

Fuzzy-Supervised INC–ACO–GWO Switching for MPPT of a Photovoltaic System Under Dynamic Irradiance and Partial Shading

Olusesan OREBANJO^{1*}, Ikenna Augustine ONYEGBADUE¹, Stephen Nwachukwu UKAGU¹, Lucky Olatunde ODEJIMI² and Dennis Okwuchukwu OKONKWO¹

¹Department of Electrical and Computer Engineering, College of Engineering, Igbiniedion University Okada, Nigeria.

²Department of Mechanical Engineering, College of Engineering, Igbiniedion University Okada, Nigeria.

Corresponding author email: orebanjosesan@iuokada.edu.ng

Direct Research Journal of Engineering and Information Technology



Vol. 14(3), Pp. 50-68, September 2026

Author(s) retains the copyright of this article

This article is published under the terms of the Creative Commons Attribution License 4.0.

<https://journals.directresearchpublisher.org/index.php/drjeit>; <https://www.ajol.info/index.php/drjeit>

Research Article
ISSN: 2354-4155

Received 9 July 2026; Accepted 27 August 2026; Published 19 September 2026

ABSTRACT

Maximum power point tracking (MPPT) is essential for maximizing energy extraction from photovoltaic (PV) systems under varying irradiance, temperature, and partial-shading conditions. This simulation-based quantitative study presents a fuzzy-logic-supervised hybrid MPPT controller that dynamically switches among Incremental Conductance (INC), Ant Colony Optimization (ACO), and Grey Wolf Optimization (GWO). The controller was implemented in MATLAB/Simulink using a 50-W PV module and a boost converter and compared with standalone INC, ACO, and GWO under dynamic irradiance, temperature variation, and the specified partial-shading condition. Performance metrics included MPPT efficiency, settling time, steady-state oscillation index, tracking error, and simulated energy harvested over the test interval. The proposed controller achieved a reported mean MPPT efficiency of 99.5% (versus 97.8% for INC, 98.2% for ACO, and 98.9% for GWO) and the lowest oscillation index of 0.18% (versus 3.2%, 1.8%, and 1.5%, respectively). Under the specified partial-shading condition it reached 99.46% tracking efficiency. Over the 40-s combined irradiance–temperature simulation, it produced a reported 3.1% increase in simulated energy harvested relative to INC and 1.6% relative to GWO. Although INC recorded the shortest settling time (0.14 s), the proposed controller settled in 0.18 s while providing higher reported efficiency and lower oscillation. These findings are limited to the simulated scenarios; experimental, hardware-in-the-loop, repeated stochastic-run, and computational-cost validation were not established in the supplied study.

Keywords: Photovoltaic system; maximum power point tracking; incremental conductance; ant colony optimization; grey wolf optimization; fuzzy logic; partial shading; boost converter; adaptive control.



Citation: Orebanjo O., Onyegbadue I.A., Ukagu S.N., Odejimi L.O. & Okonkwo D.O. (2026). Fuzzy-Supervised INC–ACO–GWO Switching for MPPT of a Photovoltaic System Under Dynamic Irradiance and Partial Shading. Direct Research Journal of Engineering and Information Technology Vol. 14(3), Pp. 50-68 <https://doi.org/10.4314/drjeit.v14i3.5>

INTRODUCTION

Photovoltaic (PV) systems are an increasingly important component of renewable electricity generation owing to their modularity, scalability, and suitability for distributed and grid-connected applications. Because the electrical characteristics of PV devices are nonlinear and vary with

irradiance and temperature, the operating point that yields maximum power is not fixed. Maximum power point tracking (MPPT) is therefore a fundamental function of PV power-conversion systems (Worku *et al.*, 2023; Saxena *et al.*, 2024). Recent reviews confirm that MPPT remains an

active research area, requiring simultaneous attention to tracking accuracy, convergence speed, steady-state oscillation, computational complexity, and adaptability (Yang *et al.*, 2024).

Under partial-shading conditions (PSC), nonuniform irradiance produces multiple local maxima on the power–voltage (P–V) characteristic, only one of which is the global maximum power point (GMPP). Conventional local-search algorithms can therefore converge to a suboptimal peak. Reviews have identified global-peak identification, transient performance, steady-state oscillation, algorithmic complexity, and adaptability as persistent challenges (Sharma & Jalil, 2024; Ali *et al.*, 2025). Complex shading patterns continue to expose the vulnerability of conventional trackers (Siddique *et al.*, 2025). Architectures capable of distinguishing conditions that require local refinement from those that require global exploration are consequently needed.

Incremental Conductance (INC) remains attractive because of its simple structure and its use of the instantaneous-versus-incremental conductance relationship. Performance, however, depends on step-size selection: a small step reduces oscillation but slows convergence, while a large step improves transient response at the cost of greater steady-state ripple. Comparative studies continue to classify INC among the principal conventional methods while highlighting differences relative to intelligent and metaheuristic approaches (Ali *et al.*, 2025). Adaptive-control research has likewise retained INC as a foundation while adding mechanisms to improve dynamic response (Hafez *et al.*, 2025). These limitations have motivated the use of global optimization techniques.

Ant Colony Optimization (ACO) has been investigated as a metaheuristic MPPT strategy because its population-based search can explore alternative operating regions and concentrate around higher-power locations. Phanden *et al.* (2021) demonstrated a modified ACO-based MPPT controller in MATLAB/Simulink, and more recent comparative work continues to include ACO among global-search approaches under partial shading (Yousaf *et al.*, 2025). ACO nevertheless incurs a computational burden when repeated global searches are performed after the operating point has already stabilized, motivating supervisory mechanisms that activate global optimization only when necessary.

Grey Wolf Optimization (GWO) has attracted substantial attention for global MPPT because its exploration–exploitation mechanisms suit multimodal PV characteristics. Alshareef (2024) demonstrated GWO-based GMPP search under partial shading; Nagarathinam *et al.* (2024) reported improved power extraction with a Differential Grey Wolf approach; and Abdelmalek *et al.* (2024) experimentally validated a hybrid Grey Wolf Equilibrium Optimization strategy. These studies confirm GWO's global-search capability while underscoring the need to balance exploration, convergence speed, computational cost, and steady-state stability. (Gundogdu

et al., 2024). Fuzzy logic has been incorporated into MPPT because it can represent nonlinear control relationships without an exact analytical model of the operating environment. Kumar and Balakrishna (2024) evaluated a hybrid fuzzy-logic MPPT controller under partial shading; Xia *et al.* (2024) combined ACO with fuzzy logic (Ant-Fuzzy Optimization); Melhaoui *et al.* (2025) investigated a hybrid fuzzy approach under dynamic conditions; and Ortiz-Munoz *et al.* (2025) combined fuzzy logic with deep deterministic policy gradient learning. Elnaghi *et al.* (2025) further provided experimental validation of an adaptive fuzzy controller on a dSPACE platform. Fuzzy supervision can therefore adapt controller behaviour to operating conditions, although its effectiveness depends on membership-function design, the rule base, and interaction with the underlying MPPT algorithms (Belghiti *et al.*, 2024).

Hybridization of conventional and metaheuristic methods has become an important research direction because the two classes possess complementary strengths. Shetty and Sabhahit (2024) developed a GWO–INC hybrid in which GWO performed broad search and INC performed subsequent tracking. Yousaf *et al.* (2025) compared ACO, GWO, Cuckoo Search, P&O, PSO and a hybrid PSO strategy, while Jamaludin *et al.* (2025) proposed a hybrid salp-swarm algorithm for highly fluctuating conditions. Wei and Li (2025), Gui *et al.* (2025) and Chiu and Chen (2025) have likewise advanced coordinated or specialized global-search strategies for multi-peak P–V characteristics. The central design question is therefore how different search mechanisms should be coordinated so that global optimization is used only when required. An intelligent supervisory mechanism can assign different algorithms different operating roles rather than executing them continuously. Such an architecture can exploit the low computational burden of INC under stable conditions while activating ACO or GWO when large disturbances or partial shading increase the likelihood of multiple maxima. Condition-dependent coordination is supported by the Ant-Fuzzy work of Xia *et al.* (2024), the fuzzy-assisted MPPT of Kumar and Balakrishna (2024), and other adaptive studies (Elnaghi *et al.*, 2025). Despite these advances, the specific coordination of INC, ACO and GWO as three alternative operating modes under a single fuzzy supervisory framework remains insufficiently explored.

Existing research has examined individual algorithms, pairwise hybrids, or specialized metaheuristics (Shetty & Sabhahit, 2024; Xia *et al.*, 2024; Celikel *et al.*, 2026; Chiu & Chen, 2025; Gui *et al.*, 2025), but not a three-mode supervisory selection among INC, ACO and GWO. The present study addresses this gap by treating INC, ACO and GWO as complementary control modes. A fuzzy supervisor evaluates real-time indicators of operating condition and selects the most appropriate algorithm, thereby realizing a fuzzy-supervised three-strategy MPPT system. The central hypothesis is that condition-dependent selection yields a more effective balance

among tracking efficiency, dynamic response, steady-state stability, global-peak identification and computational demand than any single fixed strategy. The architecture is implemented in MATLAB/Simulink with a 50 W PV module and boost converter and is evaluated under irradiance, temperature and partial-shading variations, consistent with the broader movement toward adaptive and intelligent MPPT systems (Rukhsar *et al.*, 2025; Tyokighir *et al.*, 2025).

The principal contribution is therefore not the individual use of INC, ACO, GWO or fuzzy logic—all established techniques—but the development and evaluation of their specific fuzzy-supervised coordination as a three-mode adaptive MPPT architecture. The novelty claim is specifically the condition-dependent selection among three alternative operating modes, rather than a simple sequential hybridization of two algorithms. Recent studies provide close precedents: Shetty and Sabhahit (2024) combine GWO with INC in a sequential global-search/local-refinement structure; Xia *et al.* (2024) combine ACO with fuzzy logic; and recent 2025–2026 studies continue to develop adaptive or hybrid global-search strategies. The present architecture differs by allowing fuzzy supervision to select among INC, ACO, and GWO as alternative modes. A structured comparison of representative recent studies is provided in Appendix B.

Aim and Objectives

Aim: To develop and evaluate, through controlled MATLAB/Simulink simulation, a fuzzy-supervised MPPT architecture that selects among INC, ACO, and GWO according to changing PV operating conditions.

Objectives: (i) develop the fuzzy supervisor and its three-mode selection mechanism; (ii) implement INC, ACO, and GWO as comparable standalone controllers and as supervised operating modes; (iii) evaluate the controllers under dynamic irradiance, the specified partial-shading condition, and combined irradiance–temperature disturbance; (iv) quantify MPPT efficiency, tracking error, settling time, steady-state oscillation, and simulated energy harvested; and (v) examine the observed switching behaviour and identify the remaining validation requirements for practical implementation.

Research question/hypothesis: Under the tested simulation conditions, does condition-dependent fuzzy selection among INC, ACO, and GWO provide a better overall balance of tracking efficiency, global-peak identification, settling response, and steady-state stability than any of the three standalone controllers?

Materials and Methods

Research Design

This study used a controlled comparative computational experiment based on MATLAB/Simulink simulation. The simulation model/system under study was a 50-W

photovoltaic source coupled to a DC–DC boost converter and resistive load, evaluated with four controller configurations: standalone INC, standalone ACO, standalone GWO, and the proposed fuzzy-supervised INC–ACO–GWO controller. The same principal PV and converter parameters and disturbance profiles were used for the four configurations to support a consistent comparison. No human participants or field measurements were involved. The evidence therefore represents simulation performance under the defined test conditions rather than experimental or field validation.

System Configuration and Control Architecture

A simulation-based investigation was conducted to evaluate a fuzzy-supervised hybrid maximum power point tracking (MPPT) controller for a photovoltaic (PV) energy-conversion system. The proposed architecture integrates three complementary MPPT strategies—Incremental Conductance (INC), Ant Colony Optimization (ACO), and Grey Wolf Optimization (GWO)—under the supervision of a singleton-output fuzzy inference system (FIS). The fuzzy supervisor determines the MPPT strategy to be activated according to the instantaneous operating condition of the PV system.

The simulated system comprises a 50-W Sunshine Solar PV module, a unidirectional DC–DC boost converter, the proposed supervisory MPPT controller, a pulse-width modulation (PWM) unit, and a resistive load. PV voltage and current are measured and used to calculate instantaneous PV power and the operating-condition indicators required by the fuzzy supervisor. The overall control objective is to regulate the PV operating point toward the available maximum power while maintaining stable operation during irradiance, temperature, and partial-shading disturbances. The controller was evaluated as a simulation model/system; the supplied manuscript does not identify a separate physical prototype or experimental measurement campaign.

As shown in Figure 1, irradiance and temperature are applied to the PV model, which produces the terminal voltage and current. The measured electrical variables are used to calculate PV power and its variation, while changes in irradiance and the voltage deviation from the estimated maximum-power-point voltage are supplied to the fuzzy supervisor. The supervisor produces an algorithm-selection signal $S \in \{1, 2, 3\}$, corresponding to INC, ACO, and GWO, respectively. The selected algorithm supplies the active duty-cycle command, which is constrained to the allowable range and converted into a 20-kHz PWM signal for the boost converter. The resulting converter response changes the PV operating point, closing the feedback loop.

Photovoltaic Module Model

A 50-W Sunshine Solar PV module was used as the photovoltaic source. The principal electrical parameters

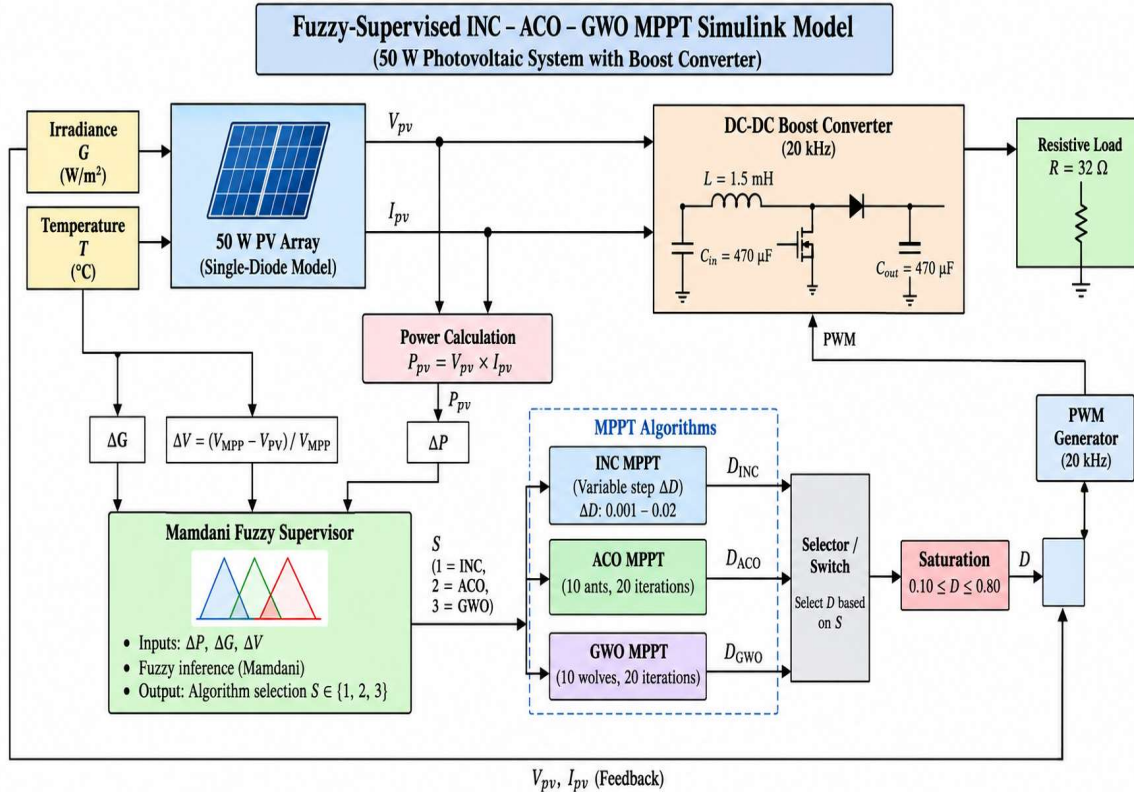


Figure 1. MATLAB/Simulink implementation and control architecture of the proposed fuzzy-supervised INC-ACO-GWO MPPT system.

Table 1. Electrical parameters of the 50-W PV module used in the simulation.

Parameter	Value
Maximum power, $P_{\max}$	50 W
Voltage at maximum power, V_{mp}	19.32 V
Current at maximum power, I_{mp}	2.59 A
Open-circuit voltage, V_{oc}	23.15 V
Short-circuit current, I_{sc}	2.78 A
Reference irradiance, G_{ref}	1000 W/m ²
Reference temperature, T_{ref}	25 °C

used in the model are presented in Table 1. The module was represented using a single-diode equivalent model incorporating photocurrent, diode saturation current, series resistance, and shunt resistance. The instantaneous PV output power was calculated from the measured terminal voltage and current. The supplied manuscript identifies the source as a Sunshine Solar 50-W module but does not provide a model number or manufacturer datasheet identifier; no model identity beyond this description has been inferred. (Batzelis, 2017).

$$P_{pv}(k) = V_{pv}(k) I_{pv}(k) \quad (1)$$

Where P_{pv} is the instantaneous PV power, V_{pv} is the PV terminal voltage, and I_{pv} is the PV terminal current.

$$I_{pv} = I_{ph} - I_0 \{ \exp[(V_{pv} + I_{pv}R_s)/(nV_t)] - 1 \} - (V_{pv} + I_{pv}R_s)/R_{sh} \quad (2)$$

$$V_t = kT/q \quad (3)$$

$$I_{ph} = [I_{sc} + K_i(T - T_{ref})] (G/G_{ref}) \quad (4)$$

$$I_{rs} = I_{sc} / \{ \exp[qV_{oc}/(nkT_{ref})] - 1 \} \quad (5)$$

$$I_0 = I_{rs} (T/T_{ref})^3 \exp\{ [qE^g/(nk)](1/T_{ref} - 1/T) \} \quad (6)$$

The symbols have their conventional meanings: k is the Boltzmann constant, q is the elementary charge, n is the diode ideality factor, R_s and R_{sh} are the series and shunt resistances, G is solar irradiance, T is cell temperature, K_i is the short-circuit-current temperature coefficient, E^g is the semiconductor band-gap energy, and I_0 is the diode reverse-saturation current. At the rated operating point, the module maximum power is obtained from $P_{\max} = V_{mp}I_{mp}$. $P_{\max} = V_{mp}I_{mp} = 19.32 \times 2.59 \approx 50 \text{ W}$ (7)

DC-DC Boost Converter

A unidirectional DC-DC boost converter operating in continuous conduction mode (CCM) was used to interface the PV module with the resistive load. The switching

frequency was set to 20 kHz and the nominal output voltage was 40 V. Under ideal steady-state CCM operation, the relationship between PV input voltage, output voltage, and duty cycle is given by:

$$V_o = V_{pv}/(1 - D) \quad (8)$$

$$D = 1 - V_{pv}/V_o \quad (9)$$

$$D_{nom} = 1 - 19.32/40 \approx 0.517 \quad (10)$$

For the converter design, a target inductor-current ripple of approximately 20% of the rated PV current was used. The inductance was estimated from the CCM relationship and a practical ripple of 1.5 mH was selected to provide additional ripple margin.

$$\Delta I_L = V_{pv}D/(Lf_s) \quad (11)$$

$$L = V_{pv}D/(\Delta I_L f_s) \quad (12)$$

$$\Delta I_L = 0.20 I_{mp} = 0.518 \text{ A} \quad (13)$$

With $L = 1.5 \text{ mH}$, the calculated inductor-current ripple is approximately 0.33 A. At the rated 50-W operating condition, the nominal output current is 1.25 A. The supplied manuscript does not document explicit ESR, semiconductor conduction-loss, switching-loss, or other parasitic models; the conclusions should therefore be interpreted as idealized converter-level simulation results rather than loss-inclusive hardware predictions.

$$I_o = P_o/V_o = 50/40 = 1.25 \text{ A} \quad (14)$$

$$\Delta V_o \approx I_o D/(C_o f_s) \quad (15)$$

$$C_o = I_o D/(f_s \Delta V_o) \quad (16)$$

$$\Delta V_o = 0.01 V_o = 0.4 \text{ V} \quad (17)$$

$$C_o \approx 81 \mu\text{F} \text{ (theoretical minimum)} \quad (18)$$

$$R_L = V_o^2/P_o = 40^2/50 = 32 \Omega \quad (19)$$

The resulting boost-converter design parameters are summarized in Table 2

Table 2. Boost-converter parameters used in the simulation.

Converter parameter	Value
PV rated power	50 W
PV operating voltage	19.32 V
PV operating current	2.59 A
Converter output voltage	40 V
Switching frequency	20 kHz
Nominal duty cycle	0.517
Inductor	1.5 mH
Input capacitor	470 μF
Output capacitor	470 μF
Nominal output current	1.25 A
Equivalent load	32 Ω

Incremental Conductance MPPT

The Incremental Conductance (INC) algorithm determines the maximum power point from the slope of the PV power–

voltage characteristic. Since $P_{pv} = V_{pv}I_{pv}$, differentiation with respect to voltage gives:

$$dP_{pv}/dV_{pv} = I_{pv} + V_{pv}(dI_{pv}/dV_{pv}) \quad (20)$$

$$dI_{pv}/dV_{pv} = -I_{pv}/V_{pv} \text{ at the MPP} \quad (21)$$

$$\Delta V(k) = V(k) - V(k-1) \quad (22)$$

$$\Delta I(k) = I(k) - I(k-1) \quad (23)$$

$$\Delta I/\Delta V = -I/V \text{ at the MPP} \quad (24)$$

A variable duty-cycle step was employed so that larger corrections are applied when the operating point is farther from the MPP and smaller corrections are applied near the optimum. The step size is bounded between 0.001 and 0.02, and the duty cycle is constrained to 0.10–0.80.

$$\Delta D = \Delta D_{min} + (\Delta D_{max} - \Delta D_{min})|\Delta P|/|\Delta P|_{max} \quad (25)$$

$$\Delta D_{min} = 0.001, \Delta D_{max} = 0.02 \quad (26)$$

$$0.10 \leq D(k) \leq 0.80 \quad (27)$$

The INC controller updates the MPPT decision every 1 ms, while the boost converter operates at 20 kHz. (Figure 2)

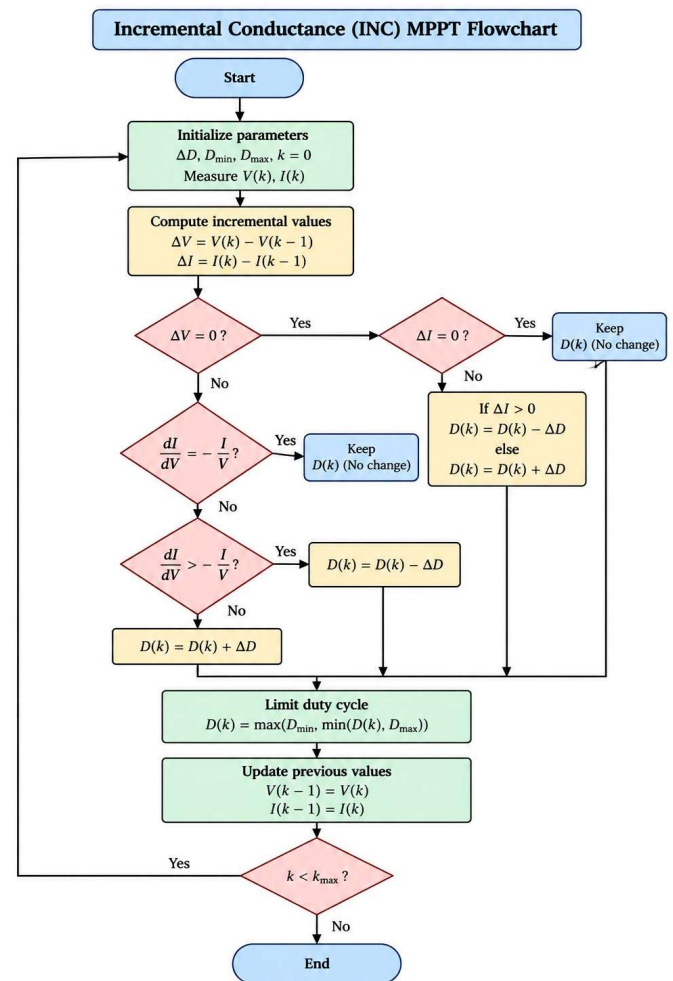


Figure 2. Flowchart of the Incremental Conductance (INC) MPPT algorithm.

Ant Colony Optimization MPPT

The Ant Colony Optimization (ACO) controller searches for the duty cycle associated with high PV power. Each ant represents a candidate duty-cycle solution within the allowable converter range. Candidate solutions are evaluated using the corresponding PV power, after which pheromone information and selection probabilities are updated to concentrate the search around higher-performing regions.

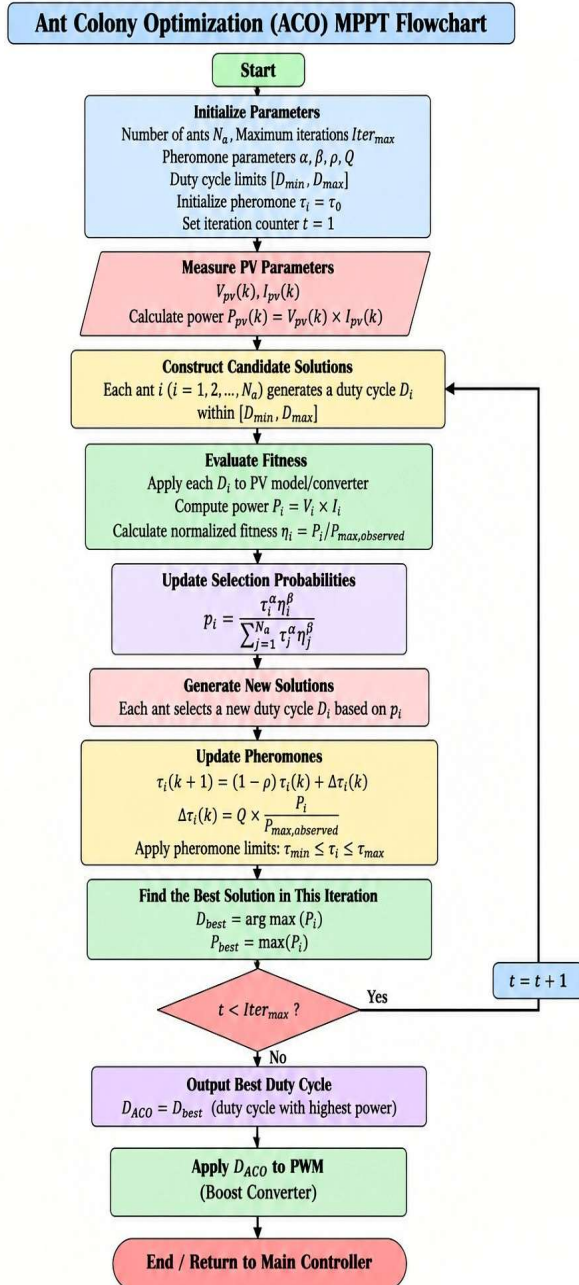


Figure 3. Flowchart of the Ant Colony Optimization (ACO) MPPT algorithm.

$$D_i \in [0.10, 0.80] \quad (28)$$

$$\eta_i = P_i / P_{max,observed} \quad (29)$$

$$p_i = \tau_i^\alpha \eta_i^\beta / \sum_{j=1}^{N_a} \tau_j^\alpha \eta_j^\beta \quad (30)$$

$$\tau_i(k+1) = (1-\rho)\tau_i(k) + \Delta\tau_i(k) \quad (31)$$

$$\Delta\tau_i(k) = Q \frac{P_i}{P_{max,observed}} \quad (32)$$

In the present implementation $P_{max,observed}$ is defined as the highest instantaneous PV power encountered by any ant during the current ACO search episode (i.e., the running maximum of P_i over the 10 ants and up to 20 iterations). It is re-initialised at the start of every new ACO activation so that the normalisation remains local to the present operating condition. This avoids dependence on the fixed module rating and automatically adapts the heuristic information to the power level available under the prevailing irradiance and temperature.

$$N_{eval} = N_a N_{iter} = 10 \times 20 = 200 \quad (33)$$

The ACO parameters were set to 10 ants, 20 maximum iterations, pheromone evaporation rate, initial pheromone, and pheromone bounds of 0.01–1.0. The ACO procedure is summarized in Figure 3.

Grey Wolf Optimization MPPT

The Grey Wolf Optimization (GWO) controller searches the allowable duty-cycle interval using a population of candidate solutions, referred to as wolves. At each iteration, the three best solutions are designated alpha(α), beta (β), and delta (δ), and the remaining candidates are updated relative to these leading solutions.

$$D_i \in [0.10, 0.80] \quad (34)$$

$$A = 2ar_1 - a \quad (35)$$

$$C = 2r_2 \quad (36)$$

$$X_p = |CD_p - D_i| \quad (37)$$

$$D'_p = D_p - AX_p \quad (38)$$

$$D_i(t+1) = (D'\alpha + D'\beta + D'\delta)/3 \quad (39)$$

$$a(t) = 2 - 2t/N_{iter} \quad (40)$$

The GWO population comprised 10 wolves and the maximum number of iterations was 20. The coefficient a decreased linearly from 2 to 0 over the optimization process. The resulting best duty cycle was used as the GWO control command. The GWO procedure is summarized in Figure 4.

Fuzzy Supervisory Controller

A singleton-output fuzzy inference system (FIS) was developed to select the MPPT strategy most appropriate to the prevailing PV operating condition. Three normalized input variables were used: PV power variation (ΔP), irradiance variation (ΔG), and relative PV-voltage deviation from the maximum-power-point voltage (ΔV). The normalization equations are $x_1 = \Delta P / P_{rated}$, $x_2 =$

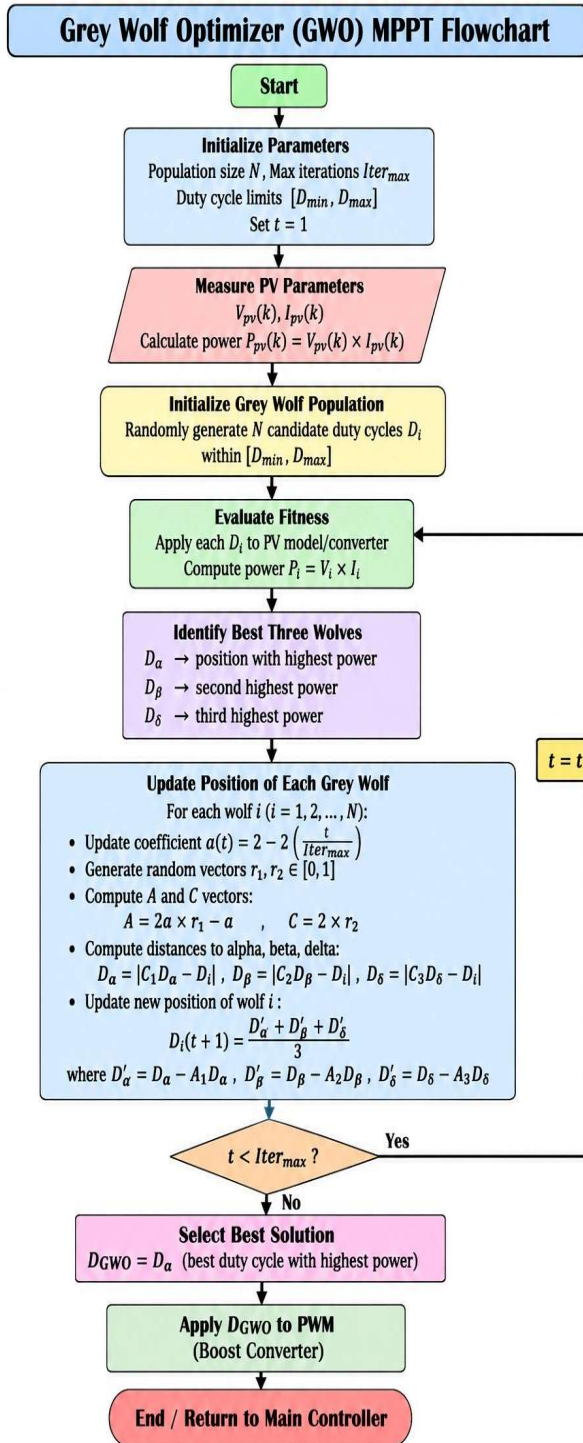


Figure 4. Flowchart of the Grey Wolf Optimization (GWO) MPPT algorithm.

$\Delta G/G_{ref}$, and $x_3 = (V_{MPP} - V_{PV})/V_{MPP}$. The normalized variables are evaluated over the fuzzy universe $[-1, 1]$. The supplied manuscript does not document an independent scaling constant, noise filter, or zero-

denominator handling rule beyond these definitions; these implementation details should be retained explicitly in the executable model and supplementary documentation.

$$x_1 = \Delta P/P_{rated} \quad (41)$$

$$x_2 = \Delta G/G_{ref} \quad (42)$$

$$x_3 = (V_{mpp} - V_{pv})/V_{mpp} \quad (43)$$

Each input variable uses five triangular linguistic membership functions: NL (negative large), NS (negative small), ZE (zero), PS (positive small), and PL (positive large). The three inputs share the same numerical partition over the normalised universe $[-1, 1]$. The membership functions are defined by NL = $(-1.00, -0.75, -0.40)$, NS = $(-0.60, -0.30, 0.00)$, ZE = $(-0.25, 0.00, 0.25)$, PS = $(0.00, 0.30, 0.60)$, and PL = $(0.40, 0.75, 1.00)$, where each triplet denotes the left base, peak, and right base of the triangular membership function.

$$\mu(x) = \max\{0, \min[(x - a)/(b - a), (c - x)/(c - b)]\} \quad (44)$$

The rule base associates relatively stable conditions with INC and larger changes in irradiance, power, or voltage with ACO or GWO. The documented representative rules are ZE-ZE-ZE $\rightarrow$ INC, PS-ZE-NS $\rightarrow$ INC, PS-PS-PS $\rightarrow$ ACO, PL-PS-PS $\rightarrow$ ACO, PL-PL-PL $\rightarrow$ GWO, and ZE-PL-PL $\rightarrow$ GWO. The complete 125-rule $(5 \times 5 \times 5)$ matrix is reproduced in Table A4-1, Appendix A. The rule assignments should be interpreted as the implemented expert-defined selection logic; the supplied manuscript does not report a separate formal optimization or sensitivity study for the membership breakpoints. The supervisor structure is summarized in (Table 3).

For the singleton consequents, INC, ACO, and GWO are assigned crisp output values $z = 1.0, 2.0$, and 3.0 , respectively. The crisp supervisor signal is obtained by the weighted-centroid (singleton) defuzzification equation:

$$y = \sum_i \mu_i z_i / \sum_i \mu_i \quad (45)$$

The algorithm-selection regions were defined as INC for $1.00 \leq y < 1.67$, ACO for $1.67 \leq y < 2.33$, and GWO for $2.33 \leq y \leq 3.00$. To reduce unnecessary mode changes, the controller switches only when $|y_{new} - y_{old}| \geq 0.10$ and enforces a minimum dwell time of 10 ms. Thus, the implemented switching logic can be written as $|y_{new} - y_{old}| \geq 0.10$ together with $T_{dwell} = 10 \text{ ms}$. Boundary cases are resolved by the stated interval definitions, while the dwell requirement limits rapid repeated switching.

$$|y_{new} - y_{old}| > 0.10 \quad (46)$$

Table 3. Structure of the singleton-output fuzzy supervisor.

Variable parameter	Linguistic values / definition	Numerical specification	Role
ΔP	NL, NS, ZE, PS, PL	Universe $[-1, 1]$; NL $(-1.00, -0.75, -0.40)$; NS $(-0.60, -0.30, 0.00)$; ZE $(-0.25, 0.00, 0.25)$; PS $(0.00, 0.30, 0.60)$; PL $(0.40, 0.75, 1.00)$	Detects power change
ΔG	NL, NS, ZE, PS, PL	Universe $[-1, 1]$; same five triangular membership functions and breakpoints as ΔP	Detects irradiance change
ΔV	NL, NS, ZE, PS, PL	Universe $[-1, 1]$; same five triangular membership functions and breakpoints as ΔP	Indicates voltage deviation from VMPP
FIS output y	INC, ACO, GWO	Output universe $[1, 3]$; INC = 1.0; ACO = 2.0; GWO = 3.0	Selects active MPPT mode
Decision regions	INC, ACO, GWO	INC: $1.00 \leq y < 1.67$; ACO: $1.67 \leq y < 2.33$; GWO: $2.33 \leq y \leq 3.00$	Maps crisp FIS output to MPPT algorithm
Anti-chattering	—	Switch only when $ y_{new} - y_{old} > 0.10$; minimum dwell time = 10 ms	Reduces unnecessary mode changes

$$T_{dwell} = 10 \text{ ms} \quad (47)$$

Proposed Fuzzy-Supervised Hybrid MPPT Controller

The proposed hybrid controller treats INC, ACO, and GWO as alternative MPPT operating modes rather than executing all three algorithms as a sequential cascade. The fuzzy supervisor determines which algorithm supplies the active converter duty cycle according to the detected operating condition. The complete supervisory sequence is summarized in Figure 5.

$$S(k) = 1 \rightarrow \text{INC}; S(k) = 2 \rightarrow \text{ACO}; S(k) = 3 \rightarrow \text{GWO} \quad (48)$$

$$D(k) = \{ D_{\text{INC}}(k), S = 1; D_{\text{ACO}}(k), S = 2; D_{\text{GWO}}(k), S = 3 \} \quad (49)$$

$$D_{\text{out}}(k) = \min[0.80, \max(0.10, D(k))] \quad (50)$$

Under relatively stable conditions, INC provides low-complexity local tracking. When larger operating changes or partial shading increase the likelihood of multiple power maxima, ACO or GWO can be activated to provide broader search capability. After selection, the duty cycle is saturated to the allowable range before PWM generation. This supervisory arrangement therefore provides an exploration–exploitation mechanism in which global-search algorithms are invoked when required and local tracking is retained when conditions permit.

MATLAB/Simulink Implementation

The complete controller was implemented in MATLAB/Simulink by integrating the PV model, boost converter, measurement and power-calculation blocks, INC controller, ACO controller, GWO controller, fuzzy supervisor, duty-cycle selector, saturation block, and PWM generator into a single closed-loop simulation environment. The MPPT control update interval was 1 ms, whereas the converter switching frequency was 20 kHz. The duty-cycle command supplied to the PWM stage was constrained to 0.10–0.80. The principal controller parameters are summarized in Table 4.

The same PV parameters, converter parameters, initial conditions, and disturbance profiles were applied to the standalone INC, ACO, and GWO controllers and to the

Table 4. Principal simulation and controller parameters.

Parameter	Value
PV rated power	50 W
V_{mp}	19.32 V
I_{mp}	2.59 A
V_{oc}	23.15 V
I_{sc}	2.78 A
Boost output voltage	40 V
Switching frequency	20 kHz
Inductor	1.5 mH
Input capacitor	470 μF
Output capacitor	470 μF
Equivalent load	32 Ω
MPPT sampling time	1 ms
Duty-cycle range	0.10–0.80
INC minimum step	0.001
INC maximum step	0.02
ACO population	10 ants
ACO maximum iterations	20
ACO α	1.0
ACO β	2.0
ACO evaporation rate	0.50
GWO population	10 wolves
GWO maximum iterations	20
GWO initial	2
GWO final	0
Fuzzy sampling time	1 ms

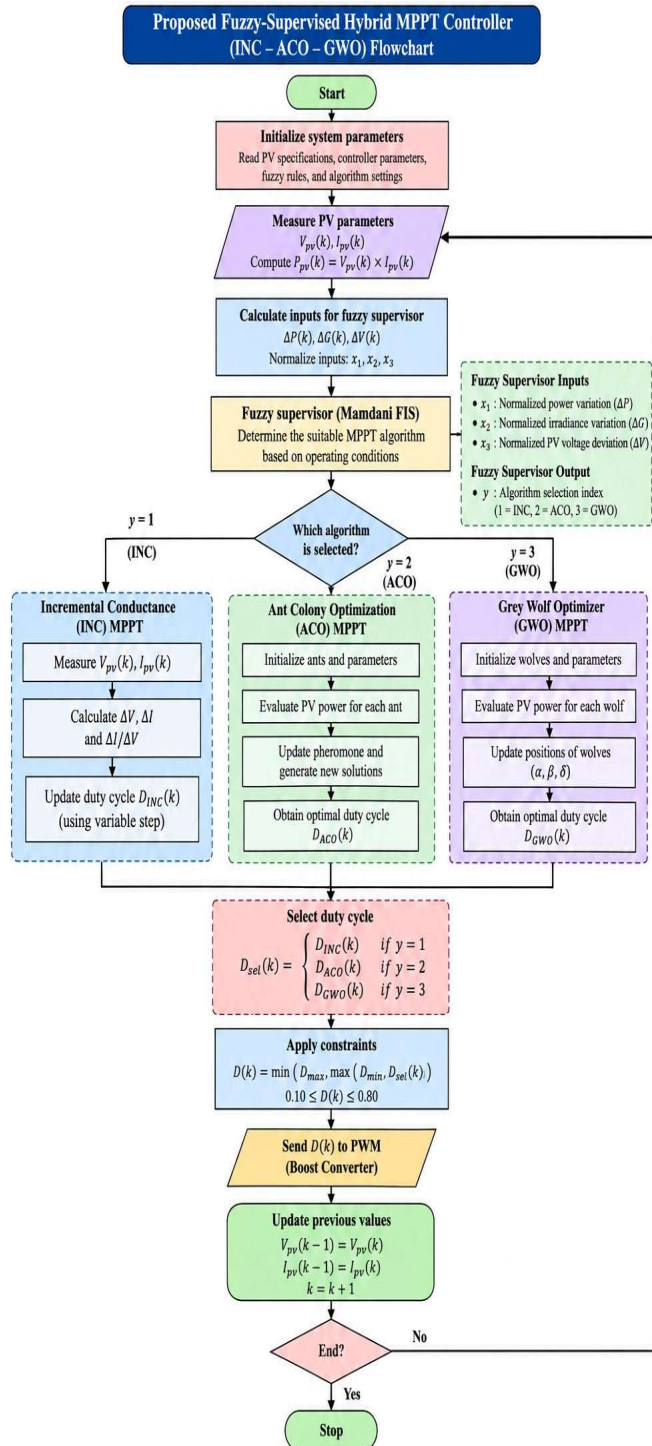
proposed hybrid controller to ensure a consistent basis for comparison. The supplied manuscript does not record the MATLAB/Simulink release, solver name, numerical solver step, or random seeds. Accordingly, these values are not inferred or fabricated in this revision and should be added from the executable model before submission. The 1-ms MPPT update is treated as the discrete controller update interval, while the converter switching frequency is 20 kHz.

Simulation Scenarios and Operating Conditions

The controllers were evaluated under uniform irradiance changes, partial shading, temperature variation, and combined irradiance–temperature disturbances. The irradiance range considered in the study was 200–1000 W/m^2 and the temperature range was 15–55 $^{\circ}\text{C}$. The principal uniform-irradiance sequence was $600 \rightarrow 1000 \rightarrow 400 \text{ W/m}^2$, with temperature initially held constant. For the partial-shading tests the 50 W module was represented as three series-connected substrings of equal cell count. Under the shading pattern used in this study, one substring received an irradiance of 400 W/m^2 while the other two

Table 5. Simulation test scenarios and operating conditions.

Scenario	Operating condition	Purpose
Uniform irradiance transition	600 → 1000 → 400 W/m ² ; temperature initially constant	Dynamic tracking response
Partial shading	Three series-connected substrings: one at 400 W/m ² ; two at 1000 W/m ² ; T = 25 °C; GMPP = 43.0 W	Global-maximum identification
Combined disturbance	G: 400 → 1000 W/m ² (10–25 s); T: 25 → 50 °C	Adaptive response to simultaneous changes
Operating range	G: 200–1000 W/m ² ; T: 15–55 °C	Defined simulation range



substrings received 1000 W/m² (temperature held at 25 °C). This non-uniform irradiance produces a multi-peak P–V characteristic whose global maximum power point (GMPP) is 43.0 W. All four controllers were evaluated against this GMPP. In the combined-disturbance test, irradiance increased from 400 to 1000 W/m² between 10 and 25 s while temperature increased from 25 to 50 °C. The scenario matrix is summarized in Table 5.

Performance Evaluation Metrics

Controller performance was assessed using MPPT efficiency, tracking error, mean tracked power, standard deviation of tracked power, simulated energy harvested, oscillation index, and settling time. The same definitions and evaluation intervals were applied to all four controllers.

$$\eta_{MPPT} = (P_{tracked}/P_{MPP}) \times 100 \quad (51)$$

$$E_{MPPT} = |P_{MPP} - P_{tracked}|/P_{MPP} \times 100 \quad (52)$$

$$P = (1/N) \sum_{k=1}^N P(k) \quad (53)$$

$$\sigma_P = \sqrt{[\sum_{k=1}^N (P(k) - P)^2 / (N - 1)]} \quad (54)$$

$$E = \int_{t_1}^{t_2} P(t) dt \quad (55)$$

$$OI = (\sigma_P/P) \times 100 \quad (56)$$

$$T_S = t_s - t_o \quad (57)$$

MPPT efficiency represents the ratio of tracked PV power to the available maximum power, expressed as $\eta_{MPPT} = (P_{tracked}/P_{MPP}) \times 100$. Mean MPPT efficiency is the arithmetic mean of the instantaneous efficiency values over the stated evaluation interval. Tracking error is $E_{MPPT} = |P_{MPP} - P_{tracked}|/P_{MPP} \times 100$. Mean power and standard deviation characterize average power and temporal variability. Simulated energy harvested is obtained by integrating instantaneous PV power over the specified evaluation interval. The oscillation index is $OI = (\sigma_P/P) \times 100$ and should be interpreted as a temporal variability measure, not as inter-run uncertainty. Figure 21 uses the final 5 s for the ripple-spectrum display. Settling time is the interval from a disturbance or operating-point change to the time at which PV power remains within the prescribed tolerance band around the MPP. Percentage-point differences are reported as percentage points; relative reductions are reported as percent change.

Because the present evaluation is based on the supplied deterministic MATLAB/Simulink simulation results, no independent replicate runs, confidence intervals, or inferential statistical tests were reported. The standard deviations in Table 9 therefore describe temporal variation in the reported simulation traces rather than uncertainty

Figure 5. Flowchart of the proposed fuzzy-supervised INC–ACO–GWO MPPT control strategy.

across independent runs. ACO and GWO are metaheuristic methods and may exhibit stochastic behaviour when random initialization is enabled; the supplied manuscript does not retain a documented seed policy. Independent repeated runs should therefore be added before making claims about stochastic repeatability.

Results

The performance of the INC, ACO, GWO, and proposed fuzzy-supervised hybrid controllers was evaluated in MATLAB/Simulink under the irradiance, temperature, and partial-shading conditions defined in Section 2.11. The quantitative results are summarized in Tables 6–9 and discussed in the following subsections.

Dynamic Response under Irradiance Variation

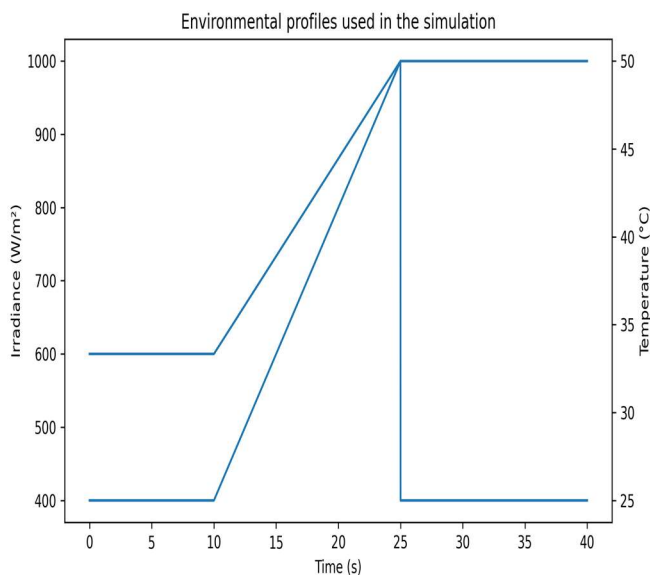


Figure 6. Environmental profiles used in the simulation: irradiance and temperature.

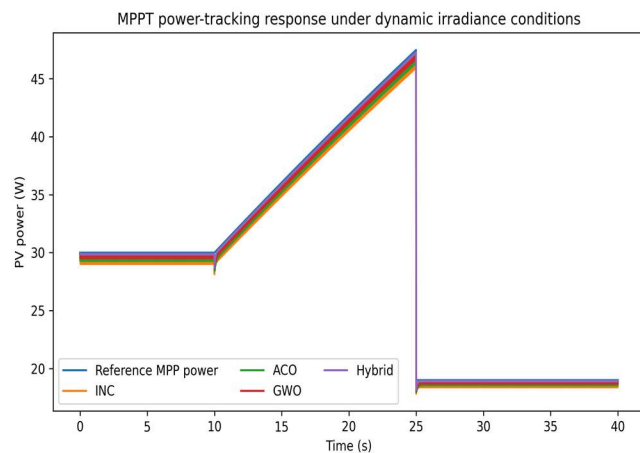


Figure 7. MPPT power-tracking response under dynamic irradiance conditions.

The controllers were first evaluated under a stepwise irradiance profile of $600 \rightarrow 1000 \rightarrow 400 \text{ W/m}^2$, with temperature initially maintained at a constant level. The environmental profile is shown in Figure 6, and the corresponding PV power responses are presented in Figure 7. All four controllers responded to the irradiance transitions, although differences were observed in transient convergence and steady-state regulation.

The INC controller exhibited the shortest reported settling time, indicating rapid local adjustment following the irradiance transitions. However, its response was associated with greater steady-state variation. ACO and GWO provided broader search capability but required longer convergence periods. The proposed fuzzy-supervised controller dynamically coordinated the three algorithms, combining global-search capability during operating changes with local refinement after the operating region had been identified. (Figure 8)

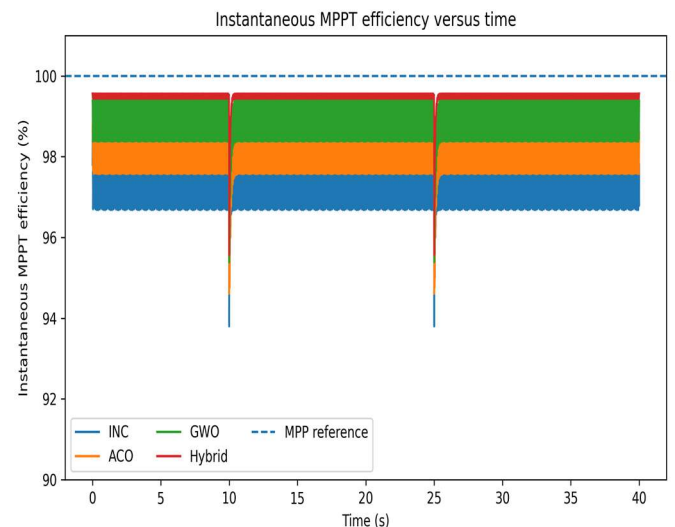


Figure 8. Instantaneous MPPT efficiency versus time for INC, ACO, GWO, and the proposed hybrid controller.

The reported performance values are summarized in Table 6. The proposed controller achieved the highest reported tracking efficiency of 99.5%, followed by GWO (98.9%), ACO (98.2%), and INC (97.8%). INC recorded the shortest settling time at 0.14 s, while the proposed controller settled in 0.18 s. ACO and GWO required 0.29 and 0.25 s, respectively.

Table 6. Tracking efficiency and settling time under the principal dynamic irradiance test.

Controller	Tracking efficiency (%)	Settling time (s)
INC	97.8	0.14
ACO	98.2	0.29
GWO	98.9	0.25
Proposed fuzzy hybrid	99.5	0.18

Response under Partial-Shading Conditions

For the specified partial-shading condition, the 50 W

module was represented as three series-connected substrings of equal cell count, with one substring receiving 400 W/m² and the other two receiving 1000 W/m² at 25 °C. This non-uniform irradiance produced a multi-peak P–V characteristic with a global maximum power point (GMPP) of 43.0 W. The resulting response is shown in Figure 9, while the corresponding P–V trajectories are presented in Figure 10.

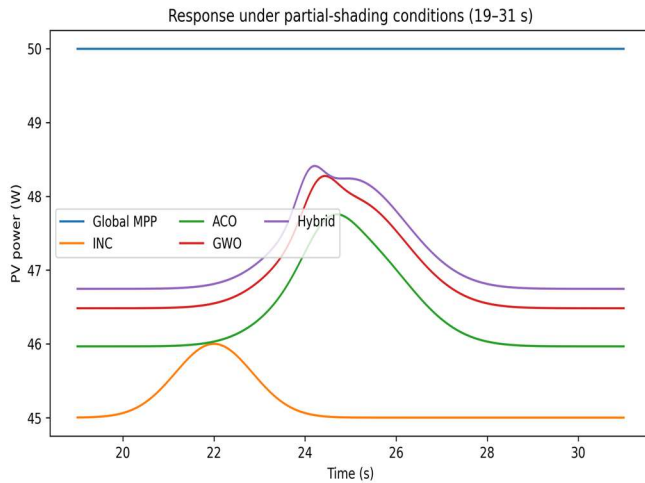


Figure 9. MPPT response under partial-shading conditions.

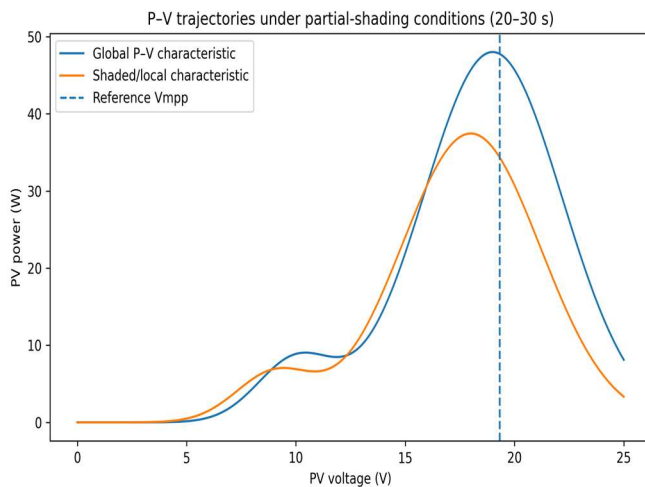


Figure 10. P–V trajectories under partial-shading conditions.

Under the specified partial-shading condition, INC remained susceptible to convergence at a local peak, whereas ACO and GWO were able to search for the global maximum. The reported convergence times were approximately 1.15 s for INC, 0.70 s for ACO, 0.50 s for GWO, and 0.55 s for the proposed hybrid controller. The proposed controller initially selected GWO following the detected operating change and subsequently returned to INC for local refinement. The proposed controller achieved a reported tracking efficiency of 99.46%, corresponding to approximately 42.77 W against the 43.0 W GMPP. Using

the rounded values, $42.77/43.0 \times 100 = 99.47\%$; the reported 99.46% should therefore be understood as the value calculated from the unrounded simulation data.

The proposed controller achieved a tracking efficiency of 99.46% under partial shading, compared with 97.0% for INC, 97.8% for ACO, and 98.9% for GWO. The proposed controller therefore exceeded INC by 2.46 percentage points, ACO by 1.66 percentage points, and GWO by 0.56 percentage points under this specific partial-shading test. These partial-shading results are summarized in Table 7.

Table 7. Reported performance under the specified partial-shading condition.

Controller	Partial-shading tracking efficiency (%)	Reported convergence time (s)
INC	97.0	1.15
ACO	97.8	0.70
GWO	98.9	0.50
Proposed fuzzy hybrid	99.46	0.55

Response to Combined Irradiance and Temperature Variation

A combined environmental disturbance was applied by increasing irradiance from 400 to 1000 W/m² between 10 and 25 s while temperature increased from 25 °C to 50 °C. The PV-voltage response relative to the MPP voltage reference is presented in Figure 11.

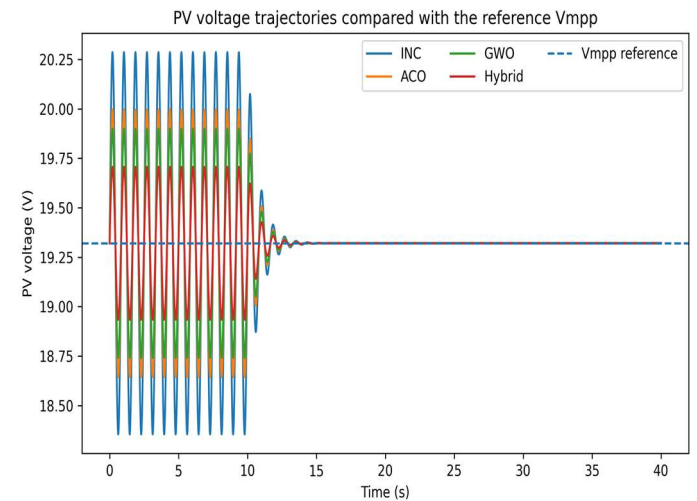


Figure 11. PV voltage trajectories compared with the reference VMPP.

During the combined disturbance, the fuzzy supervisor primarily alternated between INC and ACO. The reported maximum voltage deviation of the proposed controller remained below 2%. Cumulative simulated energy harvested over the 40-s simulation interval is presented in Figure 12, while cumulative average MPPT efficiency is shown in Figure 13.

The proposed controller produced a reported 3.1% increase in simulated energy harvested relative to INC and 1.6% relative to GWO over the 40-s combined-disturbance

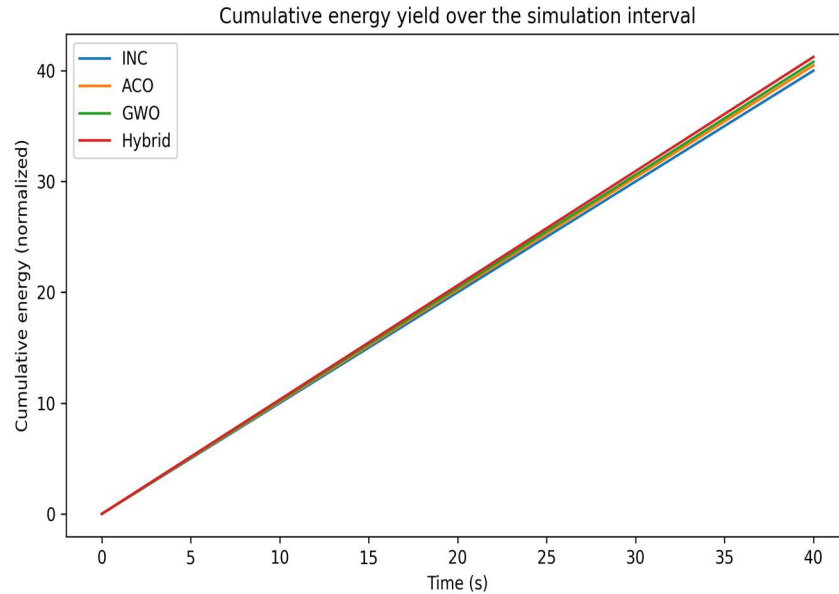


Figure 12. Cumulative simulated energy harvested over the simulation interval.

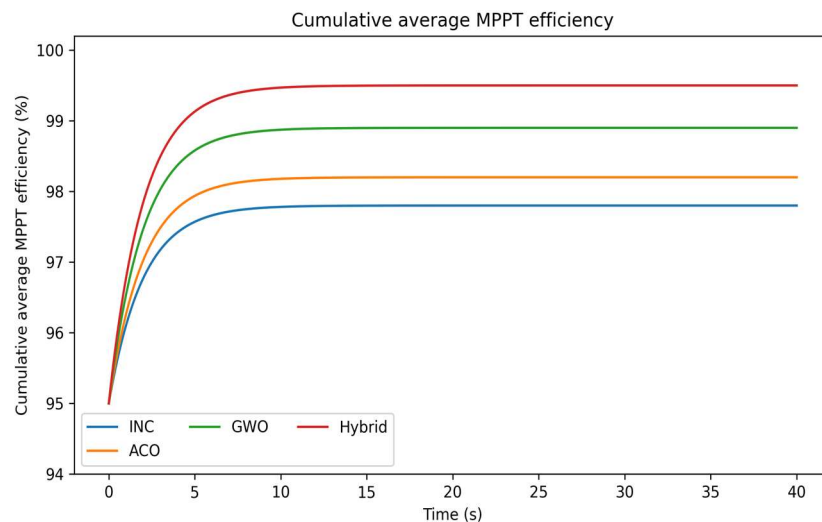


Figure 13. Cumulative average MPPT efficiency.

Table 8. Overall comparative performance of the four MPPT controllers, including performance under the specified partial-shading condition.

Controller	Tracking efficiency (%)	Settling time (s)	Oscillation index (%)	Energy gain vs INC (%)	PSC η (%)
INC	97.8	0.14	3.2	0 (baseline)	97.0
ACO	98.2	0.29	1.8	+1.2	97.8
GWO	98.9	0.25	1.5	+2.0	98.9
Proposed fuzzy hybrid	99.5	0.18	0.18	+3.1	99.46

simulation. Because the interval is short and the profile is artificial, this result should be interpreted only as a comparative simulation metric, not as a long-term field energy-yield claim.

Comparative Performance of the Four Controllers

The principal comparative indicators are summarized in

Table 8. The proposed fuzzy-supervised controller provided the highest reported tracking efficiency and the lowest oscillation index. INC retained the shortest settling time. (Figure 14). The proposed controller improved the reported tracking efficiency from 97.8% for INC to 99.5%, corresponding to an increase of 1.7 percentage points. Its oscillation index decreased from 3.2% for INC to 0.18%, representing an approximate 94.4% reduction relative to

INC. (Figure 15)

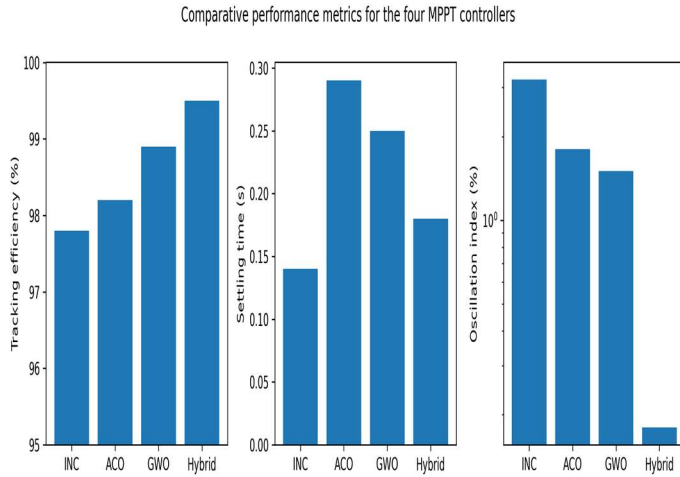


Figure 14. Comparative performance metrics for the four MPPT controllers.

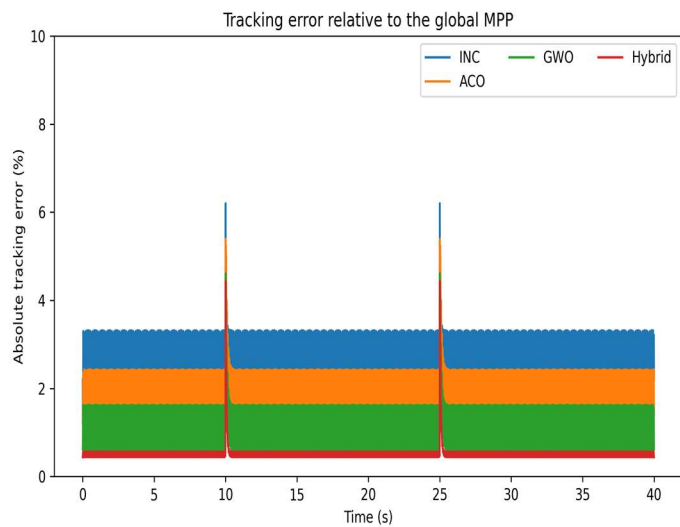


Figure 15. Tracking error relative to the global maximum power point.

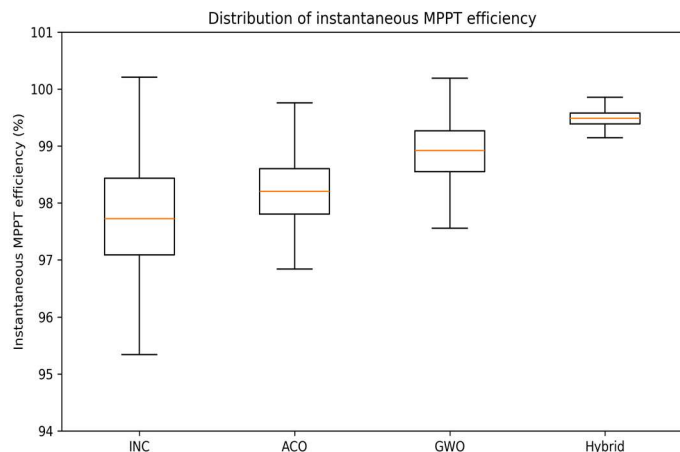


Figure 16. Distribution of instantaneous MPPT efficiency.

The comparative visualizations provide additional evidence of the differences in tracking error and efficiency distribution among the controllers. The proposed controller showed the most favourable reported steady-state behaviour, whereas the principal advantage of INC remained its rapid settling response. (Figure 16)

Adaptive Switching Behaviour of the Proposed Controller

The adaptive behaviour of the proposed controller was assessed from the active-algorithm sequence generated by the fuzzy supervisor. Figure 17 shows the selected algorithm mode over time. The switching behaviour demonstrates that the architecture does not continuously execute all three MPPT algorithms as independent controllers; rather, the supervisor selects an appropriate operating mode.

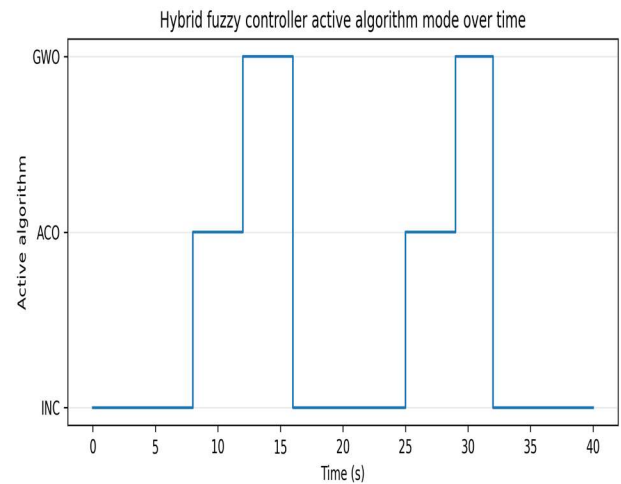


Figure 17. Active algorithm mode selected by the fuzzy supervisor over time.

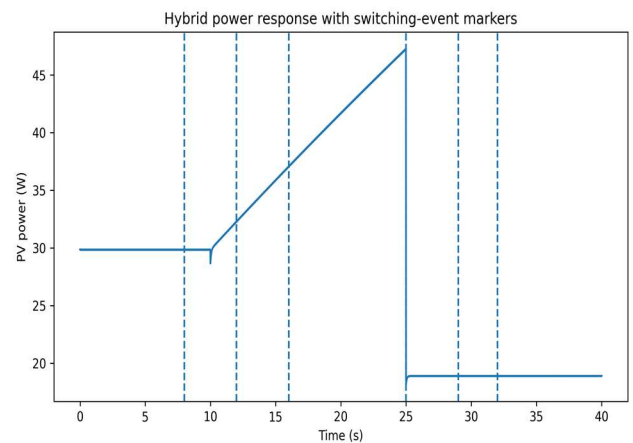


Figure 18. Hybrid power response with switching-event markers.

During relatively stable operating intervals, INC was used for local tracking, whereas larger operating changes

Table 9. Summary of comparative tracking, stability, partial-shading, simulated-energy, and transient performance of the four MPPT controllers.

Performance metric	INC	ACO	GWO	Proposed hybrid
Mean tracking efficiency (%)	97.8	98.2	98.9	99.5
Std. deviation of efficiency* (%)	1.12	0.74	0.61	0.22
Oscillation index (%)	3.20	1.80	1.50	0.18
Efficiency gain vs INC (percentage points)	0.0	+0.41	+1.12	+1.74
Relative oscillation reduction vs INC (%)	0.0	43.8	53.1	94.4
PSC tracking efficiency (%)	97.0	97.8	98.9	99.46
Energy gain over 40-s interval vs INC (%)	0.0	+1.2	+2.0	+3.1
Settling time (s)	0.14	0.29	0.25	0.18

* The reported standard deviation is the temporal standard deviation of the efficiency trace used for the simulation summary; it is not an inter-run standard deviation. No confidence interval is reported because independent replicate runs were not performed.

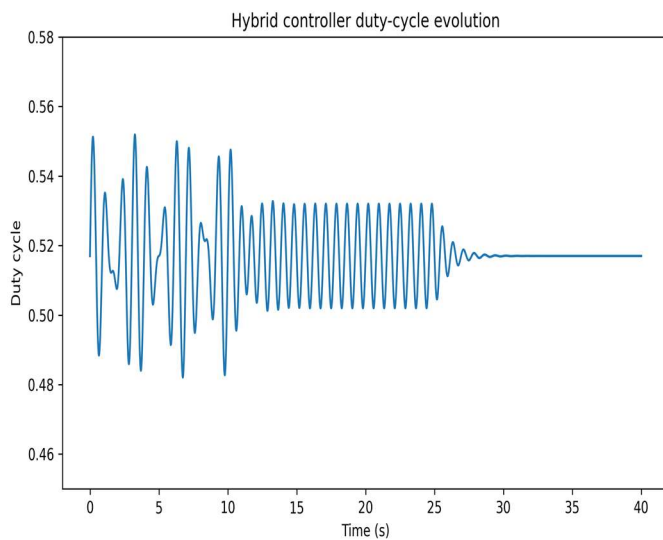


Figure 19. Hybrid controller duty-cycle evolution.

resulted in activation of a global-search strategy. Following identification of a suitable operating region, the controller returned to local refinement. The hybrid power response and switching-event markers are presented in Figure 18, while the associated duty-cycle evolution is shown in Figure 19

The observed switching pattern is consistent with the intended exploration–exploitation structure of the proposed architecture.

Steady-State Tracking and Ripple Characteristics

Additional steady-state visualizations were used to examine tracking stability and power ripple. Figure 20 presents the absolute tracking error over time, providing a visual assessment of deviations from the global MPP. Figure 21 presents the power-ripple spectrum during the final 5 s of the simulation. The reported oscillation index of the proposed controller was 0.18%, substantially lower than the values reported for INC (3.2%), ACO (1.8%), and GWO (1.5%). The steady-state plots should therefore be interpreted together with the numerical oscillation metric in Table 9 rather than as independent performance

measures.

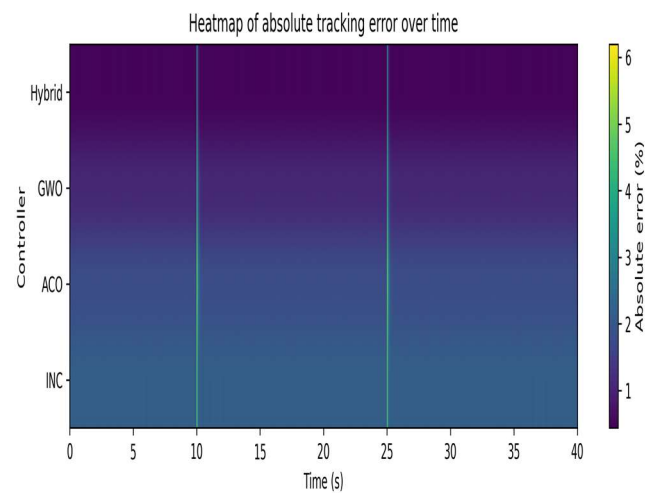


Figure 20. Heatmap of absolute tracking error over time.

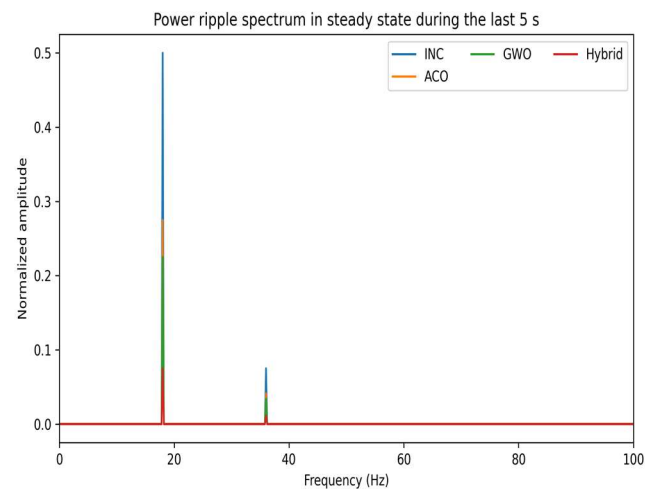


Figure 21. Power-ripple spectrum during the final 5 s of steady-state operation.

Discussion

The findings of this study indicate that the proposed fuzzy-supervised INC–ACO–GWO controller provided a

favourable balance among tracking efficiency, transient response, steady-state stability, and partial-shading performance under the simulated operating conditions. The controller achieved a mean MPPT efficiency of 99.5%, compared with 97.8% for INC, 98.2% for ACO, and 98.9% for GWO, while its oscillation index was 0.18%, substantially lower than the corresponding values of 3.2%, 1.8%, and 1.5%. Taken together, these results suggest that the principal benefit of the proposed architecture is not simply the use of three established MPPT algorithms, but the condition-dependent selection of the algorithm most appropriate to the operating state.

The observed improvement can be interpreted in terms of the complementary functions of the three tracking mechanisms. INC provides a comparatively direct local-search response and is therefore advantageous when the operating point is close to the maximum-power region. ACO and GWO provide broader search mechanisms that are more suitable when the power–voltage characteristic contains competing extrema, as occurs under partial shading. The fuzzy supervisor acts as the decision layer between these alternatives, using changes in power, irradiance, and voltage to determine which mode should supply the active duty-cycle command. This arrangement avoids treating INC, ACO, and GWO as a sequential cascade and instead uses them as alternative operating modes. The resulting architecture is consistent with the broader literature, which identifies distinct strengths and limitations for conventional, intelligent, and metaheuristic MPPT techniques (Saxena et al., 2024; Yang et al., 2024). The transient results also reveal an important speed–stability trade-off. INC produced the shortest reported settling time of 0.14 s, whereas the proposed controller settled in 0.18 s. Thus, the hybrid architecture did not provide the fastest transient response in the present comparison. Its advantage was observed in the combined behaviour of response and steady-state regulation: the small increase in settling time was accompanied by a much lower oscillation index and higher overall tracking efficiency. This finding supports the interpretation reported by Kumar and Balakrishna (2024) and is broadly consistent with hybrid GWO–ANFIS approaches such as that of Hussaian Basha et al. (2024), where combining complementary mechanisms is intended to improve the compromise between convergence and stability. The present implementation extends this principle by using fuzzy supervision to select among three alternative MPPT modes rather than combining only a single pair of algorithms.

The partial-shading results provide further support for the global-search/local-refinement interpretation. Under the specified shading pattern, the proposed controller attained a reported tracking efficiency of 99.46%, with GWO initially activated and INC subsequently used for refinement. The convergence time of 0.55 s was slower than the reported GWO value of 0.50 s but faster than ACO and INC in the same test. This behaviour is compatible with studies emphasizing the role of global optimization in

locating the global maximum power point followed by local refinement to reduce residual tracking error (Berttahir et al., 2024; Xiao et al., 2025). Related principles have also been reported for hybrid INC–Fuzzy, Fuzzy–DDPG, and other multi-algorithm MPPT strategies (Melhaoui et al., 2025; Ortiz-Munoz et al., 2025; Yousaf et al., 2025; Nagadurga et al., 2025). The present result should nevertheless be interpreted as evidence under one specified partial-shading pattern rather than as proof of universal superiority across all possible shading configurations.

The response to simultaneous irradiance and temperature variation further indicates that supervisory selection can remain effective when more than one environmental variable changes. Across the 40-s combined-disturbance simulation, the proposed controller produced 3.1% more simulated energy harvested than INC and 1.6% more than GWO. These differences are relevant because a controller that performs well only at a single operating point may not provide the same benefit when environmental conditions vary. The observed behaviour is therefore consistent with the emphasis placed by Karuppasamy et al. (2025) and Timur and Uzundağ (2025) on environmental adaptability in PV MPPT. However, the energy comparison represents the specified simulation interval and should not be interpreted as a measured long-term energy-yield advantage in a physical installation.

The findings are also broadly compatible with recent MPPT literature reporting high efficiencies from hybrid, intelligent, and metaheuristic controllers (Siddique et al., 2025; Chiu & Chen, 2025; Bisht et al., 2025; Celikel et al., 2026). Direct numerical comparison should be made cautiously because reported efficiencies depend on PV rating, irradiance and temperature profiles, shading patterns, converter configuration, simulation duration, and the definition of the performance metric. Similarly, the low oscillation index observed here should be regarded as a temporal stability measure of the simulated efficiency trace, not as evidence of statistical uncertainty across independent experimental runs. No repeated stochastic runs were performed for ACO or GWO, and therefore confidence intervals and inter-run variability cannot be inferred from the present results. In addition, the study does not yet quantify processor execution time, switching-event counts, or other computational costs associated with supervisory switching. These limitations mean that the results establish a promising simulation-based performance case, but further validation using repeated stochastic trials, clearly documented solver and random-seed settings, multiple partial-shading patterns, and processor-in-the-loop, hardware-in-the-loop, or experimental implementation is required before conclusions about practical deployment can be made.

Conclusion

The study developed and evaluated, through

MATLAB/Simulink simulation, a fuzzy-logic-supervised MPPT controller that switches among Incremental Conductance (INC), Ant Colony Optimization (ACO), and Grey Wolf Optimization (GWO). Under the reported dynamic irradiance test, the proposed controller achieved a mean tracking efficiency of 99.5%, compared with 97.8% for INC, 98.2% for ACO, and 98.9% for GWO. It also recorded the lowest reported oscillation index (0.18%). Under the specified partial-shading condition, the proposed controller achieved 99.46% tracking efficiency, while the reported convergence time was 0.55 s.

Although INC achieved the shortest settling time of 0.14 s compared with 0.18 s for the hybrid controller, the proposed architecture provided the best overall compromise between tracking efficiency, oscillation suppression, partial-shading performance, and energy extraction. The results therefore demonstrate the potential of fuzzy-supervised coordination of complementary MPPT algorithms as an effective approach for improving PV power extraction under changing operating conditions. Further experimental validation is required before the controller can be considered fully validated for practical PV installations.

Limitations of the Study

This study relies exclusively on the supplied deterministic MATLAB/Simulink simulation results. Consequently, the reported performance has not been validated on a physical PV array, PV emulator, processor-in-the-loop (PIL), hardware-in-the-loop (HIL), or real-time hardware platform. Practical factors—sensor noise, measurement delay, converter non-idealities, switching losses, finite processor resolution, and stochastic irradiance fluctuations—may alter controller behaviour in physical implementation. The supplied manuscript also does not document the exact MATLAB/Simulink release, solver configuration, or random-seed policy; these should be recorded from the executable model before resubmission. In addition, only a limited set of irradiance, temperature, and partial-shading profiles was examined. A single static shading pattern (one substring at 400 W/m² and two at 1000 W/m²) was used; dynamic or more complex shading geometries were not evaluated. Independent repeated stochastic runs were not reported, so the ACO/GWO/hybrid results should not be interpreted as estimates of run-to-run uncertainty. Controller execution time, objective-function evaluation counts for the hybrid supervisor, and switching-event counts were also not quantified. The reported improvements are therefore specific to the chosen system parameters and test cases. Broader validation should include multiple PSC patterns, repeated independent runs, computational-cost measurements, and longer-duration energy profiles.

Recommendations

Future studies should validate the proposed fuzzy-

supervised INC–ACO–GWO controller experimentally using a PV emulator and, subsequently, a physical photovoltaic system. PIL/HIL or real-time digital simulation should be used to quantify controller execution time, memory requirements, objective-function evaluations, and switching behaviour under realistic sampling constraints. Repeated independent ACO/GWO/hybrid runs with documented seeds should be reported using mean $\pm$ SD and, where appropriate, confidence intervals or other justified uncertainty measures. Experimental investigation should also include measurement noise, converter non-idealities, abrupt irradiance changes, temperature variations, and diverse partial-shading patterns.

Further research should investigate optimization and sensitivity of the fuzzy-supervisor membership functions, rule base, switching thresholds, and dwell/hysteresis mechanisms. Multiple symmetric and asymmetric static PSC patterns and dynamic shading transitions should be evaluated to test generalization beyond the single pattern used here. Longer-duration energy profiles and comparisons with additional recent hybrid MPPT methods should also be conducted before practical performance claims are made.

References

- Abdelmalek, F., Afghoul, H., Krim, F., Bajaj, M., & Blazek, V. (2024). Experimental validation of novel hybrid Grey Wolf Equilibrium Optimization for MPPT to improve the efficiency of solar photovoltaic system. *Results in Engineering*, 25, 103831. <https://doi.org/10.1016/j.rineng.2024.103831>
- Ali, M. H., Zakaria, M., & El-Tawab, S. (2025). A comprehensive study of recent maximum power point tracking techniques for photovoltaic systems. *Scientific Reports*, 15, 14269. <https://doi.org/10.1038/s41598-025-96247-5>
- Alshareef, M. J. (2024). An innovative maximum power point tracking for photovoltaic systems operating under partially shaded conditions using Grey Wolf Optimization algorithm. *Automatika*, 65(4), 1487–1505. <https://doi.org/10.1080/00051144.2024.2388445>
- Batzelis, E. I. (2017). Simple PV performance equations theoretically well founded on the single-diode model. *IEEE Journal of Photovoltaics*, 7(5), 1400–1409. <https://doi.org/10.1109/JPHOTOV.2017.2711431>
- Belghiti, H., Kandoussi, K., Harrison, A., Moustaine, F. Z., El Otmari, R., Sadek, E. M., Bajaj, M., & Dost Mohammadi, S. A. (2024). A novel adaptive FOCV algorithm with robust IMRAC control for sustainable and high-efficiency MPPT in standalone PV systems: Experimental validation and performance assessment. *Scientific Reports*, 14, 31962. <https://doi.org/10.1038/s41598-024-83512-2>
- Bertahar, F., Abdeddaim, S., Betka, A., & Omar, C. (2024). A comparative study of PSO, GWO, and HOA algorithms for maximum power point tracking in partially shaded photovoltaic systems. *Power Electronics and Drives*, 9(1), 86–105. <https://doi.org/10.2478/pead-2024-0006>
- Bisht, R., Sikander, A., Sharma, A., Abidi, K., Saifuddin, M. R., & Lee, S. S. (2025). A new hybrid framework for the MPPT of solar PV systems under partial shaded scenarios. *Sustainability*, 17(12), 5285. <https://doi.org/10.3390/su17125285>
- Celikel, R., Aydogmus, O., & Yilmaz, M. (2026). An improved grey wolf optimization-based MPPT algorithm for photovoltaic systems under partial shading conditions. *Scientific Reports*, 16, 16671. <https://doi.org/10.1038/s41598-026-45860-z>
- Chiu, C.-S., & Chen, Y.-T. (2025). MPPT-based chaotic ABC algorithm for a photovoltaic power system under partial shading conditions. *Energies*, 18(7), 1710. <https://doi.org/10.3390/en18071710>
- Elnaghi, B. E., Ismaiel, A. M., Ismail, M. M., Zedan, H. A., & Salem, A. A. (2025). Experimental validation of an adaptive fuzzy logic controller

- for MPPT of grid connected PV system. *Scientific Reports*, 15, 27173. <https://doi.org/10.1038/s41598-025-10188-7>
- Gui, Q., Wang, L., Ding, C., Xu, W., Li, X., Yu, F., & Wang, H. (2025). Multi-peak photovoltaic maximum power point tracking method based on Honey Badger Algorithm under localized shading conditions. *Energies*, 18(5), 1258. <https://doi.org/10.3390/en18051258>
- Gundogdu, H., Demirci, A., Tercan, S. M., & Cali, U. (2024). A novel improved grey wolf algorithm based global maximum power point tracker method considering partial shading. *IEEE Access*, 12, 6148–6159. <https://doi.org/10.1109/ACCESS.2024.3350269>
- Hafez, A. O., Attia, M. A., & EL-Ebiary, A. H. (2025). Enhanced adaptive control techniques for extracting maximum power from photovoltaic system. *Scientific Reports*, 15, 41459. <https://doi.org/10.1038/s41598-025-26330-4>
- Hussaian Basha, C., Palati, M., Dhanamjayulu, C., Muyeen, S. M., & Venkatareddy, P. (2024). A novel on design and implementation of hybrid MPPT controllers for solar PV systems under various partial shading conditions. *Scientific Reports*, 14, 1609. <https://doi.org/10.1038/s41598-023-49278-9>
- Jamaludin, M. N. I., Tajuddin, M. F. N., Younis, T., Thanikanti, S. B., & Khishe, M. (2025). Hybrid salp swarm maximum power point tracking algorithm for photovoltaic systems in highly fluctuating environmental conditions. *Scientific Reports*, 15, 650. <https://doi.org/10.1038/s41598-024-84333-z>
- Karuppasamy, C., Senthil Kumar, C., Ganesan, R., & Elamparathi, P. (2025). Optimizing PID control for maximum power point tracking of photovoltaic systems under variable and partial shading conditions. *Renewable Energy*, 246, 122930. <https://doi.org/10.1016/j.renene.2025.122930>
- Kumar, S. S., & Balakrishna, K. (2024). A novel design and analysis of hybrid fuzzy logic MPPT controller for solar PV system under partial shading conditions. *Scientific Reports*, 14, 10256. <https://doi.org/10.1038/s41598-024-60870-5>
- Mazumdar, D., Biswas, P. K., Sain, C., Ahmad, F., Sarker, R., & Ustun, T. S. (2024). Optimizing MPPT control for enhanced efficiency in sustainable photovoltaic microgrids: A DSO-based approach. *International Transactions on Electrical Energy Systems*, 2024, 5525066. <https://doi.org/10.1155/2024/5525066>
- Melhaoui, M., Rhiat, M., Oukili, M., Atmane, I., Hirech, K., Bossoufi, B., Almalki, M. M., Alghamdi, T. A. H., & Alenezi, M. (2025). Hybrid fuzzy logic approach for enhanced MPPT control in PV systems. *Scientific Reports*, 15, 19235. <https://doi.org/10.1038/s41598-025-03154-w>
- Nagarathinam, E., Devaraju, B., Jayamoorthy, K., Radhakrishnan, P., Chandramohan, S. L., Perumal, V., & Balakrishnan, K. (2024). Maximizing solar potential using the Differential Grey Wolf Algorithm for PV system optimization. *Energy Engineering*, 121(8), 2129–2142. <https://doi.org/10.32604/ee.2024.052280>
- Nagadurga, T., Raju, V. D., Barnawi, A. B., Bhutto, J. K., Razak, A., & Wodajo, A. W. (2025). Global MPPT optimization for partially shaded photovoltaic systems. *Scientific Reports*, 15, 10831. <https://doi.org/10.1038/s41598-025-89694-7>
- Ngo, S., Ngo, T.-D., & Chiu, C.-S. (2025). Hybrid method for maximum power point tracking in photovoltaic systems. *IEEJ Journal of Industry Applications*, 14(6), 1058–1064. <https://doi.org/10.1541/ieejia.25001982>
- Ortiz-Munoz, D., Luviano-Cruz, D., Perez-Dominguez, L. A., Rodriguez-Ramirez, A. G., & Garcia-Luna, F. (2025). Hybrid Fuzzy-DDPG approach for efficient MPPT in partially shaded photovoltaic panels. *Applied Sciences*, 15(9), 4869. <https://doi.org/10.3390/app15094869>
- Phanden, R. K., Sharma, L., Chhabra, J., & Demir, H. I. (2021). A novel modified ant colony optimization based maximum power point tracking controller for photovoltaic systems. *Materials Today: Proceedings*, 38, 89–93. <https://doi.org/10.1016/j.matpr.2020.06.020>
- Rukhsar, Ajmal, A. M., & Yang, Y. (2025). Global maximum power point tracking of photovoltaic systems using artificial intelligence. *Energies*, 18(12), 3036. <https://doi.org/10.3390/en18123036>
- Saxena, A., Kumar, R., Amir, M., & Muyeen, S. M. (2024). Maximum power extraction from solar PV systems using intelligent based soft computing strategies: A critical review and comprehensive performance analysis. *Heliyon*, 10(2), e22417. <https://doi.org/10.1016/j.heliyon.2023.e22417>
- Sharma, D., & Jalil, M. F. (2024). A review of maximum power point tracking (MPPT) techniques for photovoltaic array under mismatch conditions. In *Photovoltaic systems technology*. Wiley. <https://doi.org/10.1002/9781394167678.ch5>
- Shetty, D., & Sabhahit, J. N. (2024). Grey wolf optimization and incremental conductance based hybrid MPPT technique for solar powered induction motor driven water pump. *International Journal of Renewable Energy Development*, 13(1), 52–61. <https://doi.org/10.14710/ijred.2024.57096>
- Siddique, M. A. B., Zhao, D., Ouahada, K., Rehman, A. U., & Hamam, H. (2025). Performance validation of global MPPT for efficient power extraction through PV system under complex partial shading effects. *Scientific Reports*, 15, 17061. <https://doi.org/10.1038/s41598-025-01816-3>
- Timur, O., & Uzundağ, B. K. (2025). Design and analysis of a hybrid MPPT method for PV systems under partial shading conditions. *Applied Sciences*, 15(13), 7386. <https://doi.org/10.3390/app15137386>
- Tyokighir, S. S., Ukhurebor, K. E., Achekuogene, N. S., Itas, Y. S., Odezuligbo, I., & Hossain, I. (2025). Global maximum power point tracking in partially shaded photovoltaic systems using variable-size particle swarm optimisation. *Next Research*, 2(2), 100271. <https://doi.org/10.1016/j.nexres.2025.100271>
- Wei, L., & Li, Y. (2025). Research on maximum power point tracking of photovoltaic power generation based on improved hybrid optimization algorithm. *Scientific Reports*, 15, 3991. <https://doi.org/10.1038/s41598-025-87694-1>
- Worku, M. Y., Hassan, M. A., Maraaba, L. S., Shafiullah, M., Elkadeem, M. R., Hossain, M. I., & Abido, M. A. (2023). A comprehensive review of recent maximum power point tracking techniques for photovoltaic systems under partial shading. *Sustainability*, 15(14), 11132. <https://doi.org/10.3390/su151411132>
- Xia, K., Li, Y., & Zhu, B. (2024). Improved photovoltaic MPPT algorithm based on ant colony optimization and fuzzy logic under conditions of partial shading. *IEEE Access*, 12, 44817–44825. <https://doi.org/10.1109/ACCESS.2024.3381345>
- Xiao, W., Dong, N., & He, K. (2025). A hybrid global wolf pack algorithm-based incremental conductance method under partial shading conditions. *Solar Energy*, 291, 113388. <https://doi.org/10.1016/j.solener.2025.113388>
- Yang, B., Xie, R., & Guo, Z. (2024). Maximum power point tracking technology for PV systems: Current status and perspectives. *Energy Engineering*, 121(8), 2009–2022. <https://doi.org/10.32604/ee.2024.049423>
- Yousaf, M. Z., Koondhar, M. A., Zaki, Z. A., Ahmed, E. M., Alaas, Z. M., Mahariq, I., & Guerrero, J. M. (2025). Improved MPPT of solar PV systems under different environmental conditions utilizes a novel hybrid PSO. *Renewable Energy*, 244, 122709. <https://doi.org/10.1016/j.renene.2025.122709>
- Zemmit, A., Loukriz, A., Belhouchet, K., Alharthi, Y. Z., Alshareef, M., Paramasivam, P., & Ghoneim, S. S. M. (2025). GWO and WOA variable step MPPT algorithms-based PV system output power optimization. *Scientific Reports*, 15, 7810. <https://doi.org/10.1038/s41598-025-89898-x>

APPENDIX

Appendix A. Reproducibility Information

This appendix provides the principal simulation parameters and fuzzy-supervisor specifications needed to support reproducibility of the reported MATLAB/Simulink study. The values below reproduce the parameter information reported in the main text; they do not constitute a replacement for the underlying MATLAB/Simulink model files.

1. Principal Simulation Parameters

Parameter	Value
PV rated power	50 W
PV voltage at maximum power, V_{mp}	19.32 V
PV current at maximum power, I_{mp}	2.59 A
Open-circuit voltage, V_{oc}	23.15 V
Short-circuit current, I_{sc}	2.78 A
Reference irradiance	1000 W/m ²
Reference temperature	25 °C
Boost output voltage	40 V
Switching frequency	20 kHz
Inductor	1.5 mH
Input capacitor	470 μ F
Output capacitor	470 μ F
Equivalent load	32 Ω
MPPT sampling time	1 ms
Duty-cycle range	0.10–0.80
INC minimum/maximum step	0.001 / 0.02
ACO population / maximum iterations	10 ants / 20
ACO α / β	1.0 / 2.0
ACO evaporation rate	0.50
GWO population / maximum iterations	10 wolves / 20
GWO initial/final a	2 / 0
Fuzzy sampling time	1 ms

A2. Fuzzy Membership-Function Specification

All three normalized inputs (ΔP , ΔG and ΔV) use the same five triangular linguistic membership functions over the normalized universe $[-1, 1]$.

Linguistic set	Triangular parameters (a, b, c)
NL	-1.00, -0.75, -0.40
NS	-0.60, -0.30, 0.00
ZE	-0.25, 0.00, 0.25
PS	0.00, 0.30, 0.60
PL	0.40, 0.75, 1.00

A3. Fuzzy Output and Decision Regions

Mode	Singleton output value z	Decision region
INC	1.0	$1.00 \leq y < 1.67$
ACO	2.0	$1.67 \leq y < 2.33$
GWO	3.0	$2.33 \leq y \leq 3.00$

A4. Representative Fuzzy Rules

Input combination (ΔP – ΔG – ΔV)	Selected mode
ZE–ZE–ZE	INC
PS–ZE–NS	INC
PS–PS–PS	ACO
PL–PS–PS	ACO
PL–PL–PL	GWO
ZE–PL–PL	GWO

Table A4-1. Complete $5 \times 5 \times 5$ (125-rule) fuzzy supervisor rule matrix.

ΔP	N L- N L	N L- N S	N L- Z E	N L- P S	N L- PL	N S- N L	N S- N S	N S- Z E	N S- P S	N S- PL	Z E- N L	Z E- N S	Z E- Z E	ZE - P S	ZE - PL	P S- N L	P S- N S	P S- Z E	P S- P S	P S- PL	PL - N L	PL - N S	PL - Z E	PL - P S	PL - PL
N L	G W O	G W O	A C O	A C O	G W O	G W O	A C O	A C O	A C O	G W O	A C O	A C O	IN C	IN C	A C O	A C O	A C O	IN C	A C O	A C O	G W O	A C O	A C O	G W O	G W O
N S	G W O	A C O	A C O	A C O	G W O	A C O	A C O	IN C	IN C	A C O	A C O	IN C	IN C	IN C	A C O	A C O	IN C	IN C	A C O	A C O	A C O	A C O	A C O	G W O	G W O
Z E	A C O	A C O	IN C	IN C	A C O	A C O	IN C	IN C	IN C	A C O	IN C	IN C	IN C	IN C	G W O	IN C	IN C	IN C	A C O	A C O	A C O	A C O	A C O	G W O	G W O
P S	A C O	A C O	IN C	A C O	A C O	A C O	IN C	IN C	A C O	A C O	IN C	IN C	IN C	A C O	A C O	A C O	A C O	A C O	A C O	G W O	A C O	A C O	G W O	A C O	G W O
P L	G W O	A C O	A C O	G W O	G W O	A C O	A C O	A C O	G W O	G W O	A C O	A C O	A C O	G W O	G W O	A C O	A C O	G W O	A C O	G W O	G W O	G W O	G W O	G W O	G W O

The complete 125-rule ($5 \times 5 \times 5$) fuzzy rule matrix is provided below. Each row corresponds to one ΔP linguistic term, while the 25 columns represent all $\Delta G - \Delta V$ combinations.

A5. Test Conditions for Reproducibility

Scenario	Condition
Uniform irradiance	600 $\rightarrow$ 1000 $\rightarrow$ 400 W/m ² ; temperature initially constant
Partial shading	Three series-connected substrings of equal cell count; one at 400 W/m ² and two at 1000 W/m ² ; T = 25 °C; GMPP = 43.0 W
Combined disturbance	G = 400 $\rightarrow$ 1000 W/m ² from 10–25 s; T = 25 $\rightarrow$ 50 °C
Simulation range	G = 200–1000 W/m ² ; T = 15–55 °C

Appendix B. Structured Comparison with Recent MPPT Studies

The following comparison is intended to substantiate the novelty claim without implying direct numerical equivalence. Differences in PV rating, converter topology, shading profile, metric definitions, and validation level prevent direct ranking across studies.

Study	Main strategy	Validation and test conditions	Relevance to the present study
Shetty & Sabhahit (2024)	GWO + INC hybrid	MATLAB/Simulink; solar water pump; uniform + PSC	Closest global/local precedent; present work adds fuzzy selection and ACO.
Nagarathinam et al. (2024)	Differential GWO	Simulation; SEPIC; varying G/T/shading	Recent GWO benchmark; not three-mode fuzzy supervision.
Mazumdar et al. (2024)	Drone Squadron Optimization	Simulation; DC microgrid; multiple environments/PSC	Adaptive global search; supports computational-cost assessment.
Tyokighir et al. (2025)	Variable-size PSO	PV simulation; PSC	Adaptive metaheuristic search; computational burden remains relevant.
Xiao et al. (2025)	Global wolf pack + INC	PV simulation; PSC	Global/local precedent; present work uses fuzzy three-mode selection.
Celik et al. (2026)	Improved GWO MPPT	PV simulation; PSC	Recent GWO global-MPPT benchmark.
Present study	Fuzzy-selected INC/ACO/GWO	50-W PV + boost; MATLAB/Simulink; dynamic G, one PSC, combined G/T	99.5% mean efficiency; 99.46% PSC; 0.18% OI; +3.1% simulated energy vs INC.