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Hybrid PSC-aware ANN–incremental conductance MPPT strategy using P–V curve probing for photovoltaic systems

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ABSTRACT

This work introduces a hybrid maximum power point tracking (MPPT) strategy for photovoltaic (PV) systems under partial shading conditions (PSCs), combining a PSC-aware artificial neural network (ANN) with adaptive incremental conductance (INC) refinement. A power-voltage (P-V) curve probing mechanism samples the PV output at five predefined voltage levels scaled by the open-circuit voltage. A multilayer perceptron processes the resulting normalized power features to estimate the global maximum power point (GMPP) voltage. The ANN provides global estimation, while INC performs local refinement to compensate for residual prediction errors. A finite-state supervisory mechanism coordinates both stages and reactivates global prediction following significant operating changes. MATLAB/Simulink simulations are conducted under uniform irradiance, temperature variations, and several partial shading scenarios. Compared with the standalone PSC-aware ANN, the hybrid strategy increases MPPT efficiency from 96.30% to 97.04% under static PSC, from 90.84% to 93.15% under severe PSC, and from 94.17% to 96.40% under dynamic PSC. The results confirm the benefit of combining ANN-based global GMPP voltage estimation with adaptive INC local refinement under complex shading conditions. Experimental/HIL validation remains for future work.

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1. INTRODUCTION

The increasing integration of photovoltaic (PV) systems into modern energy infrastructures has reinforced their importance as a sustainable power generation solution [1], [2]. However, PV characteristics are nonlinear and strongly affected by variations in solar irradiance and temperature [3], [4]. Maximum power point tracking (MPPT) is therefore essential to maximize the energy extracted from PV systems under changing operating conditions [1], [5], [6].

Under uniform irradiance, the power–voltage (P–V) characteristic exhibits a single maximum power point, whereas partial shading conditions (PSCs) generate multiple local maxima and a global maximum power point (GMPP), making accurate tracking more challenging [2], [7], [8]. Conventional methods such as perturb-and-observe (P&O) and incremental conductance (INC) are widely used because of their simplicity

[9]-[11]. However, their local search mechanisms may lead to convergence toward a local maximum under PSCs, reducing energy extraction [12], [13].

Artificial neural network (ANN)-based MPPT techniques provide an alternative due to their nonlinear mapping and predictive capabilities [14], [15]. Nevertheless, ANN prediction may retain residual estimation errors, while conventional INC remains effective for accurate local tracking. Moreover, exploiting global information from the P–V characteristic can improve GMPP identification under partial shading [16], [17]. This motivates a cooperative strategy in which ANN-based global estimation is complemented by local INC refinement.

Accordingly, this paper proposes a hybrid PSC-aware ANN–INC MPPT strategy based on P–V curve probing. Five normalized P–V power samples enable ANN-based global GMPP voltage estimation, followed by adaptive INC local refinement. A finite-state supervisor coordinates both stages under changing operating conditions. The main contributions are:

i) A P–V probing mechanism providing global information under PSCs;
ii) A hybrid ANN–INC architecture combining global ANN estimation with adaptive INC refinement;
iii) A supervisory mechanism for mode coordination and global-stage reactivation after significant operating changes; and
iv) Comparative evaluation of the standalone PSC-aware ANN and hybrid ANN–INC under uniform, temperature-varying, and partial-shading conditions.

2. PV SYSTEM AND SIMULATION CONFIGURATION

The investigated system consists of a 4S×1P PV array composed of four 250 W series-connected modules, a DC–DC boost converter, and a resistive load. The PV array is modeled using the single-diode model [11], [18], with bypass diodes included to reproduce multiple P–V peaks under partial shading conditions (PSCs). The boost converter regulates the PV operating voltage according to the MPPT reference through its duty cycle [19], [20]. Operating in continuous conduction mode, its voltage conversion ratio is expressed as (1) [21], [22].

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

Where V_{pv} and V_o are the PV and output voltages, respectively, and D is the duty cycle. The proposed hybrid ANN–INC MPPT first estimates the GMPP reference voltage from the P–V probing features, after which adaptive INC refines the operating point through the voltage-control loop. The main simulation parameters are summarized in Table 1.

Table 1. Main PV array and boost converter parameters

PV parameter	Value	Converter parameter	Value
Array configuration	4S×1P	Inductance L	2.5 mH
Module rated power	250 W	Input capacitance C_{in}	470 µF
Voc	37.3V	Output capacitance C_o	220 µF
Isc	8.69A	Load resistance R_{load}	50 Ω
Vmpp	30.2 V	Parasitic resistance R_L	0.221 Ω
Impp	8.27 A	Diode forward V_d	0.1 V
-	-	Switching frequency f_{sw}	50 Khz

3. PROPOSED HYBRID PSC-AWARE ANN–INC MPPT STRATEGY

The proposed MPPT strategy combines global P–V curve information with ANN-based GMPP voltage estimation and adaptive incremental conductance (INC) refinement. A supervisory mechanism coordinates two operating modes: a global mode, in which the ANN estimates the GMPP voltage and a PI controller drives the PV operating point toward this reference, and a local mode, in which adaptive INC refines and maintains the operating point. The controller returns to global estimation when a significant operating change is detected.

3.1. P–V Curve probing and feature extraction

Under partial shading conditions, the P–V characteristic may exhibit multiple local maxima, making GMPP identification difficult [7], [8], [23]. To provide the ANN with global information about the P–V characteristic, the PV power is evaluated at five predefined voltage levels normalized with respect to the open-circuit voltage:

$$\alpha_k = (\{0.15, 0.35, 0.55, 0.75, 0.90\}) \; ; \; V_k = \alpha_k V_{oc} \quad (2)$$

The five probing locations were selected to provide a distributed representation of the P–V curve over the useful voltage range while limiting the number of ANN inputs and the associated online computational burden. The corresponding probing powers P_1–P_5 are calculated as (3):

$$P_k = V_k I(V_k) \; , \qquad k= 1,….,5 \quad (3)$$

and normalized according to (4).

$$P_{norm,k} = \frac{P_k}{\max(P_1,P_2,P_3,P_4,P_5)} \quad (4)$$

The resulting normalized power vector $P_{norm} = [P_{norm1}, P_{norm2}, P_{norm3}, P_{norm4}, P_{norm5}]$ is used as the ANN input and provides a compact representation of the global P–V characteristic. Irradiance and temperature are not used as ANN input features. In the present simulation framework, however, the instantaneous environmental conditions are used internally by the PV model to evaluate the five probing powers at the predefined voltage levels.

3.2. ANN-based global GMPP voltage estimation

A multilayer perceptron (MLP) neural network is used to estimate the optimal operating voltage. The ANN processes normalized power samples and predicts the voltage corresponding to the GMPP [14], [24]. The network follows a 5–25–15–1 architecture, comprising five input neurons corresponding to Pnorm,1–Pnorm,5, two hidden layers with 25 and 15 neurons using tansig activation function, and a linear output neuron providing the normalized GMPP voltage, as shown in Figure 1.

The ANN was trained offline using 3,000 samples comprising 30% uniform irradiance, 25% mild PSC, 25% severe PSC, and 20% randomly generated shading patterns. The generated irradiance values covered an overall range of 100–1200 W/m², while the module temperature was varied from 15 to 55 °C. The dataset was randomly divided into 70% training, 15% validation, and 15% testing subsets. Training was performed using the Levenberg–Marquardt algorithm with mean-squared error as the loss function. The trained network achieved R2=0.9811 and an RMSE of approximately 3.3269 V.

$$V_{ANN} = V_{OC} \times \hat{V}_{mpp} \quad (5)$$

During GLOBAL operation, VANN is periodically updated and tracked by the PI voltage controller, which adjusts the boost-converter duty cycle. The ANN therefore provides global GMPP localization without an online iterative optimization procedure. Since network training is performed offline, the online ANN computation is limited to forward propagation through the trained network.

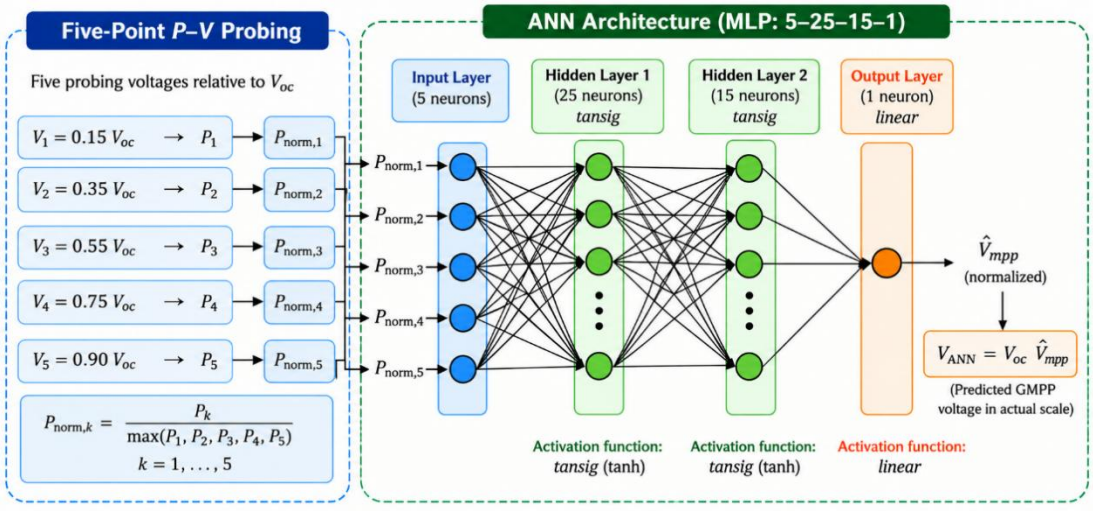

Figure 1. Architecture of the proposed ANN-MLP model for GMPP voltage prediction using normalized P–V curve probing features

3.3. Adaptive INC local refinement

Although the ANN provides global GMPP localization, residual prediction errors may remain because of the finite training dataset and the approximation capability of the network. Adaptive INC is therefore employed after global localization to refine the operating point. For the PV power P=VI, the MPP condition is expressed as (6).

$$\frac{\mathrm{dP}}{\mathrm{dV}} = \mathrm{I} + \mathrm{V}\frac{\mathrm{dI}}{\mathrm{dV}} = 0 \tag{6}$$

This gives (7).

$$\frac{\mathrm{dI}}{\mathrm{dV}} = -\frac{\mathrm{I}}{\mathrm{V}} \tag{7}$$

The local controller compares the incremental conductance $\frac{\mathrm{dI}}{\mathrm{dV}}$ with the instantaneous conductance $-\frac{\mathrm{I}}{\mathrm{V}}$ to determine the direction of the duty–cycle adjustment. To provide fast correction away from the MPP while limiting steady-state oscillations, the duty-cycle step is adapted according to the relative power variation:

$$\Delta D = max\left[\Delta D_{min}, min\left(\Delta D_0, 10\,\Delta D_0 \frac{|\Delta P|}{P}\right)\right] \tag{8}$$

Where D is the boost-converter duty cycle, ΔD is its adaptive adjustment step $\Delta \mathrm{D}_0$ and $\Delta \mathrm{D}_{\mathrm{min}}$ denote the initial and minimum duty-cycle steps, respectively, and $\Delta \mathrm{P} = \mathrm{p(k)} - P(k-1)$ is the power variation between two successive MPPT samples.

A dead-band is introduced when:

$$\frac{|\Delta \mathrm{P}|}{\mathrm{P}} < \varepsilon \tag{9}$$

where ε is the INC tolerance defining the neighborhood of the MPP. Within this dead-band, the duty cycle is maintained, reducing unnecessary perturbations around the operating point. Importantly, INC does not perform the initial global search in the proposed architecture. It is activated only after ANN-based global localization and therefore operates as a local refinement mechanism around the estimated GMPP region.

3.4. Supervisory global–local control

The finite-state supervisory mechanism coordinates the transition between the GLOBAL and LOCAL modes as illustrated in Figure 2. In GLOBAL mode, five-point P–V probing is periodically performed, and the ANN estimates VANN. The PI controller then regulates the PV voltage toward this predicted reference. To prevent premature switching to INC, the transition from GLOBAL to LOCAL occurs only when three conditions are simultaneously satisfied: i) the measured PV voltage remains sufficiently close to the ANN reference, ii) the ANN reference remains stable over consecutive scans, and iii) the filtered relative power variation falls below a predefined settling threshold. A minimum residence time in GLOBAL mode is also imposed.

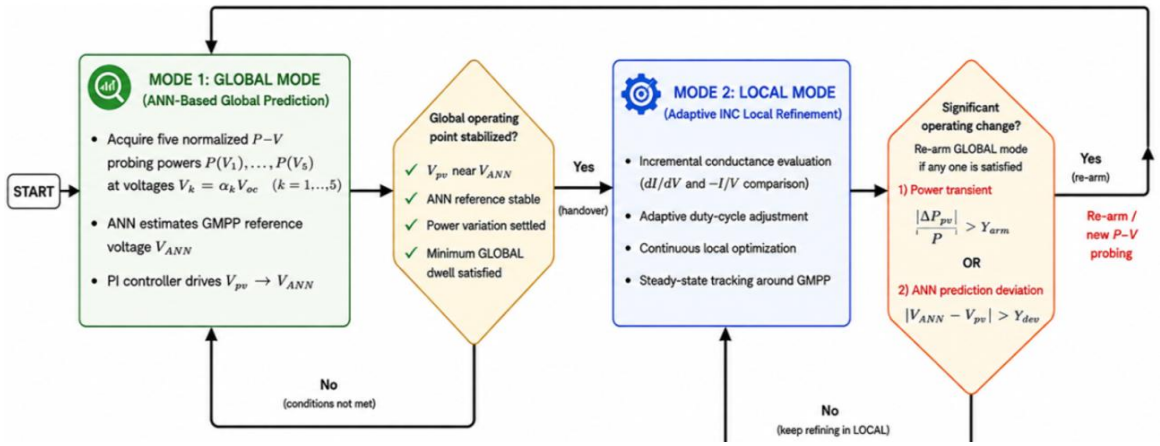

Figure 2. Supervisory architecture of the proposed hybrid PSC-aware ANN–INC MPPT strategy

In LOCAL mode, adaptive INC directly refines the converter duty cycle. To detect changes in operating conditions, two complementary reactivation criteria are employed. The first monitors the filtered relative power variation to detect significant transients. The second periodically evaluates the ANN prediction in the background and compares the predicted GMPP voltage with the actual PV operating voltage. Global reactivation occurs when:

$$\frac{|\Delta D_{filt}|}{P} > \gamma_{arm} or \left|V_{ANN} - V_{pv}\right| > \gamma_{dev} \quad (10)$$

where γ_{arm} is the power-transient threshold and γ_{dev} is the ANN prediction-deviation threshold. If either criterion is satisfied, the controller returns to GLOBAL mode for renewed P–V probing and GMPP estimation.

The resulting operating sequence can therefore be summarized as P-V probing → ANN global estimation → PI voltage tracking → adaptive INC local refinement. Global estimation is automatically reactivated following significant operating changes. This supervisory structure prevents INC from independently searching the multi-peak P–V characteristic while retaining its local tracking capability around the ANN-estimated GMPP.

4. PERFORMANCE METRICS

Table 2 summarizes the performance metrics used to evaluate the proposed hybrid PSC-aware ANN–INC MPPT strategy. These metrics include tracking efficiency, convergence time, steady-state ripple, tracking error, and extracted energy. The corresponding evaluation criteria are based on [20], [22], [25].

Table 2. Performance metrics used for evaluation

Metric	Mathematical definition
MPPT efficiency $\eta_{MPPT}(\%)$	$\frac{1}{N}\sum_{k=1}^{N} \min\left(\frac{P_{pv}(k)}{P_{GMPP}(k)}\right) \times 100.$
Convergence time $t_{conv}(s)$	Time required for $P_{pv} \geq 0.95\ P_{GMPP}$
Steady-state ripple $Osc_{pp}(W)$	$\max(P_{pv}) - \min(P_{pv})$.
RMS tracking error $e_{track}(\%)$	$\frac{mean\left(\left\|P_{GMPP} - P_{pv}\right\|\right)}{mean\ (P_{GMPP})} \times 100$
Extracted energy $E(J)$	$\int_0^T P_{pv}(t)dt$

5. RESULTS AND DISCUSSION

The performance of the proposed hybrid PSC-aware ANN–INC MPPT strategy is evaluated under various operating conditions. The evaluation assesses its tracking accuracy and robustness. Simulations are conducted in MATLAB/Simulink, as shown in Figure 3, considering variations in irradiance, temperature, and partial shading patterns.

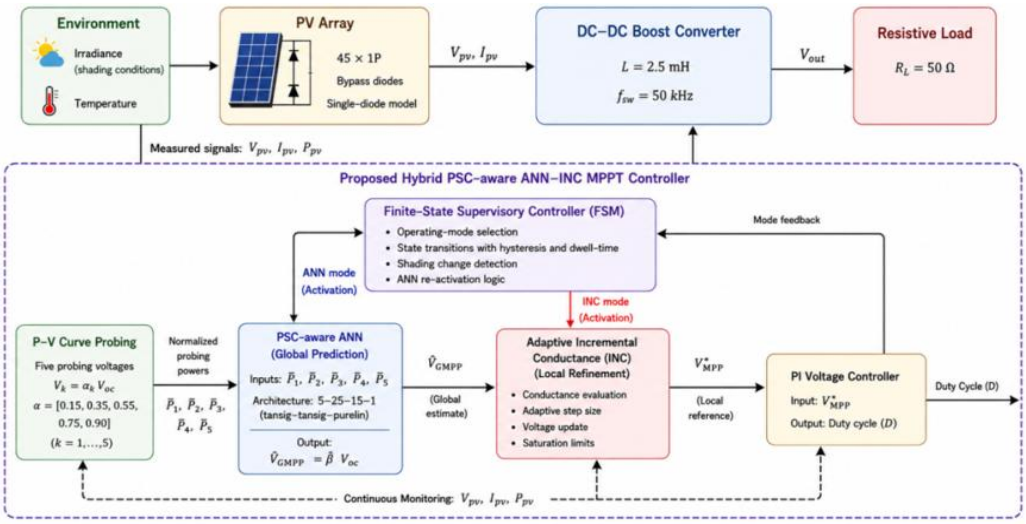

Figure 3. Overall architecture of the proposed hybrid PSC-aware ANN–INC MPPT controller under partial shading conditions

5.1. Uniform irradiance and temperature variations

Under uniform irradiance (Figure 4), both controllers closely follow the theoretical GMPP trajectory. The standalone ANN achieves 99.93% efficiency compared with 99.19% for the hybrid ANN–INC. Similarly, under temperature variations (Figure 5), efficiencies of 99.68% and 99.32% are obtained, respectively. These results indicate that the ANN prediction alone is already highly accurate when the P–V characteristic contains a single dominant maximum. Although the hybrid controller provides slightly lower efficiency, it reduces the RMS power oscillation from 1.98 W to 1.20 W under temperature variations, confirming stable operation without significant degradation of the baseline performance.

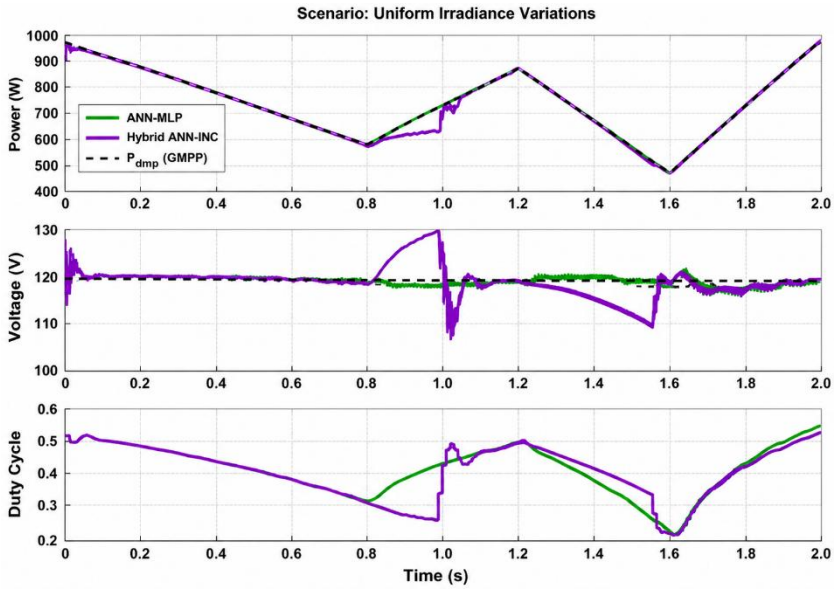

Figure 4. MPPT performance comparison of the standalone PSC-aware ANN and proposed hybrid ANN–INC under uniform irradiance variations

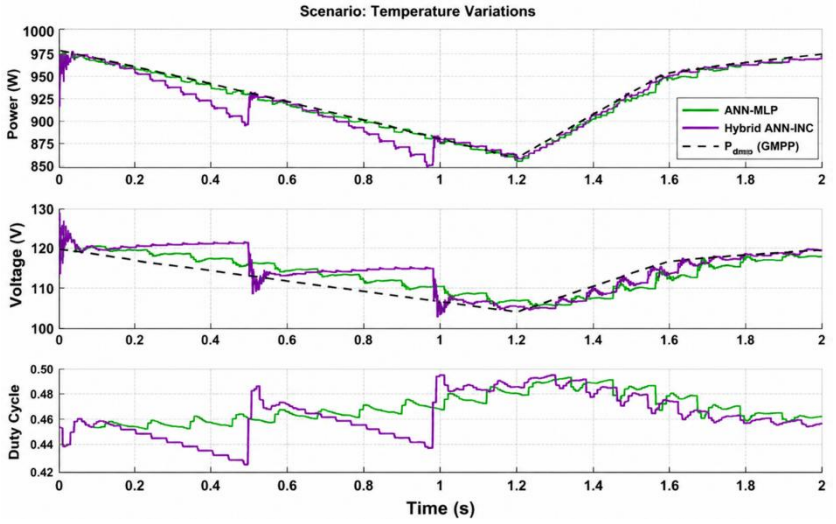

Figure 5. MPPT performance comparison of the standalone PSC-aware ANN and proposed hybrid ANN–INC under temperature variations

5.2. Static and severe partial shading

Figures 6 and 7 compare the standalone PSC-aware ANN and the proposed hybrid ANN–INC under static and severe partial shading. Under static PSC, the hybrid controller achieves an MPPT efficiency of 97.04%, compared with 96.30% for the standalone ANN, while reducing the convergence time from 0.0337 s

to 0.0012 s and increasing the extracted energy from 1023.7 J to 1044.6 J. Under severe PSC with multiple local maxima, the improvement becomes more pronounced: the hybrid strategy reaches 93.15% efficiency compared with 90.84% for the ANN, reduces the convergence time from 0.2604 s to 0.1490 s, and increases the extracted energy from 732.6 J to 747.9 J. These results indicate that adaptive INC refinement compensates for residual ANN prediction errors and improves localization of the final operating point under complex P–V characteristics.

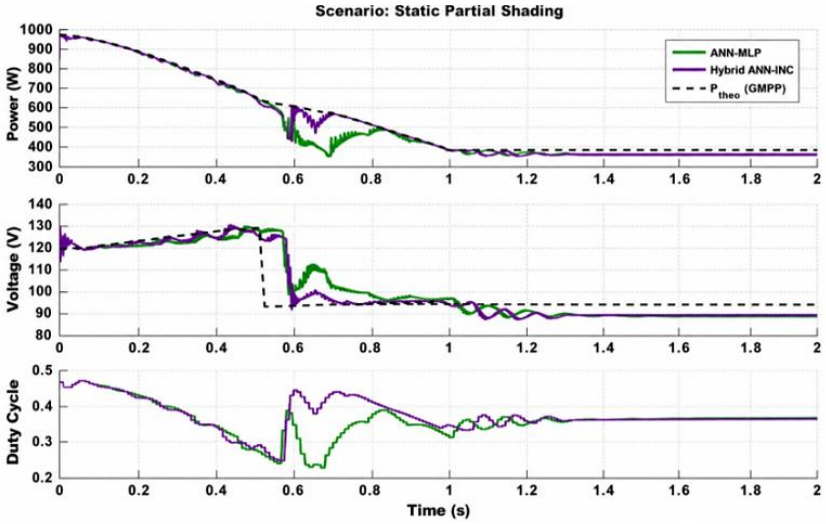

Figure 6. MPPT performance comparison of the standalone PSC-aware ANN and proposed hybrid ANN–INC under static partial shading conditions

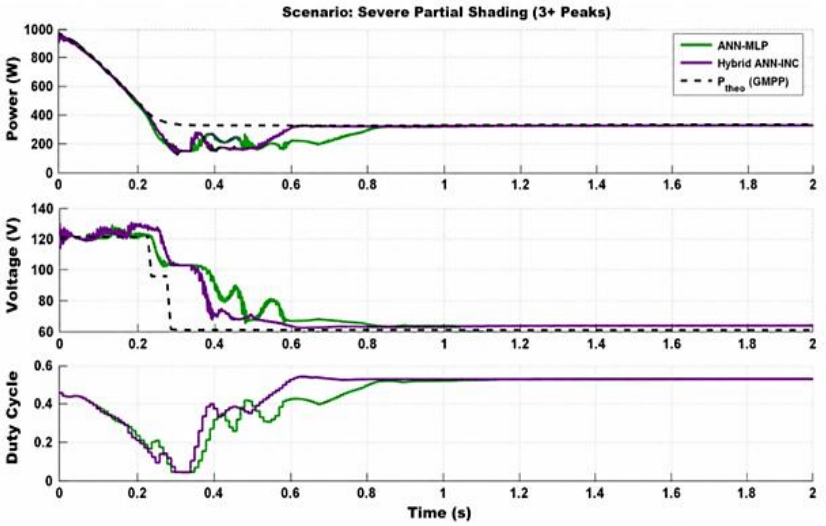

Figure 7. MPPT performance comparison of the standalone PSC-aware ANN and proposed hybrid ANN–INC under severe partial shading conditions with multiple local maxima

5.3. Dynamic partial shading

Figure 8 evaluates the controllers under dynamic partial shading, where the GMPP changes continuously with the shading pattern. The proposed hybrid ANN–INC achieves 96.40% MPPT efficiency, compared with 94.17% for the standalone ANN, while reducing the convergence time from 0.0590 s to 0.0355 s. The extracted energy also increases from 875.6 J to 894.6 J. The improved dynamic response results from the complementary operation of the two stages: P–V probing and ANN prediction provide global GMPP localization after significant operating changes, whereas adaptive INC performs local refinement between global updates. Consequently, the hybrid controller maintains more accurate tracking during rapidly changing partial-shading conditions.

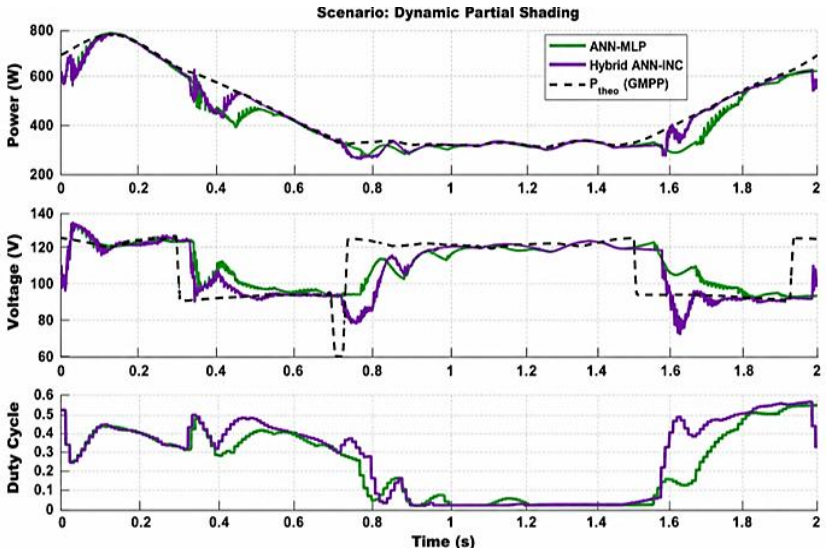

Figure 8. MPPT performance comparison of the standalone PSC-aware ANN and proposed hybrid ANN–INC under dynamic partial shading conditions

5.4. Discussion

The results presented in Table 3 demonstrate that the proposed hybrid ANN–INC strategy preserves the high tracking performance of the standalone PSC-aware ANN under uniform conditions while providing greater benefits under partial shading. Under static, severe, and dynamic PSC, the hybrid controller achieves MPPT efficiencies of 97.04%, 93.15%, and 96.40%, respectively, compared with 96.30%, 90.84%, and 94.17% for the standalone ANN. The hybrid strategy also reduces convergence time and increases the extracted energy under all three PSC scenarios.

The improvement under PSC results from the complementary roles of the two stages. The normalized P–V probing powers provide global information on the array characteristic, allowing the ANN to estimate the GMPP reference voltage without environmental sensors or iterative global optimization. Adaptive INC then compensates for residual ANN prediction errors through local refinement, which becomes particularly beneficial when multiple local maxima occur or the shading pattern changes dynamically.

The standalone PSC-aware ANN was previously directly benchmarked against P&O, INC, and PSO under partial shading conditions in [26], where its global tracking capability was established. To avoid duplicating these previously reported benchmark results, the present study focuses on quantifying the additional improvement obtained by integrating adaptive INC refinement with the PSC-aware ANN. The present validation remains simulation-based; therefore, the reported computational and tracking performance should not be interpreted as experimental real-time performance. Future work will focus on HIL and embedded implementation to assess robustness to sensor noise, parameter uncertainties, and real-time computational constraints.

Table 3. Comparative performance of standalone PSC-aware ANN and hybrid ANN–INC MPPT

Scenario	ANN η (%)	Hybrid η (%)	ANN (t_{conv}) (s)	Hybrid (t_{conv}) (s)	ANN energy (J)	Hybrid energy (J)
Uniform	99.93	99.19	0.0011	0.0011	1458.7	1449.9
Temperature	99.68	99.32	0.0012	0.0012	1823.0	1817.4
Static PSC	96.30	97.04	0.0337	0.0012	1023.7	1044.6
Severe PSC	90.84	93.15	0.2604	0.1490	732.6	747.9
Dynamic PSC	94.17	96.40	0.0590	0.0355	875.6	894.6

5.5. Comparison with recent intelligent and hybrid MPPT methods

Recent hybrid ANN–INC methods combine ANN prediction with INC tracking. The novelty of the proposed strategy lies in its PSC-aware global–local architecture: five normalized P–V probing powers provide the ANN with information on the global P–V curve shape to directly estimate the GMPP voltage, while adaptive INC subsequently refines the operating point. Unlike approaches relying on irradiance/temperature inputs or ANN–INC switching, the proposed method requires no environmental sensors and is specifically designed for complex partial shading as depicted in Table 4. This combination improves GMPP tracking accuracy while retaining a relatively simple online control structure.

Table 4. Comparison with recent intelligent and hybrid MPPT methods under partial shading conditions

Ref.	Method	Main input/information	PSC evaluation	Online iterative search	Main distinction
[27]	Hybrid ANN–INC	ANN-assisted PV/MPPT information	Yes	INC local iteration	Adaptive hybrid ANN and incremental conductance MPPT
[28]	Hybrid ANN–INC	(V), (I), (G), (T)	Limited	No	Irradiance-dependent ANN/INC operation with boost VMS
[29]	ANFIS	PV operating variables	Yes	No	Neuro-fuzzy MPPT under uniform and PSC conditions
[30]	GA	Candidate operating points	Yes	Yes	Evolutionary global GMPP search
[31]	HBA–GA	Candidate operating points	Yes	Yes	Hybrid metaheuristic GMPP search
[32]	PPO–LSTM	PV states/observations	Yes	No	Recurrent DRL-based MPPT policy
This work	PSC-aware ANN–INC	Five normalized P–V probing powers	Yes	No global iterative search	ANN global GMPP-voltage estimation + adaptive INC local refinement

6. CONCLUSION

This paper presented a PSC-aware hybrid ANN–INC MPPT strategy combining P–V curve probing, ANN-based global GMPP voltage estimation, and adaptive INC local refinement. The proposed approach was evaluated in MATLAB/Simulink under uniform irradiance, temperature variations, and static, severe, and dynamic partial shading conditions. The standalone ANN achieved 99.93% and 99.68% efficiency under uniform and temperature-varying conditions, respectively, while the hybrid strategy achieved 97.04%, 93.15%, and 96.40% under static, severe, and dynamic PSC, respectively. The results show that the proposed global–local cooperation improves GMPP tracking under complex shading by using five normalized P–V probing powers for global ANN estimation followed by adaptive INC refinement, without requiring irradiance or temperature inputs. Experimental/HIL validation, embedded implementation, and robustness assessment under measurement noise and parameter uncertainties will be considered in future work.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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Rachid Marrakh				✓	✓		✓			✓			✓	
Meriem Mossaddek				✓	✓					✓		✓		

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

The authors state no conflict of interest.

DATA AVAILABILITY

The simulation data that support the findings of this study are available from the corresponding author upon reasonable request.

REFERENCES

[1] D. Mazumdar, C. Sain, P. K. Biswas, P. Sanjeevikumar, and B. Khan, "Overview of solar photovoltaic MPPT methods: a state of the art on conventional and artificial intelligence control techniques," *International Transactions on Electrical Energy Systems*, vol. 2024, pp. 1–24, Apr. 2024, doi: 10.1155/2024/8363342.

[2] M. Y. Worku *et al.*, "A comprehensive review of recent maximum power point tracking techniques for photovoltaic systems under partial shading," *Sustainability*, vol. 15, no. 14, Jul. 2023, doi: 10.3390/su151411132.

[3] K. Ishaque and Z. Salam, "A review of maximum power point tracking techniques of PV system for uniform insolation and partial shading condition," *Renewable and Sustainable Energy Reviews*, vol. 19, pp. 475–488, Mar. 2013, doi: 10.1016/j.rser.2012.11.032.

[4] M. A. Eltawil and Z. Zhao, "MPPT techniques for photovoltaic applications," *Renewable and Sustainable Energy Reviews*, vol. 25, pp. 793–813, Sep. 2013, doi: 10.1016/j.rser.2013.05.022.

[5] C. G. Villegas-Mier, J. Rodriguez-Resendiz, J. M. Álvarez-Alvarado, H. Rodriguez-Resendiz, A. M. Herrera-Navarro, and O. Rodríguez-Abreo, "Artificial neural networks in MPPT Algorithms for optimization of photovoltaic power systems: a review," *Micromachines*, vol. 12, no. 10, p. 1260, Oct. 2021, doi: 10.3390/mi12101260.

[6] C. R. Çırak and H. Çalık, "Hotspots in maximum power point tracking algorithms for photovoltaic systems – A comprehensive and comparative review," *Engineering Science and Technology, an International Journal*, vol. 43, Jul. 2023, doi: 10.1016/j.jestch.2023.101436.

[7] A. M. Eltamaly and H. M. H. Farh, "Dynamic global maximum power point tracking of the PV systems under variant partial shading using hybrid GWO-FLC," *Solar Energy*, vol. 177, pp. 306–316, Jan. 2019, doi: 10.1016/j.solener.2018.11.028.

[8] K. Charu, P. Thakur, and F. Ansari, "Performance analysis of conventional MPPT techniques for a solar PV system," *Journal of Graphic Era University*, Apr. 2023, doi: 10.13052/jgeu0975-1416.1121.

[9] S. Gul, S. M. Malik, Y. Sun, and F. Alsaif, "An artificial neural network based MPPT control of modified flyback converter for PV systems in active buildings," *Energy Reports*, vol. 12, pp. 2865–2872, Dec. 2024, doi: 10.1016/j.egyr.2024.08.082.

[10] S. Ngo, C.-S. Chiu, and T.-D. Ngo, "The athletics running algorithm-based improved incremental conductance method for photovoltaic power systems under partial-shading conditions: the athletics running algorithm based on improved incremental conductance method for PV power systems under PSCS," *IEEE Industry Applications Magazine*, vol. 30, no. 2, pp. 38–50, Mar. 2024, doi: 10.1109/MIAS.2023.3325089.

[11] D. Saadaoui *et al.*, "Extraction of single diode PV cell/module model parameters using a hybrid BMO approach with Lambert's W function," *International Journal of Ambient Energy*, vol. 45, no. 1, Dec. 2024, doi: 10.1080/01430750.2024.2304331.

[12] G. S. Reddy, T. B. Reddy, and M. V. Kumar, "A MATLAB based PV module models analysis under conditions of nonuniform irradiance," *Energy Procedia*, vol. 117, pp. 974–983, Jun. 2017, doi: 10.1016/j.egypro.2017.05.218.

[13] P. Gupta and K. S. Sandhu, "Performance analysis of solar panel under different operating conditions," in *2019 3rd International Conference on Electronics, Communication and Aerospace Technology (ICECA)*, Jun. 2019, pp. 900–905, doi: 10.1109/ICECA.2019.8822041.

[14] F. Z. El Hamzaoui, T. Abderrahime, and B. D. Taoufiq, "Comparison between perturb & observe, fuzzy logic MPPT technique, and the artificial neural network techniques at different temperature conditions," *IFAC-PapersOnLine*, vol. 58, no. 13, pp. 599–604, 2024, doi: 10.1016/j.ifacol.2024.07.548.

[15] H. Ahessab, A. Gaga, and B. Elhadadi, "Enhanced MPPT controller for partially shaded PV systems using a modified PSO algorithm and intelligent artificial neural network, with DSP F28379D implementation," *Science Progress*, vol. 107, no. 4, Oct. 2024, doi: 10.1177/00368504241290377.

[16] G. I. Orfanoudakis, E. Lioudakis, G. Foteinopoulos, E. Koutroulis, and W. Wu, "Dynamic global maximum power point tracking for partially shaded PV arrays in grid-connected PV systems," *IEEE Journal of Emerging and Selected Topics in Industrial Electronics*, vol. 5, no. 4, pp. 1481–1492, Oct. 2024, doi: 10.1109/JESTIE.2024.3389686.

[17] S. Lyden and M. E. Haque, "Maximum power point tracking techniques for photovoltaic systems: a comprehensive review and comparative analysis," *Renewable and Sustainable Energy Reviews*, vol. 52, pp. 1504–1518, Dec. 2015, doi: 10.1016/j.rser.2015.07.172.

[18] J. C. Teo, R. H. G. Tan, V. H. Mok, V. K. Ramachandaramurthy, and C. Tan, "Impact of partial shading on the P-V characteristics and the maximum power of a photovoltaic string," *Energies*, vol. 11, no. 7, Jul. 2018, doi: 10.3390/en11071860.

[19] M. Kouihi, M. Moutchou, and A. Ait Elmahjoub, "Maximum power extraction of solar PV system using DC-DC buck converter and backstepping control based on P&O MPPT algorithm," *E3S Web of Conferences*, vol. 336, Jan. 2022, doi: 10.1051/e3sconf/202233600046.

[20] A. L. Saleh, A. A. Obed, Z. A. Hassoun, and S. J. Yaqoob, "Modeling and simulation of a low cost perturb & observe and incremental conductance MPPT techniques in proteus software based on flyback converter," *IOP Conference Series: Materials Science and Engineering*, vol. 881, no. 1, p. 012152, Jul. 2020, doi: 10.1088/1757-899X/881/1/012152.

[21] M. C. Argyrou, P. Christodoulides, and S. A. Kalogirou, "Modeling of a photovoltaic system with different MPPT techniques using MATLAB/Simulink," in *2018 IEEE International Energy Conference (ENERGYCON)*, Jun. 2018, pp. 1–6, doi: 10.1109/ENERGYCON.2018.8398734.

[22] I. Rougab, A. Cheknane, And N. Abouchabana, "Study and simulation of MPPT techniques to control a stand-alone photovoltaic system under varying irradiance," *Revista Română de Informatică și Automatică*, vol. 31, no. 4, Dec. 2023, doi: 10.33436/v31i4y202109.

[23] M. S. Wasim, M. Amjad, M. A. Abbasi, A. R. Bhatti, and A. Rasool, "An improved grasshopper-based MPPT approach to reduce tracking time and startup oscillations in photovoltaic system under partial shading conditions," *PLOS ONE*, vol. 18, no. 8, 2023, doi: 10.1371/journal.pone.0290669.

[24] C. Pavithra, R. Dhayalan, S. A. Kumar, Y. Dharshan, R. Haridharan, and M. Vijayadharshini, "A novel comparative analysis of solar P&O, ANN-based MPPT controller under different irradiance condition," *EAI Endorsed Transactions on Energy Web*, vol. 11, Jan. 2024, doi: 10.4108/ew.4942.

[25] A. Aifan G. Alsulami *et al.*, "A comparison of several maximum power point tracking algorithms for a photovoltaic power system," *Frontiers in Energy Research*, vol. 12, May 2024, doi: 10.3389/fenrg.2024.1413252.

[26] A. Jamaa, A. Moutabir, and R. Marrakh, "A PSC-aware ANN-based global MPPT strategy using power–voltage curve probing for photovoltaic systems," *Journal of Electrical Systems and Information Technology*, vol. 13, no. 1, Aug. 2026, doi: 10.1186/s43067-026-00386-2.

[27] R. K. Rai and U. K. Sinha, "Adaptive hybrid ANN and incremental conductance approach for maximum power point tracking in solar PV systems," *Indian Journal of Pure and Applied Physics*, vol. 63, no. 8, pp. 719–740, 2025, doi: 10.56042/ijpap.v63i8.19481.
[28] M. A. N. Abed, M. K. Ali, A. Zurfi, and M. J. A. Alkhafaji, "Hybrid ANN-INC MPPT integrated with a high-efficiency boost VMS converter for photovoltaic systems," *International Journal of Robotics and Control Systems*, vol. 6, no. 2, pp. 1593–1616, 2026, doi: 10.31763/ijrcs.v6i2.2344.
[29] M. Atillah, H. Stitou, A. Boudaoud, and M. Aqil, "Comparative study of two ANFIS-based MPPT controls under uniform and partial shading conditions," *Solar Energy and Sustainable Development Journal*, pp. 89–103, Dec. 2024, doi: 10.51646/jsesd.v14iSI_MSMS2E.400.
[30] F. M. de Oliveira, M. H. M. Brandt, F. Salvadori, J. E. E. Izquierdo, M. R. Cavallari, and O. H. Ando Junior, "Development of an MPPT-based genetic algorithm for photovoltaic systems versus classical MPPT techniques in scenarios with partial shading," *Inventions*, vol. 9, no. 3, May 2024, doi: 10.3390/inventions9030064.
[31] Z.-K. Fan, A. Setianingrum, K.-L. Lian, and S. Suwarno, "A hybrid approach for photovoltaic maximum power tracking under partial shading using honey badger and genetic algorithms," *Energies*, vol. 17, no. 16, Aug. 2024, doi: 10.3390/en17163935.
[32] A. Wadehra, S. Bhalla, V. Jaiswal, K. P. S. Rana, and V. Kumar, "A deep recurrent reinforcement learning approach for enhanced MPPT in PV systems," *Applied Soft Computing*, vol. 162, Sep. 2024, doi: 10.1016/j.asoc.2024.111728.

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