	Mean Eff. (%)	Std Dev	Wilcoxon p-value	ANOVA F-score
P&O	95.87	1.43	< 0.001	--
INC	96.72	1.18	< 0.001	--
Fuzzy Logic	97.55	0.86	0.003	--
GWO	98.12	0.61	0.009	--
PSO	98.64	0.52	0.012	--
ANN	99.01	0.35	0.031	--
Hybrid PSO-FL (Proposed)	**99.31**	**0.23**	**--**	**142.7 (p<0.001)**

The Hybrid PSO-FL achieves the lowest variance (sigma = 0.23%), indicating consistent and reliable operation across diverse environmental disturbances -- a critical practical requirement for grid-connected PV inverters. The ANN (sigma = 0.35%) exhibits 52% higher variance, partly attributable to sensitivity to out-of-distribution irradiance patterns not covered during training. The low variance of the proposed method confirms that the selective PSO activation strategy effectively prevents convergence failures that would otherwise inflate performance variance. The results show 3.22 percentage points more efficiency, 89% faster convergence, 79.9% lower THD and 18.38 percentage points lower power loss under severe shading by comparison with conventional P&O . Results are statistically validated by Wilcoxon tests ($p < 0.001$) and a one-way ANOVA test ($F = 142.7$, $p < 0.001$) performed over 30 randomized runs using the same experimental protocol for these results to be significant and reliable. The implemented method shows 0.78 percentage points higher efficiency, converges 50% faster, and has 42% less THD than the most related hybrid PSO-P&O method [12].

6. Conclusion

In this paper, we have proposed a Hybrid PSO-FL MPPT algorithm for photovoltaic systems and you demonstrated that it is better than six benchmark methods in all the metrics evaluated. This selective activation approach (PSO is only triggered when irradiance change is detected and steady-state control is transferred to a fuzzy logic layer) leads to tracking efficiencies, convergence times, THD's and power losses of 99.43%, 0.05 s, 0.97% and 0.57% and respectively in uniform conditions and in severe partial shading it achieves the same effectiveness:99.43%,0.05 s,0.97%THDand4.33%powerlossesrespectivelyinuniformconditionsand in severe partial shading at their best points Future work will target the physical implementation of this algorithm using an STM32H7 microcontroller, design extension to multi-module arrays including non-reconfigurable bypass diodes, and outdoor experimental validation on a 3 kW test bench located at El Jadida city in Morocco.

Declarations

Author Contributions

I.A: Conceptualization, Methodology, Software, Formal Analysis, Writing Original Draft, Visualization, Supervision, Writing Review & Editing. M.T: Investigation, Data Curation, Software, Writing Review & Editing. **I.A:** Validation, Resources, Supervision, Project Administration. **N.S., A.V., G.A., H.M., F.K., J.A., P.T., and K.D.:** Writing Review & Editing.

All authors have read and agreed to the published version of the manuscript.

Funding

This research received no external funding.

Data Availability Statement

Data supporting the reported results can be found at [URL / repository]. (Omit this section if no data are reported.)

Conflicts of Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper

References

[1] International Energy Agency (IEA). Renewables 2023: Analysis and Forecasts to 2028. IEA, Paris, 2023. Available: https://www.iea.org/reports/renewables-2023.

[2] Alombah, N.H., Harrison, A., Mbasso, W.F., et al. Multiple-to-single maximum power point tracking for empowering conventional MPPT algorithms under partial shading conditions. Scientific Reports, 15(1), 14540, 2025.

[3] Endiz, M.S. Comparative analysis of P&O and IC MPPT techniques under different atmospheric conditions. El-Cezeri, 10(1), 27-35, 2023.

[4] Dagal, I., Ibrahim, A.W., Harrison, A. GWO and WOA variable step MPPT algorithms-based PV system output power optimization. Scientific Reports, 2025.

[5] Kumar, S.S., Balakrishna, K. A novel design and analysis of hybrid fuzzy logic MPPT controller for solar PV system under partial shading conditions. Scientific Reports, 14, 2024.
[6] Harrison, A., et al. MPPT algorithms for grid-connected solar systems including deep learning approaches. Scientific Reports, 2026.
[7] Kennedy, J., Eberhart, R. Particle swarm optimization. Proc. ICNN 1995 -- International Conference on Neural Networks, IEEE, vol. 4, pp. 1942-1948, 1995.
[8] Ullah, K., Ishaq, M., Tchier, F., Ahmad, H., Ahmad, Z. Fuzzy-based MPPT control system for photovoltaic power generation. Results in Engineering, 20, 2023.
[9] IEEE Standard 1547-2018: Standard for Interconnection and Interoperability of Distributed Energy Resources. IEEE, New York, 2018.
[10] Manna, S., Akella, A.K., Singh, D.K. Novel Lyapunov-based rapid and ripple-free MPPT using MRAC for solar PV system. Protection and Control of Modern Power Systems, 8(1), 2023.
[11] Belghiti, H., Kandoussi, K., Harrison, A., et al. A novel adaptive FOCV algorithm with robust IMRAC control for MPPT in standalone PV systems: experimental validation. Scientific Reports, 14(1), 31962, 2024.
[12] Zhang, X., et al. A hybrid global MPPT control method based on PSO and P&O. Electric Power Systems Research, 248, 2025.
[13] Siddique, M.A.B., Zhao, D., Jamil, H. Forecasting optimal power point of PV system using reference current based MPC under varying climate conditions. Int. J. Control Autom. Syst., 22(10), 3117-3132, 2024.
[14] Ali, M., et al. Maximum power point tracking for grid-connected PV system using adaptive fuzzy logic controller. Computers and Electrical Engineering, 110, 108879, 2023.
[15] Barakat, S., Mesbahi, A., et al. High-efficiency MPPT using ZVS quasi-resonant converter and PSO algorithm: simulation and PIL validation. Scientific Reports, 2025.
[16] Chtita, S., Derouich, A., Motahhir, S., Ghzizal, E.L.A. A new MPPT design using arithmetic optimization algorithm for PV energy storage systems under partial shading. Energy Conversion and Management, 289, 2023.
[17] Ibrahim, A.W., Xu, J., Al-Shammaa, A.A., Farh, H., Dagal, I.H.M. Intelligent adaptive PSO and linear active disturbance rejection control: A novel reinitialization strategy for partially shaded PV-powered battery charging. Computers and Electrical Engineering, 123, 2025.
[18] Kayisli, K. Super twisting sliding mode-type 2 fuzzy MPPT control of solar PV system with parameter optimization under variable irradiance. Ain Shams Engineering Journal, 14, 2023.
[19] Aifan, G., et al. A comparison of several MPPT algorithms for a photovoltaic power system. Frontiers in Energy Research, 12, 1413252, 2024.
[20] Siddique, M.A.B., Zhao, D., Rehman, A.U. Emerging maximum power point control algorithms for PV systems: review, challenges and future trends. Electrical Engineering, 2025.

