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Confidence-driven adaptive operating-point optimization for photovoltaic systems under partial shading conditions

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ABSTRACT

Partial shading conditions (PSC) generate highly nonlinear multi-peak photovoltaic (PV) characteristics, complicating reliable global maximum power point tracking (GMPP). Although numerous intelligent optimization techniques exist, most rely on extensive exploration mechanisms that limit their applicability in embedded real-time controllers. This paper introduces a confidence-driven adaptive maximum power point tracking (MPPT) framework in which the optimization search space is dynamically regulated according to the reliability of a predictive operating-region estimator. Unlike standard artificial neural network (ANN)-assisted MPPT strategies that offer only power prediction, the proposed approach exploits a confidence index to continuously contract or expand the exploration domain, minimizing search effort while preserving global tracking capability. The framework was developed using real measurements from the PV-DAQ database and validated through a nonlinear two-diode thermal-electrical PV model incorporating irradiance mismatch and temperature-dependent effects. Static and dynamic PSC scenarios were investigated to evaluate convergence behavior and computational performance. Experimental results demonstrate that the proposed confidence-governed strategy achieves an average tracking efficiency of 90.89%, reduces convergence effort through adaptive search-space contraction, and matches real measurements with an R^2 value of 0.8664, offering a low-complexity solution for real-time embedded PV energy management.

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1. INTRODUCTION

Photovoltaic (PV) energy systems have become one of the most promising renewable-energy technologies for sustainable electricity generation and distributed power-generation applications [1]. However, their performance strongly depends on environmental operating conditions, particularly solar irradiance and temperature. Among the various factors affecting PV power production, partial shading conditions (PSC) remain one of the most challenging issues because they generate highly nonlinear power–voltage (P–V) characteristics containing multiple local maxima [2]. Under such conditions, reliable global maximum power point tracking (GMPP) becomes considerably more difficult, and conventional maximum power point tracking (MPPT) techniques often converge toward local operating points rather than the true global optimum [3]-[5].

Traditional MPPT methods such as perturb and observe (P&O) and incremental conductance (IC) offer low computational complexity and simple implementation. Nevertheless, their performance significantly deteriorates under PSC because of the presence of multiple power peaks and rapidly changing irradiance conditions [4], [6], [7]. To overcome these limitations, numerous intelligent optimization approaches have been proposed, including particle swarm optimization (PSO), grey wolf optimization (GWO), differential evolution (DE), salp swarm algorithm (SSA), hybrid metaheuristics, reinforcement learning (RL), and deep reinforcement learning (DRL) [8]-[18]. These techniques generally improve global search capability and enhance GMPP localization accuracy under complex operating conditions. More broadly, intelligent data-driven techniques have increasingly been adopted to enhance PV monitoring, prediction, and maximum power point tracking under complex operating conditions [19].

Despite their effectiveness, most intelligent MPPT strategies rely on extensive exploration of the PV operating domain. Large search intervals, repeated fitness-function evaluations, and computationally intensive training procedures often increase convergence effort and execution cost, limiting their suitability for lightweight embedded PV controllers operating under rapidly varying environmental conditions. Consequently, maintaining reliable GMPP localization while reducing unnecessary exploration remains an open research challenge. Recent studies have also emphasized the importance of lightweight embedded MPPT architectures and low-complexity AI-assisted control strategies capable of real-time operation under dynamic environmental conditions [20], [21].

To address this limitation, this paper proposes a confidence-regulated adaptive MPPT framework that dynamically adjusts the exploration interval according to prediction reliability. Unlike conventional artificial neural network (ANN)-assisted MPPT approaches, where prediction is primarily used to estimate the operating point, the proposed framework exploits a confidence indicator to directly regulate the optimization domain. The search space contracts when confidence is high and expands when uncertainty increases, concentrating exploration around probable high-power operating regions while preserving global-search capability under PSC conditions.

The main contributions of this work, centered on the concept of confidence-regulated search-space contraction, are summarized as follows:

– A confidence-governed search-space contraction mechanism that dynamically regulates the optimization domain according to prediction reliability.
– A prediction-guided adaptive optimization framework that reduces redundant exploration while preserving GMPP localization capability under PSC conditions.
– Experimental validation using real PVDAQ measurements and a nonlinear thermal–electrical PV model incorporating irradiance mismatch, bypass-diode activation, and temperature-dependent effects.
– Demonstration of low-complexity real-time suitability for embedded PV energy-management applications.

Real photovoltaic dataset. The proposed confidence-regulated MPPT framework was developed and validated using real PV measurements obtained from the open energy data initiative (OEDI) PVDAQ database. The selected utility-scale PV installation provides electrical and environmental operating variables, including PV power, voltage, current, and temperature measurements. Prior to model development, normalization, noise filtering, and operating-condition verification were applied to improve data consistency and reliability. The resulting dataset constitutes a realistic benchmark for evaluating predictive performance and MPPT behavior under practical outdoor operating conditions. Figure 1 presents the measured PV power profile extracted from the PVDAQ database.

PV system validation model. A nonlinear thermal–electrical PV model was employed to provide a realistic validation environment for the proposed framework. Such models are widely used for reproducing PV behavior and parameter-identification studies under varying operating conditions [22]. The PV array was partitioned into multiple series-connected submodules subjected to nonuniform irradiance distributions, enabling the generation of representative multi-peak operating conditions for evaluating the effectiveness of the proposed confidence-regulated optimization strategy.

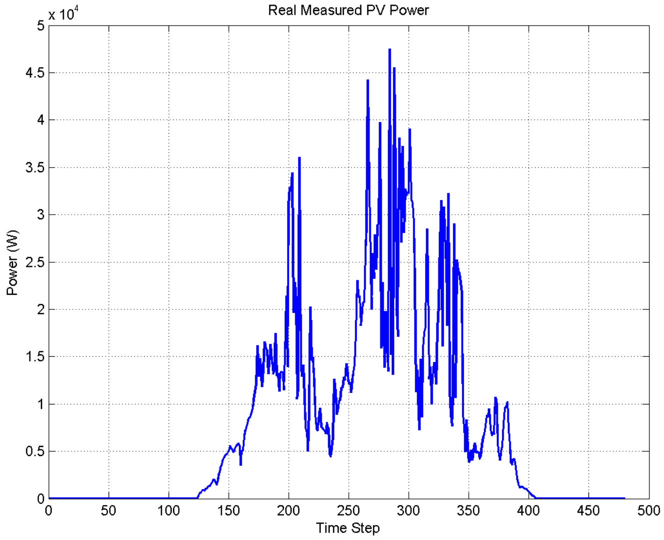


Figure 1. Measured photovoltaic power profile extracted from the PVDAQ database

2. VALIDATION SCENARIOS UNDER PARTIAL SHADING CONDITIONS

The effectiveness of the proposed confidence-regulated optimization framework was assessed under progressively increasing levels of PV operating uncertainty. The objective was not only to evaluate GMPP tracking performance under PSC, but also to investigate the ability of the adaptive search-space contraction mechanism to preserve reliable decision-making when the ambiguity of the optimization landscape increases.

2.1. Static partial shading scenarios

Three representative operating scenarios were designed to generate distinct levels of irradiance mismatch, multi-peak complexity, and GMPP ambiguity.

- Case 1 — Severe irradiance mismatch: $G = [1000,\ 500,\ 300,\ 150,\ 50]$ W/m^2.
- Case 2 — Progressive irradiance gradient: $G = [1000,\ 800,\ 600,\ 400,\ 200]$ W/m^2.
- Case 3 — High multi-peak ambiguity: $G = [1000,\ 1000,\ 200,\ 200,\ 50]$ W/m^2.

These configurations were intentionally selected to challenge different aspects of the optimization process. Case 1 introduces substantial power degradation caused by strong irradiance mismatch. Case 2 represents a smoother but still nonuniform operating environment. Case 3 constitutes the most demanding scenario, producing multiple closely spaced local maxima that increase the probability of incorrect GMPP identification and therefore represent a critical test for confidence-guided exploration strategies.

From an optimization perspective, these scenarios progressively increase the ambiguity of the search landscape, making them particularly suitable for evaluating the ability of the proposed framework to dynamically regulate exploration effort according to prediction reliability.

Figure 2 illustrates the limitations of a conventional P&O controller under severe shading conditions. Owing to the presence of multiple local optima, the algorithm converges toward a suboptimal operating point rather than the true GMPP.

2.2. Dynamic operating conditions

Practical PV systems operate under continuously varying irradiance and temperature conditions, resulting in time-varying GMPP locations and evolving prediction uncertainty. To reproduce these realistic operating conditions, dynamic irradiance perturbations were applied across PV submodules, generating continuously changing multi-peak power characteristics.

These scenarios provide a demanding validation environment for the proposed confidence-regulated framework, requiring continuous adaptation of the exploration domain according to operating uncertainty. Consequently, they enable assessment of tracking robustness, convergence stability, computational efficiency, and real-time adaptability under realistic PV conditions.

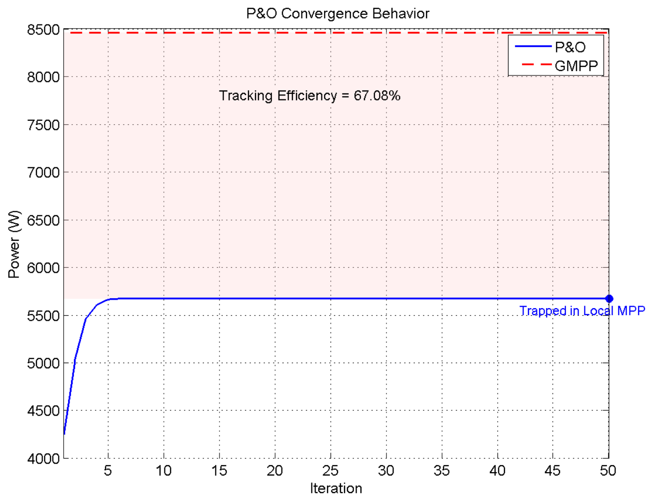


Figure 2. Failure of conventional local-search MPPT under multi-peak PSC conditions

3. ADAPTIVE CONFIDENCE-REGULATED OPTIMIZATION FRAMEWORK

The proposed methodology is founded on the principle that optimization effort should be proportional to operating uncertainty. Conventional MPPT algorithms typically employ fixed exploration strategies regardless of the reliability of available information. Consequently, considerable computational resources may be spent exploring operating regions with a low probability of containing the GMPP.

To address this limitation, the proposed framework introduces a confidence-regulated search-space contraction mechanism that dynamically adapts the optimization domain according to prediction reliability. The resulting strategy combines predictive operating-region estimation, confidence quantification, and adaptive PSO exploration within a unified decision framework.

3.1. Predictive operating-region estimation

A lightweight data-driven predictor was employed to estimate the probable location of high-power operating regions from real-time PV measurements.

The predictive model receives electrical and environmental operating variables extracted from the PV system and generates an estimate of the most probable high-power operating region. By supplying an informed initialization of the search process, the predictive stage reduces the need for exhaustive exploration while preserving adaptability under irradiance mismatch and PSC.

As illustrated in Figure 3, the predictive model demonstrates satisfactory agreement between measured and estimated PV power, yielding an R^2 value of 0.8664. Although prediction accuracy is not the primary objective of the proposed framework, the obtained estimation provides sufficiently reliable prior information for adaptive exploration regulation.

3.2. Confidence-regulated search-space contraction

The central contribution of this work is the introduction of a confidence index that establishes a direct coupling between prediction reliability and optimization behavior. Instead of maintaining a fixed exploration strategy, the proposed framework dynamically regulates the accessible search domain according to the estimated certainty of the predictive stage.

The confidence index is defined as:

$$CI = 1 - \frac{|P_{pred} - P_{measured}|}{P_{max}} \quad (1)$$

where P_{pred} denotes the predicted PV power, $P_{measured}$ represents the measured operating power, and P_{max} corresponds to the maximum power observed within the experimental dataset.

The confidence index acts as a lightweight normalized uncertainty indicator that directly links prediction reliability to exploration intensity while preserving low computational complexity for embedded MPPT applications. High confidence values indicate that the predicted operating region is likely to contain the GMPP, enabling aggressive search-space contraction and reduced computational effort. Conversely, lower confidence values automatically expand the exploration domain to preserve global-search capability and avoid premature convergence toward local optima [23].

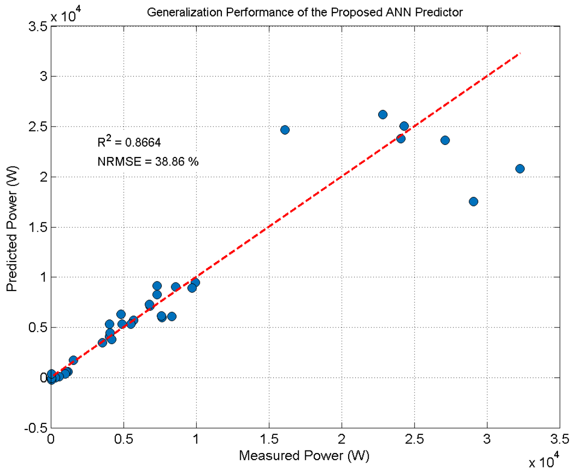


Figure 3. Generalization performance of the predictive operating-region estimator under unseen operating conditions

3.3. Adaptive optimization strategy

Based on the confidence index, the optimization process dynamically regulates the accessible search interval around the predicted operating region. The adaptive search range is expressed as:

$$SearchRange = (0.05 + 0.45(1 - CI))(V_{max} - V_{min}) \quad (2)$$

This formulation establishes a direct relationship between operating uncertainty and exploration intensity. When confidence is high, the search domain contracts around the predicted GMPP region, thereby reducing redundant particle movements and unnecessary fitness evaluations. Under uncertain operating conditions, the search interval automatically expands to maintain sufficient global exploration capability.

Figure 4 illustrates how the proposed framework continuously adjusts exploration effort according to prediction reliability. This adaptive behavior enables efficient allocation of computational resources while preserving robust GMPP localization capability.

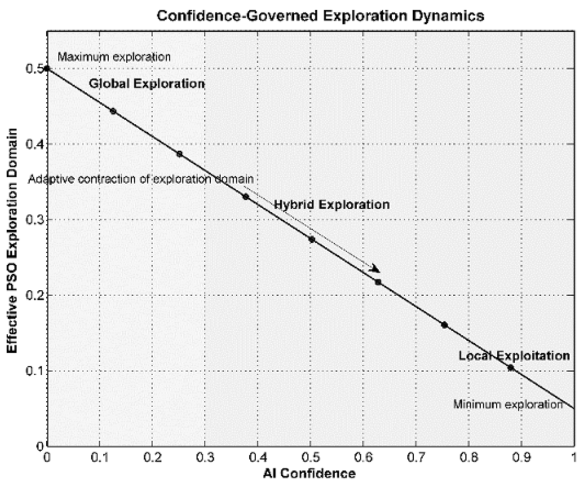
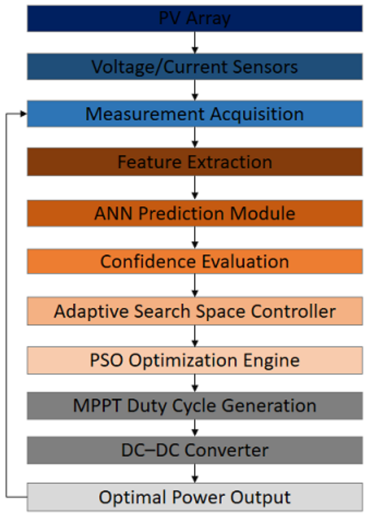


Figure 4. Adaptive search-space contraction as a function of the confidence index

The overall operating principle of the proposed framework is summarized in Figure 5. Real-time PV measurements are first processed by the predictive estimator to identify probable high-power operating regions. The confidence index is subsequently computed and used to regulate the exploration domain before the adaptive PSO stage performs final GMPP localization. This sequential decision process enables the optimization effort to be continuously adjusted according to the actual level of operating uncertainty.



Block diagram of the proposed confidence-driven adaptive MPPT framework for photovoltaic systems under partial shading conditions.

Figure 5. Architecture of the proposed confidence-regulated adaptive MPPT framework

4. RESULTS AND DISCUSSION

This section evaluates the proposed confidence-regulated optimization framework under static and dynamic PSC. Particular attention is devoted to assessing the effectiveness of the confidence-guided search-space contraction mechanism in terms of tracking accuracy, convergence behavior, computational efficiency, and robustness under operating uncertainty.

4.1. Predictive operating-region estimation performance

The predictive operating-region estimator achieved an RMSE of 3268.48 W, a prediction error of 19.23%, and an R^2 value of 0.8664 between predicted and measured PV power.

Although the predictive model exhibits a prediction error of 19.23%, its role within the proposed framework is fundamentally different from that of a conventional PV power forecasting model. The predictor is intentionally employed as a coarse operating-region estimator whose objective is to identify probable high-power regions rather than accurately estimate the exact power output. The obtained R^2 value of 0.8664 indicates that the model successfully captures the dominant trends governing PV power evolution under varying environmental conditions. This information is subsequently processed by the confidence-regulated mechanism, which dynamically adjusts the exploration domain according to prediction reliability.

Consequently, the overall tracking performance does not depend solely on ANN prediction accuracy. Instead, the confidence-guided adaptation compensates for residual prediction uncertainty and enables efficient GMPP localization. This behavior is confirmed by the achieved tracking efficiency of 90.89%, which remains significantly higher than the predictive accuracy itself. Figure 6 presents the comparison between the measured photovoltaic power and the power predicted by the proposed hybrid ANN-PSO model under varying outdoor operating conditions.

4.2. Static operating-point convergence performance

The proposed framework achieved the lowest mean tracking error (7.74%) and the highest tracking efficiency (90.89%) among the evaluated MPPT strategies. Furthermore, the maximum tracking error was reduced to 18.99%, indicating improved robustness under irradiance mismatch and temperature variations.

The observed improvement is not solely attributable to the predictive stage itself. Rather, it results from the ability of the confidence-regulated mechanism to dynamically allocate exploration effort according to operating uncertainty. By concentrating the search process around confidence-supported operating regions, the framework reduces the likelihood of convergence toward misleading local maxima while preserving sufficient global-search capability.

4.3. Dynamic tracking performance

Figure 7 illustrates the dynamic behavior of the proposed framework under rapidly varying PSC conditions. As illustrated in Figure 7, the proposed framework maintains stable convergence despite continuous displacement of the GMPP caused by irradiance fluctuations. Specifically, Figures 7(a)–(d) respectively present the dynamic convergence response, oscillation analysis, tracking stability under PSC, and adaptive convergence behavior of the proposed framework. The adaptive search-space regulation mechanism limits unnecessary oscillatory behavior while preserving responsiveness to rapidly changing operating conditions.

The results further demonstrate that confidence-guided exploration enables a more effective balance between local exploitation and global exploration. Consequently, the proposed framework achieves improved convergence stability while maintaining robust tracking performance under highly dynamic operating environments.

4.4. Computational efficiency analysis

A computational analysis was conducted to evaluate the suitability of the proposed framework for real-time PV control applications. Table 1 summarizes the obtained computational performance.

Table 1. Computational performance comparison of MPPT strategies under PSC conditions

Method	Category	Efficiency (%)	Conv. Steps	Exec. Time(s)	Oscillation Std. (%)	GMPP Accuracy (%)	Mean Error (%)	RT Suitability
P&O	Classical	73.55	120	0.0078	High	73.87	26.13	High
Conventional PSO	Metaheuristic	87.57	56	0.0003	17.45	91.70	8.30	Moderate
Proposed Framework	Confidence-Guided	90.89	41	0.0005	15.16	92.26	7.74	High

Compared with conventional perturbation-based tracking, the proposed framework reduced the average convergence requirement from 120 to 41 steps while simultaneously improving GMPP accuracy and reducing oscillatory behavior.

Unlike conventional optimization approaches that employ fixed exploration domains, the proposed strategy dynamically regulates the effective search region according to prediction reliability. Consequently, computational resources are concentrated on operating regions with a higher probability of containing the GMPP, reducing redundant particle updates and unnecessary fitness evaluations.

The measured execution times remained within the millisecond range under identical simulation conditions and swarm settings for all compared methods, indicating the suitability of the proposed framework for real-time embedded PV control applications.

4.5. Ablation study of the proposed framework

An ablation study was conducted to quantify the individual contribution of predictive estimation and confidence-regulated search-space adaptation. The ablation results confirm that the observed performance gains originate from the interaction between predictive estimation and confidence-regulated search-space adaptation. The full framework achieves the best compromise between tracking accuracy, convergence speed, robustness, and computational efficiency. The detailed quantitative comparison of the evaluated configurations is presented in Table 2.

Table 2. Ablation study of the proposed adaptive MPPT framework

Configuration	Efficiency (%)	Tracking stability	Convergence speed
PSO only	82.39	Moderate	Moderate
ANN only	80.77	Low	Fast
ANN + PSO	87.45	Good	Good
ANN + Adaptive search	89.02	Better	Faster
Proposed full framework	90.89	High	Fast

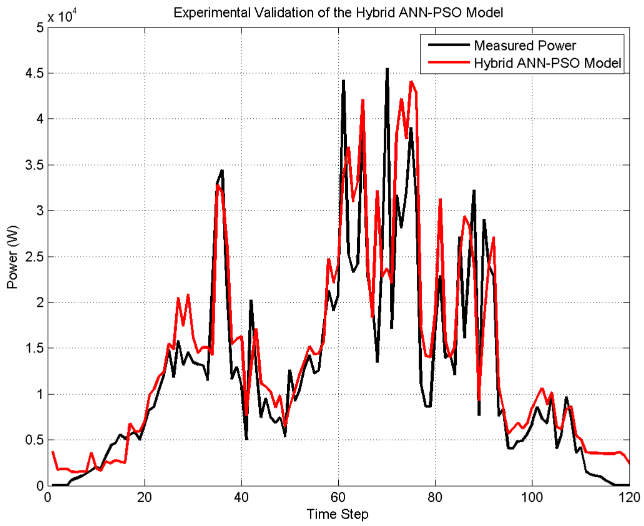


Figure 6. Comparison between measured and simulated photovoltaic power under varying outdoor conditions

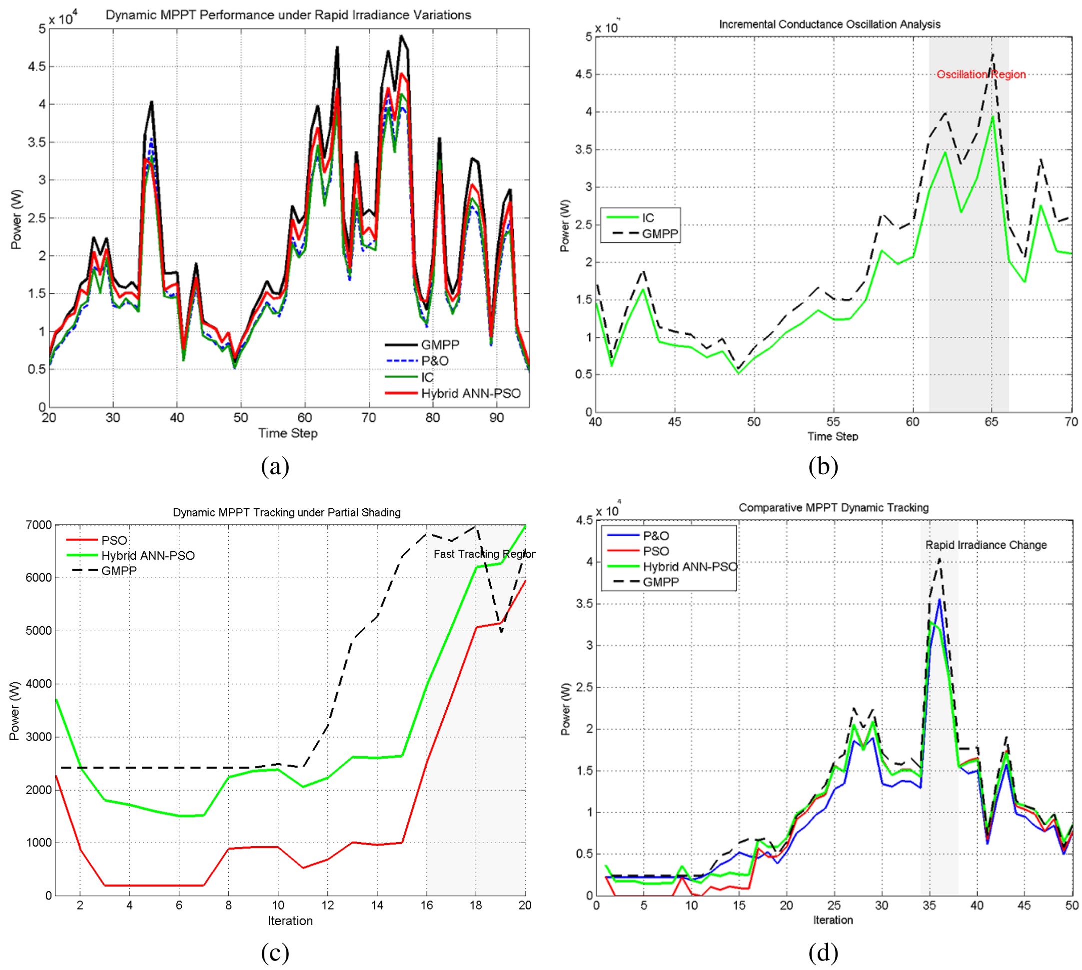


Figure 7. Dynamic convergence and oscillation behavior under PSC conditions;
(a) dynamic convergence response, (b) oscillation analysis, (c) tracking stability under PSC, and
(d) adaptive convergence behavior

5. POSITIONING RELATIVE TO EXISTING MPPT APPROACHES

Table 3 compares the proposed framework with recent MPPT strategies reported in the literature. Recent representative approaches include DRL-based MPPT strategies, adaptive metaheuristics, and hybrid optimization frameworks designed for PSC environments [15]-[18], [24].

Unlike accuracy-oriented MPPT approaches that rely on extensive exploration or computationally intensive learning procedures, the proposed framework focuses on confidence-regulated exploration. This design prioritizes computational efficiency, adaptive decision-making, and embedded implementation feasibility while maintaining competitive GMPP tracking performance under PSC conditions.

Beyond the comparative performance discussed above, the proposed confidence-regulated optimization framework also provides a promising foundation for future embedded photovoltaic energy-management systems. In particular, extending the proposed confidence-guided optimization strategy toward advanced real-time PV energy-management architectures represents an important research direction, as highlighted in recent studies on intelligent photovoltaic energy management [25].

Table 3. Comparative positioning of recent MPPT strategies under PSC conditions

Method	Exploration strategy	Computational cost	Training burden	Adaptivity	Embedded suitability	Main limitation
P&O	Local search	Very low	None	Low	High	Local optimum trapping
Conventional PSO	Global exploration	Moderate	None	Moderate	Good	Large search domain
GWO-PSO hybrid	Hybrid exploration	Moderate–High	None	High	Moderate	Increased complexity
NGWO-Based MPPT	Adaptive exploration	Moderate	None	High	Moderate	Parameter tuning sensitivity
ISSA-P&O Hybrid	Metaheuristic-guided	High	None	High	Moderate	High computational burden
DRL-based MPPT	Policy learning	Very high	High	Very high	Limited	Training complexity
DQN/DDPG-based MPPT	Deep reinforcement learning	Very high	Very high	Very high	Limited	Large data requirement
Adaptive GWO/PSO/POA	Adaptive metaheuristic	Moderate–High	None	High	Moderate	Exploration overhead
Proposed framework	**Confidence-regulated exploration**	**Low–Moderate**	**Low**	**Adaptive**	**High**	**Prediction-dependent**

6. CONCLUSION

This paper introduced a confidence-regulated search-space contraction framework for adaptive MPPT in PV systems under PSC. Unlike conventional intelligent MPPT approaches that employ fixed exploration strategies, the proposed methodology dynamically adjusts the optimization domain according to prediction reliability through a confidence-guided search-space contraction mechanism.

The obtained results demonstrate that linking exploration effort to operating uncertainty enables more efficient allocation of computational resources while preserving robust GMPP localization capability. Experimental evaluation under static and dynamic PSC scenarios showed improved tracking stability, reduced convergence effort, and an average tracking efficiency of 90.89%. Furthermore, validation against real PVDAQ measurements yielded an R^2 value of 0.8664. Although the predictive stage was not intended to provide highly accurate power forecasting, it successfully supplied reliable operating-region information for confidence-guided exploration control. The obtained results demonstrate that coupling a coarse predictor with adaptive confidence-regulated optimization can achieve robust GMPP localization while maintaining low computational complexity.

The proposed confidence-regulated search-space contraction strategy establishes a direct connection between predictive information and optimization behavior, allowing exploration intensity to adapt continuously to changing operating conditions. This characteristic makes the framework particularly attractive for lightweight embedded PV controllers where computational efficiency and real-time responsiveness are critical design requirements.

Future work will focus on hardware implementation, experimental real-time validation, and evaluation of the proposed framework under more diverse real-world photovoltaic operating conditions.

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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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Mourad Benmessaoud		✓					✓			✓		✓	✓	

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

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

The experimental photovoltaic measurements used in this study were obtained from the Open Energy Data Initiative (OEDI) PVDAQ database. Additional processed data and simulation results supporting the findings of this work are available from the corresponding author upon reasonable request.

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