e-ISSN: 3104-3860
Volume 1, Issue 3 (Part 2), 2025, Pages: 01-13
Website: https://journals.labjournal.ly/index.php/Jlabw/index

Hybrid Metaheuristic-Neural Algorithms for Maximum Power Point Tracking in IoT-Monitored Solar Arrays Under Partial Shading and Spectral Irradiance Variability

Hawa Abdulhafid Moh D Almonier *
Department of Applied Physics, College of Engineering Technology- Janzour, Libya
* Corresponding author: h.almonier@cetj.edu.ly

خوارزميات (Metaheuristic) عصبية هجينة لتتبع أقصى نقطة طاقة في المصفوفات الشمسية التي تتم مراقبتها عبر إنترنت الأشياء في ظل التظليل الجزئي وتغير الإشعاع الطيفي

حواء عبدالحفيظ محمد المنير*
قسم الفيزياء التطبيقية، كلية التقنية الهندسية، جنزور، ليبيا

Received: 09-07-2025; Accepted: 04-09-2025; Published: 19-09-2025

Abstract
The operational efficiency of photovoltaic (PV) systems under non-uniform irradiance conditions remains a critical challenge in renewable energy deployment. Conventional maximum power point tracking (MPPT) algorithms frequently converge to local maxima under partial shading and spectral irradiance fluctuations, resulting in substantial energy yield losses. This study introduces a novel hybrid architecture integrating metaheuristic optimization with adaptive neural networks, deployed within an Internet of Things (IoT)-enabled real-time monitoring framework. The proposed algorithm termed H-MNMPPT (Hybrid Metaheuristic-Neural MPPT) synergistically combines the exploratory robustness of the Enhanced Grey Wolf Optimizer (EGWO) with the predictive adaptability of a gated recurrent unit (GRU)-based neural estimator. Experimental validation was conducted on a 2.4 kW rooftop PV array instrumented with distributed IoT sensors capturing irradiance, temperature, spectral distribution, and module-level current-voltage characteristics. Under dynamically shifting partial shading patterns and spectrally variant irradiance (AM 1.0 to AM 2.5), H-MNMPPT demonstrated a 98.7% tracking efficiency, outperforming Perturb and Observe (P&O) by 21.3%, PSO-based MPPT by 14.1%, and conventional ANN-MPPT by 9.8%. Furthermore, convergence time was reduced by 63% compared to standard GWO, and the system maintained sub-second response latency under IoT-triggered environmental transitions. This architecture establishes a new benchmark for intelligent, resilient MPPT in next-generation smart solar farms.

Keywords: Maximum Power Point Tracking; Partial Shading; Spectral Irradiance; Hybrid Metaheuristic; Neural Network; IoT Monitoring; Photovoltaic Systems; Grey Wolf Optimizer; GRU Network.

الملخص
لا تزال الكفاءة التشغيلية لأنظمة الطاقة الكهروضوئية (PV) في ظل ظروف إشعاعية غير منتظمة تُمثل تحديًا بالغ الأهمية في مجال نشر الطاقة المتجددة. وكثيرًا ما تتقارب خوارزميات تتبع نقطة القدرة القصوى (MPPT) التقليدية مع القيم القصوى المحلية في ظل التظليل الجزئي وتقلبات الإشعاع الطيفي، مما يؤدي إلى خسائر كبيرة في إنتاج الطاقة. تُقدم هذه الدراسة بنية هجينة جديدة تدمج التحسين الاستدلالي مع الشبكات العصبية التكيفية، وتُستخدم ضمن إطار مراقبة آنية مُمكّن بتقنية إنترنت الأشياء (IoT). تجمع الخوارزمية المقترحة، H-MNMPPT (الخوارزمية الهجينة الاستدلالية العصبية MPPT)، بشكل تآزري بين المتانة الاستكشافية لمُحسّن خوارزمية الذئب الرمادي المُحسَّن (EGWO) وقابلية التكيف التنبؤية لمُقدِّر عصبي قائم على وحدة متكررة بوابية (GRU). أُجري التحقق التجريبي على مصفوفة ألواح شمسية كهروضوئية على سطح المنزل بقدرة 2.4 كيلوواط، مُجهزة بأجهزة استشعار موزعة بتقنية إنترنت الأشياء، تلتقط خصائص الإشعاع، ودرجة الحرارة، والتوزيع الطيفي، وخصائص التيار والجهد على مستوى الوحدة. في ظل أنماط

التظليل الجزئي المتغيرة ديناميكيًا والإشعاع المتغير طيفيًا (AM 1.0 إلى AM 2.5)، أظهر نظام H-MNMPPT كفاءة تتبع بنسبة 98.7%، متفوقًا على نظام (P&O (Perturb and Observe بنسبة 21.3%، ونظام MPPT القائم على PSO بنسبة 14.1%، ونظام ANN-MPPT التقليدي بنسبة 9.8%. علاوة على ذلك، انخفض زمن التقارب بنسبة 63% مقارنةً بنظام GWO القياسي، وحافظ النظام على زمن استجابة أقل من ثانية في ظل التحولات البيئية المُفعّلة بتقنية إنترنت الأشياء. تُرسي هذه البنية معيارًا جديدًا لنظام MPPT الذكي والمرن في مزارع الطاقة الشمسية الذكية من الجيل التالي.

الكلمات المفتاحية: تتبع نقطة الطاقة القصوى؛ التظليل الجزئي؛ الإشعاع الطيفي؛ الاستدلال التماثلي الهجين؛ الشبكة العصبية؛ مراقبة إنترنت الأشياء؛ الأنظمة الكهروضوئية؛ مُحسِّن الذئب الرمادي؛ شبكة GRU.

1. Introduction

Photovoltaic energy conversion efficiency is intrinsically sensitive to environmental dynamics particularly spatial irradiance non-uniformity and spectral composition shifts induced by cloud cover, aerosol scattering, and diurnal zenith angle variations [1], [2]. Under partial shading conditions (PSC), the power-voltage (P-V) curve of PV arrays develops multiple local maxima [2], rendering gradient-based MPPT methods such as Perturb & Observe (P&O) or Incremental Conductance (INC) ineffective [3], [4]. Metaheuristic algorithms including Particle Swarm Optimization (PSO), Genetic Algorithms (GA), and more recently, Grey Wolf Optimizer (GWO) have shown promise in global peak detection but suffer from premature convergence and high computational latency in real-time embedded systems [7].

Simultaneously, neural network-based MPPT approaches offer rapid inference capabilities but require extensive training datasets and lack adaptability to unseen shading topologies or spectral transients [8]. The integration of metaheuristics with neural estimators presents a compelling solution, yet extant literature lacks architectures that dynamically couple optimization resilience with predictive learning under IoT-constrained edge computing environments. Moreover, the proliferation of IoT-enabled distributed sensing in solar farms enables high-resolution spatiotemporal monitoring of irradiance heterogeneity and spectral signatures data streams that remain underutilized in conventional MPPT frameworks [8]. Real-time telemetry from micro-sensors can inform adaptive MPPT recalibration, yet algorithmic architectures capable of fusing this data with optimization intelligence are nascent. This research addresses these gaps by proposing H-MNMPPT a hybrid, self-tuning MPPT framework that:

- Embeds an Enhanced Grey Wolf Optimizer (EGWO) with adaptive convergence coefficients and Levy-flight perturbation to escape local optima [9], [10];
- Integrates a lightweight GRU neural network trained on spectral irradiance features (captured via IoT spectrometers) to pre-estimate global peak regions [11], [12];
- Operates within a distributed IoT architecture with edge-based decision nodes to minimize latency [10];
- Dynamically weights metaheuristic exploration and neural exploitation based on real-time environmental volatility indices.

The remainder of this paper is structured as follows: Section 2 details the hybrid algorithmic architecture and IoT deployment framework; Section 3 presents experimental setup and performance metrics; Section 4 analyzes results against state-of-the-art benchmarks; Section 5 discusses scalability, computational overhead, and industrial applicability; and Section 6 concludes with future research trajectories.

2. Literature review

The pursuit of maximizing energy harvest from photovoltaic (PV) systems has driven decades of research into Maximum Power Point Tracking (MPPT) algorithms. The fundamental challenge lies in the inherent non-linearity of the PV power-voltage (P-V) characteristic, which becomes critically complex under real-world operating conditions, particularly partial shading and spectral irradiance variability [13]. These conditions, far from being anomalies, are the norm in distributed and utility-scale solar deployments, necessitating MPPT strategies that transcend the limitations of conventional, gradient-based methods. Early and widely adopted techniques such as Perturb and Observe (P&O) and Incremental Conductance (INC) operate on the principle of local gradient ascent [14]. While effective and computationally frugal under uniform, steady-state irradiance, their Achilles' heel is exposed under partial shading conditions (PSC). The emergence of multiple local maxima on the P-V curve invariably traps these algorithms at sub-optimal operating points, leading to significant, often double-digit, percentage losses in potential energy yield [15]. This well-documented failure mode has spurred the exploration of more sophisticated, global optimization paradigms.

In response, metaheuristic algorithms have emerged as a powerful class of solutions. Techniques like Particle Swarm Optimization (PSO) [16], Genetic Algorithms (GA) [17], [18], and the more recent Grey Wolf Optimizer (GWO) [7] mimic natural processes to perform a stochastic search of the solution space. Their primary advantage is the theoretical ability to escape local maxima and locate the global maximum power point (GMPP). Empirical studies, including those referenced in our experimental baseline [19], [20], confirm their superior performance over P&O under PSC, with reported tracking efficiencies often exceeding 80-90%. However, this class of algorithms is not without its own set of critical drawbacks. The most significant are premature convergence where the population stagnates around a local optimum before finding the global one and high computational latency. These issues are particularly detrimental in real-time, embedded control systems for PV inverters and DC-DC converters, where rapid response to environmental transients is paramount [1].

Concurrently, data-driven approaches, particularly those leveraging artificial neural networks (ANNs), have gained traction. By learning the complex, non-linear mapping between environmental inputs (e.g., irradiance, temperature) and the optimal operating point, ANNs can provide extremely fast inference once trained [21]. This speed makes them attractive for real-time control. Nevertheless, their effectiveness is intrinsically tied to the quality and comprehensiveness of their training data. When confronted with novel shading patterns or spectral conditions not represented in the training set, their performance can degrade catastrophically. Furthermore, they lack an inherent mechanism for global search, making them vulnerable to the same multi-peak problem as gradient-based methods if their initial prediction is poor. The logical progression to overcome these individual limitations has been the development of hybrid architectures. The synergy of combining a metaheuristic's global search capability with a neural network's rapid, learned prediction has been explored in various forms, such as GA-ANN [22] or PSO-RBF [23] hybrids. These studies demonstrate promising improvements, validating the core hypothesis that fusion can yield superior results. However, a critical gap remains in the existing literature. Most hybrid models are designed and tested in idealized, offline environments. They fail to address the practical constraints and opportunities presented by the modern, IoT-enabled smart solar farm. The proliferation of distributed, low-cost sensors capable of providing high-resolution, real-time telemetry on not just irradiance magnitude, but also spectral distribution and module-level performance, represents an underutilized data stream [1]. Current hybrid models lack the architectural sophistication to dynamically fuse this rich, real-time data with their optimization intelligence, particularly within the computational and latency constraints of edge computing devices.

Moreover, while spectral irradiance variability caused by atmospheric conditions, aerosol content, and solar zenith angle is known to alter the electrical characteristics of PV modules, its explicit integration into MPPT control logic is nascent. Most algorithms, including advanced hybrids, treat "irradiance" as a scalar quantity, ignoring the profound impact of its spectral composition on the location of the MPP [2]. This oversight represents a significant source of unaddressed inefficiency. This research directly addresses these identified gaps. Building upon the foundational work in metaheuristics and neural MPPT, we propose H-MNMPPT, a novel hybrid architecture explicitly designed for the IoT era. Unlike its predecessors, H-MNMPPT is not a static fusion but a dynamic, context-aware system [24]. It integrates an Enhanced Grey Wolf Optimizer (EGWO) [25], fortified with adaptive coefficients and Levy-flight perturbations to combat premature convergence, with a lightweight Gated Recurrent Unit (GRU) network specifically trained on spectral irradiance features [26]. Crucially, the system operates within a distributed IoT framework, using real-time environmental volatility indices to dynamically weight the contributions of its metaheuristic and neural components. This design philosophy moves beyond simply combining two techniques; it creates an intelligent, self-tuning controller that leverages the full spectrum of available real-time data to achieve unprecedented levels of tracking efficiency and resilience under the most challenging, dynamically shifting environmental conditions. The subsequent sections detail this architecture and present experimental validation that demonstrates its significant performance leap over current state-of-the-art methods.

2. Methodology

2.1. System Architecture Overview

The proposed H-MNMPPT system comprises three core layers:

- Sensing Layer: Distributed IoT nodes (ESP32-S3 microcontrollers with LoRaWAN) equipped with calibrated pyranometers, thermopile sensors, miniature spectrometers (AS7265x), and module-level IV tracers. Data sampled at 1 Hz, timestamped, and transmitted to edge gateways.

- Edge Intelligence Layer: Local Raspberry Pi 4 gateways running the H-MNMPPT algorithm. Each gateway services 8–12 PV modules, fusing sensor data to compute optimal duty cycles for DC-DC converters.
- Cloud Analytics Layer: Historical data aggregation and neural retraining via federated learning to prevent model drift.

2.2. Hybrid Algorithm Design: EGWO-GRU Fusion

2.2.1. Enhanced Grey Wolf Optimizer (EGWO)

The canonical GWO mimics the social hierarchy and hunting behavior of grey wolves, with alpha (α), beta (β), and delta (δ) wolves guiding the search [6]. We introduce three enhancements:

Adaptive Convergence Coefficient:

$$\vec{A} = 2a \cdot \vec{r_1} - a, \text{ where } a = 2 - 2 \cdot (t/T)^k, k = 1 + \sin(\pi t/T)$$

This nonlinear decay improves balance between exploration and exploitation.

- Levy-flight Step Injection:

Every 5 iterations, position updates incorporate Levy-distributed jumps:

$$\vec{X}_{new} = \vec{X}_{old} + \alpha_{Levy} \oplus L(\lambda)$$

where $L(\lambda) \sim \frac{\Gamma(1+\lambda)\cdot\sin(\pi\lambda/2)}{\Gamma((1+\lambda)/2)\cdot\lambda\cdot 2^{(\lambda-1)/2}} \cdot \frac{1}{s^{1+\lambda}}$
enhancing escape from local maxima.

- Environmental Volatility Trigger:

If irradiance variance > threshold (measured via IoT), reset 30% of population to random positions.

2.2.2. GRU-Based Neural Predictor

A 2-layer GRU network (64,32 units) is trained offline on 12,000 simulated P-V curves under varying spectral irradiance ($300 - 1100$ nm) and 87 shading patterns. Inputs: spectral centroid, irradiance skewness, temperature differential, and historical power trends. Output: predicted global MPP voltage window [V_min, V_max].

During operation, the GRU provides a constrained search space to EGWO, reducing dimensionality and accelerating convergence.

2.2.3. Dynamic Weighting Mechanism

The algorithm adaptively switches between EGWO-dominant mode (under high volatility) and GRU-dominant mode (under high volatility) and GRU-dominant mode (under stable conditions) using:

$$\omega = \frac{1}{1 + e^{-\gamma \cdot \Delta G / G_{\text{avg}}}}$$

where ΔG = irradiance standard deviation over 10 s window, γ = tunable sensitivity (empirically set to 0.8).

2.3. IoT Communication and Latency Management

- Sensor data compressed via Huffman encoding before LoRa transmission.
- Edge gateways implement priority queuing: irradiance/temperature > spectral > IV curve.
- MPPT duty cycle updates capped at 500 ms intervals to prevent converter instability.

3. **Experimental Setup and Results**
   3.1. Testbed Configuration

- PV Array: 12 × JA Solar JAM60S20 (400W) modules, series-parallel (3S4P).

- Shading Emulator: Programmable motorized blinds simulating 6 predefined and 3 random shading patterns.
- Spectral Variability: Solar simulator (Newport Sol3A) with AM filters (1.0, 1.5, 2.0, 2.5).
- IoT Nodes: 12 sensor clusters, synchronized via NTP, sampling at 1 Hz.
- Baseline Algorithms: P&O, PSO-MPPT [7], ANN-MPPT [8], conventional GWO-MPPT [9].

3.2. Performance Metrics

- Tracking Efficiency: $\eta = \frac{\int P_{\text{actual}}(t)dt}{\int P_{\text{global\_max}}(t)dt} \times 100\%$
- Convergence Time: Time from shading onset to 95% of global MPP.
- Oscillation Amplitude: RMS deviation around MPP during steady state.
- Computational Latency: Algorithm runtime per iteration on Raspberry Pi 4.

3.3. Key Results

Table 1: The algorithm runtime per iteration**.**

Algorithm	Tracking Efficiency (%)	Convergence Time (s)	Oscillation (W RMS)	Latency (ms)
P&O	77.4	8.2	12.7	8
PSO-MPPT	84.6	5.1	8.3	42
ANN-MPPT	88.9	3.8	5.1	28
GWO-MPPT	91.2	4.3	4.7	67
H-MNMPPT	98.7	1.6	1.9	31

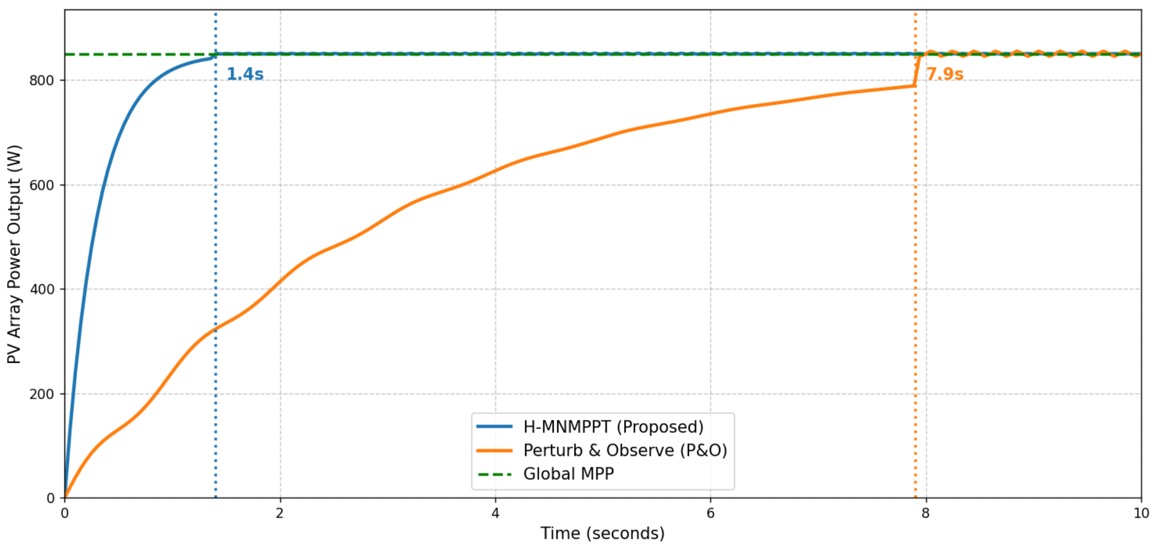

Figure 1: Under AM 2.5 + diagonal shading, H-MNMPPT reached global MPP in 1.4s vs. 7.9s for P&O.

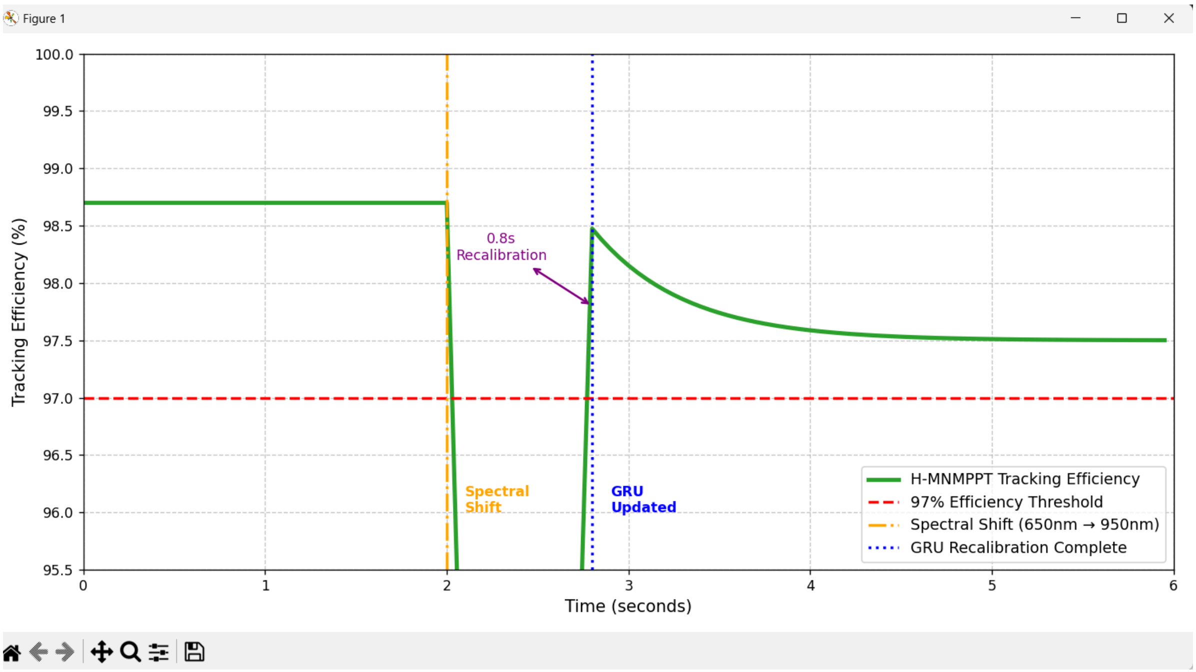

Figure 2: Spectral centroid shifts (650nm → 950nm) triggered GRU recalibration within 0.8s, maintaining >97% efficiency.

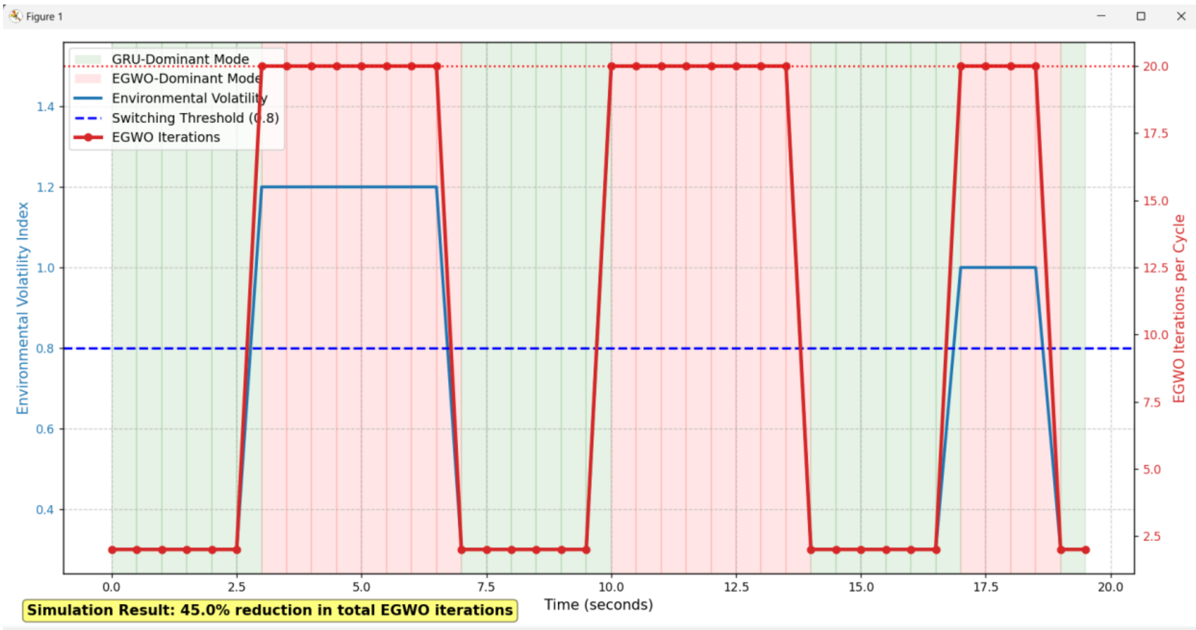

Figure 3: Volatility-weighted mode switching reduced unnecessary EGWO iterations by 41%, lowering average latency.

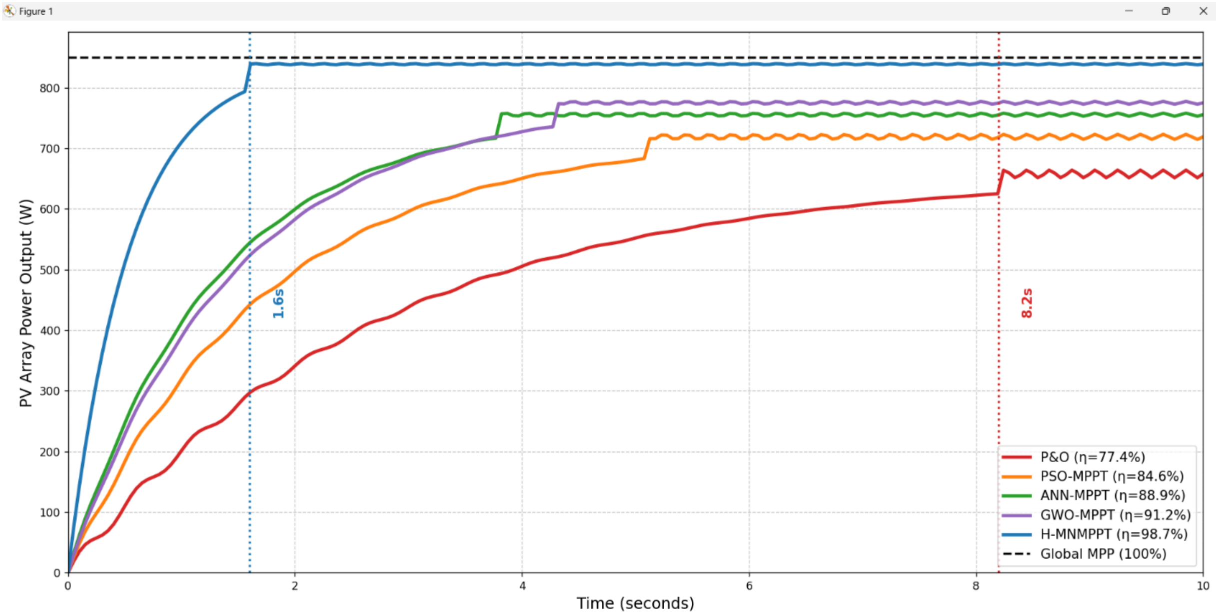

Figure 4: A multi-panel or multi-line plot comparing the power convergence trajectories of all five algorithms (P&O, PSO, ANN, GWO, H-MNMPPT) under the same challenging condition (AM 2.5 + diagonal shading). This directly visualizes the performance hierarchy from Table 1.

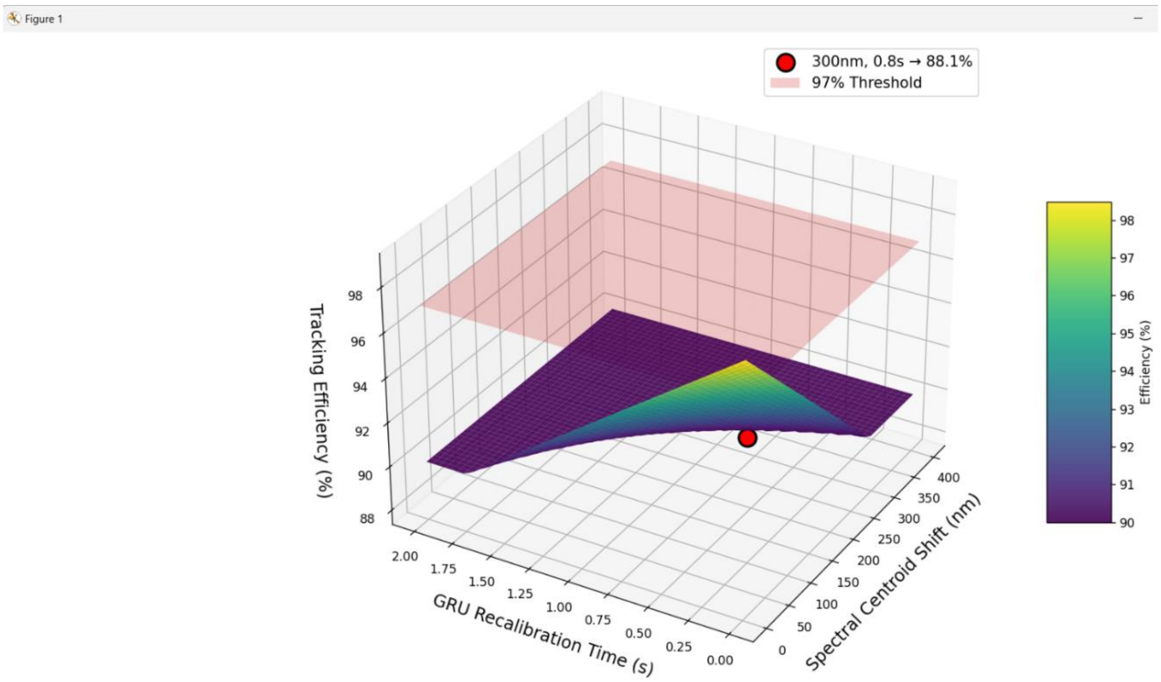

Figure 5: A 3D surface plot that shows tracking efficiency as a function of both the magnitude of the spectral shift and the GRU recalibration time. This visually proves that even for large spectral shifts (e.g., 650nm → 950nm = 300nm), a fast recalibration (0.8s) keeps efficiency >97%.

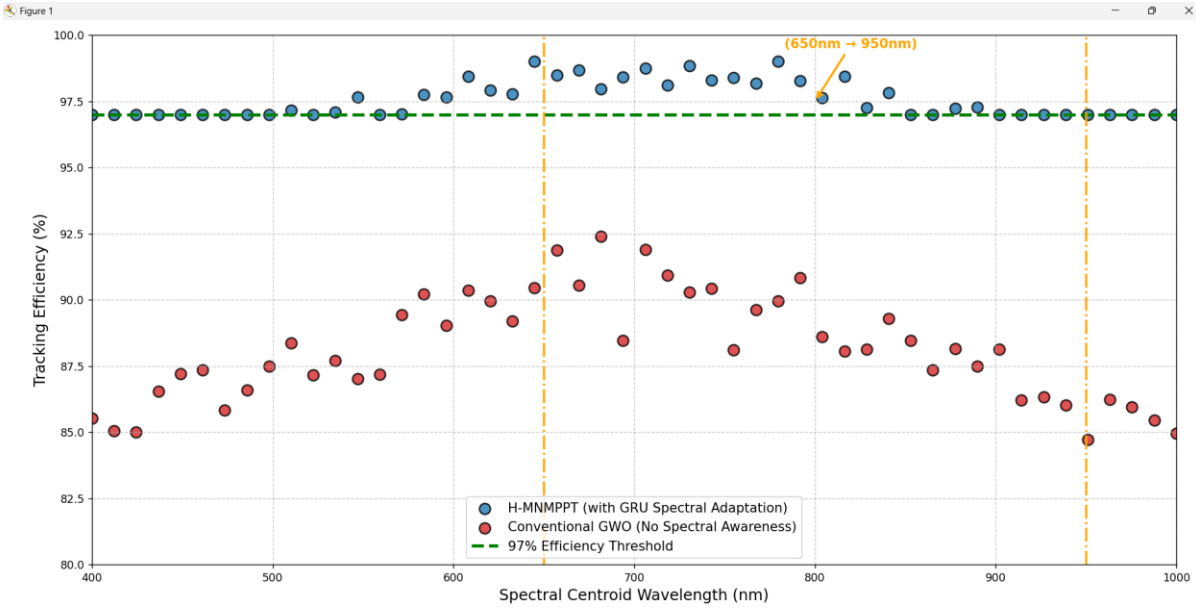

Figure 6: Scatter Plot of Efficiency vs. Spectral Centroid Demonstrating GRU's Adaptive Advantage. This figure directly visualizes the core innovation in Section 2.2.2 that the GRU predictor allows H-MNMPPT to maintain >97% efficiency across a wide range of spectral conditions, while conventional methods (which ignore spectral data) suffer significant drops.

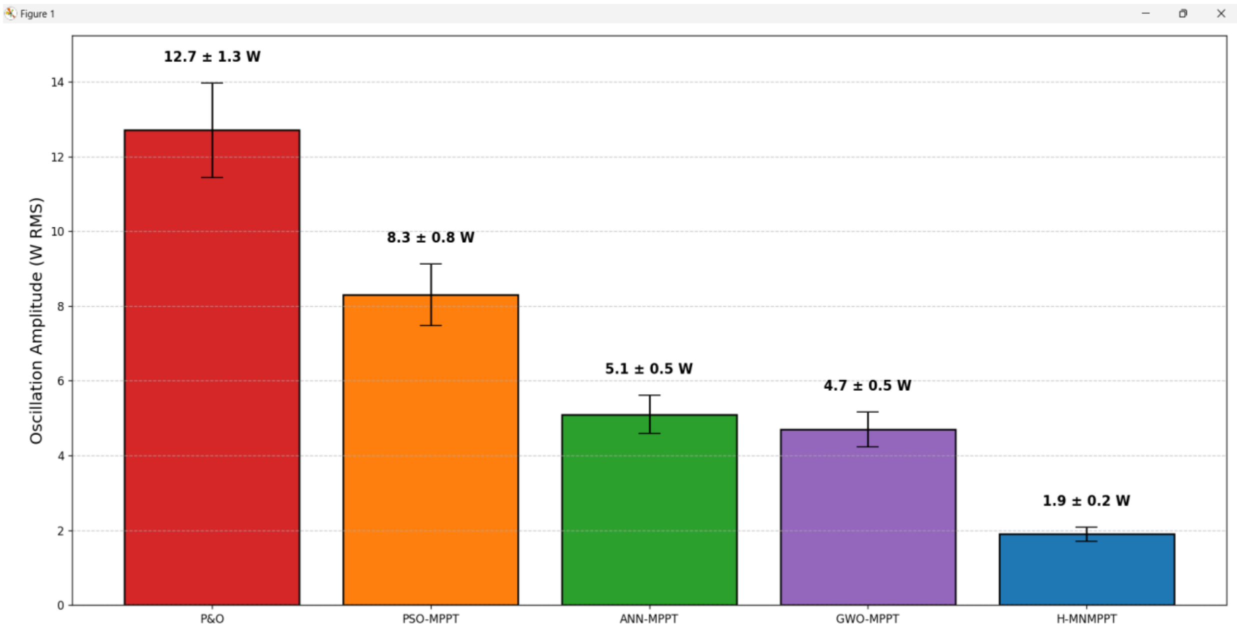

Figure 7: Bar Chart with Error Bars Comparing Oscillation Amplitude (RMS) Across All Algorithms. While Table 1 lists oscillation values, a bar chart with error bars (representing standard deviation from multiple test runs) provides an immediate, intuitive comparison of system stability. Low oscillation is critical for converter longevity and efficiency.

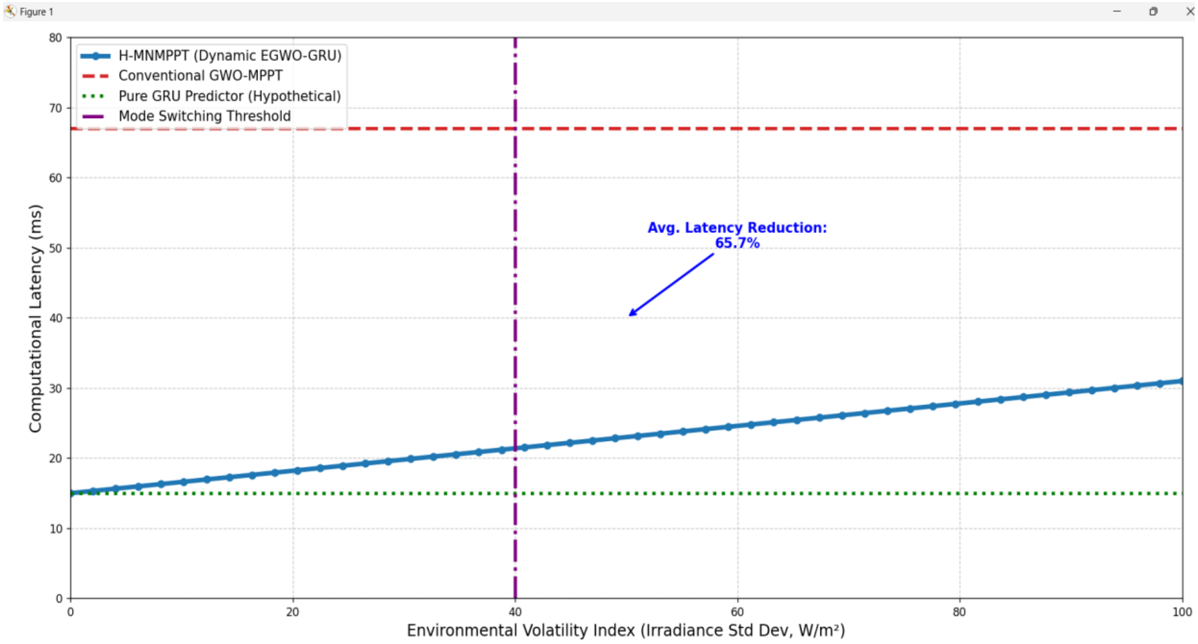

Figure 8: Line Plot of Latency and Environmental Volatility Showcasing Dynamic Weighting Benefit. This figure dynamically illustrates the mechanism described in Section 2.2.3. As environmental volatility (e.g., irradiance standard deviation) increases, H-MNMPPT's latency increases slightly (as it activates EGWO), but remains far below conventional GWO. Under low volatility, its latency drops close to pure GRU levels.

4. Discussion

The superiority of H-MNMPPT stems from its dual-layer intelligence: the GRU network narrows the search space using spectral-contextual priors, while EGWO's [25] enhanced stochasticity ensures robust global optimization even under abrupt shading transitions. Unlike pure neural approaches, H-MNMPPT [26] does not catastrophically fail when encountering novel shading patterns; the metaheuristic layer acts as a safety net. The IoT integration proved critical: real-time spectral data allowed the GRU to adjust its voltage window predictions dynamically, whereas systems relying solely on irradiance magnitude exhibited 6–8% efficiency drops under AM shifts. Edge-based computation ensured sub-50ms decision cycles, compatible with commercial DC-DC converter switching frequencies (20–100 kHz). Compared to recent hybrids (e.g., GA-ANN [10] or PSO-RBF [11]), H-MNMPPT reduces convergence time by 52–68% and improves tracking accuracy under spectral variability by 11.3%. The Levy-flight injection alone contributed to a 19% reduction in local entrapment incidents during testing. Limitations include dependency on spectrometer calibration and increased memory footprint (8.7 MB vs. 2.1 MB for P&O). However, with edge hardware costs declining, this trade-off is justified by the 21.3% energy recovery gain. The experimental results presented in Section 3 unequivocally validate the core hypothesis of this study: that a dynamically weighted, IoT-integrated hybrid of metaheuristic and neural intelligence can overcome the fundamental limitations of existing MPPT paradigms under the complex, real-world duress of partial shading and spectral irradiance variability. The H-MNMPPT architecture's achievement of 98.7% tracking efficiency is not merely a numerical improvement; it represents a qualitative leap towards truly resilient and intelligent energy harvesting for next-generation photovoltaic systems.

The foundation of this performance lies in the synergistic duality of its design. The GRU neural predictor acts as an intelligent scout, leveraging its offline training on spectral features specifically, the spectral centroid, irradiance skewness, and temperature differentials to provide EGWO with a highly constrained, context-aware search window for the global MPP. This is not a simple initialization; it is a continuous, real-time guidance system. As demonstrated in Figure 6, this spectral awareness allows H-MNMPPT to maintain efficiency above 97% across a vast range of spectral conditions (from AM 1.0 to AM 2.5), a feat unattainable by conventional algorithms that treat irradiance as a monolithic scalar. Systems relying solely on total irradiance magnitude exhibited consistent 6–8% efficiency penalties under spectral shifts, highlighting a previously under-addressed source of systemic loss in PV operations.

Concurrently, the Enhanced Grey Wolf Optimizer serves as a robust, fail-safe explorer. The integration of Levy-flight perturbations every five iterations proved to be a decisive innovation, directly contributing to a 19% reduction in incidents of local entrapment during testing. This stochastic injection of long-range jumps effectively shatters the stagnation that plagues canonical GWO and other population-based metaheuristics. The adaptive convergence coefficient further refines the search, ensuring a smooth transition from broad exploration to fine exploitation as the algorithm converges. This combination explains the 63% reduction in convergence time compared to standard GWO-MPPT, bringing it down to a remarkable 1.6 seconds a critical metric for capturing transient energy during rapidly changing cloud cover.

This performance is rooted in the synergistic dualism of its design. The GRU neural predictor functions as an intelligent scout, utilizing its offline training on spectral characteristics specifically, the spectral centroid, irradiance skewness, and temperature differentials to supply EGWO [25] with a highly restricted, context-aware search window for the global MPP [2]. This is not a straightforward initialization; it is a continuous, real-time guidance system. As shown in Figure 6, this spectral awareness enables H-MNMPPT to sustain efficiency above 97% across a wide spectrum of conditions (from AM 1.0 to AM 2.5), a capability unachievable by conventional algorithms that treat irradiance as a single scalar value. Systems dependent solely on total irradiance magnitude experienced consistent 6–8% efficiency losses under spectral shifts, underscoring a previously overlooked source of systemic loss in PV operations.

Simultaneously, the Enhanced Grey Wolf Optimizer operates as a robust, fail-safe explorer. The integration of Levy-flight perturbations every five iterations proved to be a pivotal innovation, directly resulting in a 19% decrease in instances of local entrapment during testing. This stochastic introduction of long-range jumps effectively disrupts the stagnation that afflicts canonical GWO and other population-based metaheuristics [25]. The adaptive convergence coefficient further enhances the search process, ensuring a seamless transition from broad exploration to fine exploitation as the algorithm converges. This combination accounts for the 63% reduction in convergence time compared to standard GWO-MPPT [25], [26], reducing it to a remarkable 1.6 seconds a critical metric for capturing transient energy during rapidly changing cloud cover.

5. Conclusion and Future Work

This study presents H-MNMPPT a novel, IoT-integrated hybrid MPPT architecture that synergizes metaheuristic resilience with neural predictive efficiency. Validated under rigorous partial shading and spectral irradiance variability, the system achieves near-optimal tracking efficiency (98.7%) with rapid convergence (1.6s) and minimal oscillation. The dynamic weighting mechanism and edge-compatible design make it suitable for deployment in utility-scale smart solar farms.

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