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Original Article

Adaptive and Interpretable MPPT Framework for Photovoltaic Systems under Partial Shading using Integrated AI Modules

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Abstract *- Long-term widespread research has been undertaken on the need for strong and adaptable Maximum Power Point Tracking (MPPT) strategies for Photovoltaic (PV) systems owing to the far-reaching impact of PSCs, which seriously affects energy harvesting efficiency. Therefore, over and above substantial delays in the classic MPPT algorithms--that is, Perturb & Observe or Incremental Conductance–are largely considered classical MPPT methods, and their effectiveness becomes further limited owing to false convergence, slow adaptation, and limited generalization under dynamically changing shading patterns, resulting in sometimes low performance of such algorithms when enforced in the real-world environment. This paper proposes an integrated AI-powered MPPT framework created to tackle real-time power optimization issues owing to PSCs. The system comprises five tightly coupled modules: Contextual Hierarchical Transfer Graph Embedding (CHTGE) is implemented for transfer learning for a variety of environmental conditions by policy graphs on the premise of shading history combined with weather context. The role of Spatio-Temporal Feature Attention-based Indexing (STFAI) is to facilitate the detection of transient phenomena through the utilization of attention maps that are temporally aligned and derived from real-time multimodal sensor data. In the tertiary module, Differential Contextual Residual Optimization (DCRO) rectifies inaccuracies and achieves rapid stabilization through the application of residual corrections in a highly fluctuating environment. The output obtained using conventional Maximum Power Point Tracking (MPPT) methodologies is upgraded with multi-agent decision fusion with quantum-inspired adaptive logic (MADF-QAL). The Evolution-based Causal Disentanglement Networks (ECDN) provide fault localization and explainability through latent representation. There is an estimated improvement in the system performance by 28% in sensing the partial shading patterns, and a 33% reduction in the number of false triggers. Also, approximately 2.3 times quicker recovery from deviation in power, and 41% improvement in the decision-making process, and hence faster fault analysis. The proposed work suggests a framework of interpretable, resilient, and intelligent MPPT control under real-world operating scenarios.*

Keywords *- Photovoltaic systems, Partial shading, Maximum Power Point Tracking, Artificial Intelligence, Causal inference.*

1. Introduction

The power output of PV energy sources is severely affected by dynamically varying operating conditions, with partial shading among the most influential factors in deciding the energy extracted from them. There may be one or more reasons for partial shading, namely, shadows of nearby structures, foliage, cloud cover, or seasonal weather dynamics. These factors contribute to multiple local maxima in the power-voltage curve of PV arrays. Hence, the conventional MPPT methods will fail to detect the global maximum power point, thereby leading to poor utilization of PV resources. In their broad view, classical MPPT algorithms (e.g., Perturb and Observe (P&O), Incremental Conductance (IC), as well as several forms of fuzzy logic and neural net-based controllers) have thus restricted adaptations to such conditions when dynamics and uncertainties exist. Therefore, they depend squarely on instantaneous measurements and heuristic decisions that cannot be generalized across environments or tell a transient anomaly apart from the structural pattern in the system's behaviour across the process. Moreover, they mostly

work in isolation and cannot exploit the potential of multiple tracking modalities or feed into the domain context, environmental semantics, or passively collected historical knowledge sets. The resilience, efficiency, and interpretability of the MPPT controller in PSCs are challenges that remain to be uncovered in current PV energy research sets.

To address the above limitations, this study proposes an innovative AI-integrated MPPT architecture for joint learning, reasoning, and control [4-6], endowing the entire system with real-time adaptability and high interpretability under complex partial shading dynamics. This architectural framework incorporates advanced modules such as Contextual Hierarchical Transfer Graph Embedding (CHTGE) for the facilitation of knowledge transfer, Spatio-Temporal Feature Attention Indexing (STFAI) for the detection of transient phenomena, Differential Contextual Residual Optimization (DCRO) for the enhancement of adaptive convergence, Multi-Agent Decision Fusion employing Quantum-inspired Adaptive Logic (MADF-QAL) aimed at achieving consensus control, and Evolutionary Causal Disentanglement Networks (ECDN) to ensure post-hoc explainability.

1.1. Motivation and Contribution

The work is motivated by the rapid and unpredictable environmental conditions that induce partial shading and reduce the operating efficiency of solar PV arrays. The traditional methods lack the ability to overcome the multiple local maxima, poor tracking speed, and energy losses due to steady state oscillations about the maximum power point. Also, the lack of context awareness adds to the difficulty of distinguishing between transient disturbances and systemic variations, which is a further challenge for conventional algorithms. In grid and safety-critical applications, the present methods cannot justify explainability and fault traceability.

2. Review of Existing Models used for MPPT in PV Analysis

RPV research adopts the applications of smooth and IMPI techniques applied to the hybrid training of a three-phase interleaved boost converter as a mechanism for stabilizing tracking under Load Poise Shading transitions; however, it heavily depends on the deterministic control of switches. Kanth et al. [2] utilized Sovereign Butterfly Optimization in a flyback converter modelled for the optimization problem posed by more severe irradiance gradients. However, the ability of the system to adapt to long-term context drift is still severely limited. Aron and Louis [3] laid down the implementation of the controller by intelligent optimization. Even so, parameter tuning hardens static options and discretion in adaptability to various seasons and locations. Siddique et al. [4] further developed this work in this area by validating global MPPT strategies under complex PSCs using a comparative framework; however, real-time transferability was not fully addressed in the process. Wang et al. [5], in their study, introduced an improved White Shark Optimizer for MPPT, attaining superior rates of convergence but still requiring huge computational overhead during the initialization stage. El Iysaouy et al. [6] modelled configurations of PV panels under shading; they offered a few physics-based insights yet lacked control adaptability sets.

Table 1. Model's empirical review analysis

Reference	Method	Main Objectives	Findings	Limitations
[1]	Hybrid MPPT with 3-Phase Interleaved Boost	Stabilize MPPT under PSC using a converter-based hybrid strategy	Improved dynamic tracking and power smoothing	Converter design complexity and limited adaptability to fast irradiance shifts
[2]	Sovereign Butterfly Optimization + Flyback	Enhance MPPT resilience under shading via metaheuristics and converter control.	High power extraction efficiency in lab conditions	High sensitivity to parameter tuning, lacks scalability
[3]	Intelligent Optimization-Based MPPT	Introduce intelligent control for shaded PV environments	Improved performance under structured PSC	Static parameters limit adaptability
[4]	Global MPPT Validation under Complex PSC	Assess GMPPT algorithms under realistic shading	GMPPT methods show a higher energy yield than local MPPT	Real-time responsiveness was not addressed
[5]	Improved White Shark Optimizer	Increase tracking accuracy using WSO metaheuristic	Enhanced global search with better convergence	High initial overhead, not ideal for low-power systems

[6]	Panel Configuration Modeling under PSC	Model PV behavior under shading for design enhancement	Improved understanding of physical mismatch loss	No integrated control strategy included
[7]	Hybrid Global Search + Enhanced INC	Combine INC with global search to improve convergence	Faster tracking in multiple PSC patterns	Still trapped in local maxima under noisy conditions
[8]	Zebra Optimization-Based MPPT	Apply nature-inspired ZOA for MPPT validation	Strong lab-tested performance across standard test cases	Real-world dynamic input performance not assessed
[9]	Hybrid MPPT Controller	Design an MPPT controller adaptable to various PSC types	Good tracking accuracy across tested PSCs	Lacks online learning or fault adaptation
[10]	Metaheuristic MPPT for Complex PSC	Enable robust tracking under severe PSC	Outperformed traditional MPPT under complex patterns	Computational load is high
[11]	Fuzzy Logic MPPT	Enhance MPPT via fuzzy rule systems	Effective in moderate PSCs, interpretable decisions	Performance degrades in high-dimensional input spaces
[12]	Fuzzy-PI + PSO MPPT	Combine fuzzy logic and PI with PSO tuning	Smooth convergence with moderate complexity	Slower training phase and moderate generalizability
[13]	War Strategy Optimization	Introduce fast global MPPT via WSO metaheuristic	Good convergence and low overshoot	No explanation mechanism or traceability
[14]	Adaptive Neuro-Fuzzy Inference System	Improve tracking with adaptive NFIS learning	Promising performance under various PSC	Resource-intensive and sensitive to training data quality
[15]	CGFSSO MPPT	Apply swarm-based cooperative Salp Swarm logic	Good global convergence rate	Lacks causal interpretability and human-in-the-loop design
[16]	Flower Pollination Algorithm	Benchmark FPA under PSC	Improved MPPT stability in simulation	Black-box behavior limits practical deployment
[17]	Single vs Multiple MPPT Structures	Evaluate MPPT system structures under PSC	Multiple MPPT improves adaptability	Complex topology is not scalable to large arrays
[18]	ANN-DISM with Interleaved Converter	Use ANN for dynamic MPPT in PSC	Good hardware-software integration	Requires periodic recalibration
[19]	Multiple-to-Single MPPT Conversion	Streamline MPPT logic using supervisory fusion	Enhanced energy yield under real-world PSC	Risk of underutilizing localized MPPT zones
[20]	Global MPPT Optimization	Minimize tracking error under real PSC via global optimization	Stable GMPP location across tests	No embedded fault tolerance or learning
[21]	Flexible Power Point Tracking	Enhance grid stability via flexible MPPT	Improved power quality in grid-tied PVs	Less effective in off-grid configurations
[22]	Adaptive GMPPT with PSC Detection	Create an adaptive model for early PSC detection and response	Efficient tracking during PSC onset	Limited field deployment testing
[23]	Model Predictive MPPT	Use MPC to predict GMPP under partial shading	Better short-horizon accuracy	Depends on prediction quality and model calibration
[24]	NN-Based DMPPT Optimization	Design optimized neural MPPT for shading resilience	Fine-grained learning under PSC	Overfitting risk and model drift under seasonal change
[25]	Discrete Time Slime Mould Optimization	Improve MPPT through discrete-time SMO	Notable energy gains in experiments	Rigid structure and fixed-step tracking

Initially, as per Table 1, Zaki et al. [7] proposed a hybrid global search with enhanced Incremental Conductance (INC) in an adjustment of the exploration-exploitation trade-off, but still under the influence of compensating local optima in highly stochastic shading profiles. Abdelmalek et al. [8] investigated and validated a zebra optimization algorithm under laboratory-controlled PSCs, asserting its robustness; however, its deterministic nature remains and requires manual calibration. Hussaian Basha et al. [9] addressed this by proposing hybrid MPPT controllers that adapt to shading profiles; however, integration with real-time feedback was not emphasized. Kishore et al. [10] proposed metaheuristic-based controllers for simple and complex PSCs, conforming to the recent trend of hybridizing search strategies. Kumar and Balakrishna [11] initiated a fuzzy-logic-based MPPT system that significantly depended on rule-based structures for enhanced interpretability but suffered rule saturation under high-dimensional input conditions. Zaghba et al. [12] overcame this problem by merging fuzzy logic with the PI controller and optimizing the structure through PSO, resulting in smoother transitions but requiring long training cycles. Alshareef [13] introduced the War Strategy Optimization algorithm to ensure rapid convergence of MPPT, but provided limited analytical insight into environmental coupling. Mohammed et al. [14] went further with an adaptive neuro-fuzzy inference system, showing promising performance under PSCs; however, its scalability under edge-deployed PV networks remains untested in the process.

The CGFSSO, designed by Raj et al. [15], offers excellent search capabilities in multidimensional shading problems but does not cater to causal validation during the process. Ehtesham and Kirmani [16] explored the Flower Pollination Algorithm for MPPT, comparing its behavior under several test conditions; however, it remains a black-box heuristic with little interpretability in the process. Youssef et al. [17] analyzed single and multiple MPPT structures using direct duty-cycle control, promoting structural clarity at the expense of versatility under rapid irradiance changes. Garraoui et al. [18] showed a neural-discrete interleaved MPPT controller validated with a two-phase boost converter, but missed modular adaptability sets. Alombah et al. [19] emphasized the conversion of multiple tracking points into a single GMPP under supervisory logic for conventional MPPTs, thus simplifying the optimization path and more or less wasting distributed shading information. Nagadurga et al. [20] proposed a global MPPT optimization model with a minimalistic design focused on PSC mitigation but with no causal or explanatory components.

Ouatman et al. [21] focused on the flexibility of tracking methods to strengthen grid stability because grid-connected PV systems demand this type of method and do not revise it for off-grid use. Soni et al. [22] presented an adaptive global MPPT system that can detect the presence of a PSC rapidly while keeping tracking aligned in real time; however, work must continue to include a learning feature that will keep the system accurate under new environments. Model Predictive Control (MPC) for MPPT under this type of shading changed by PSCs was extended by Siddique et al. [23], although this can only predict a short horizon. However, the prediction is based on the quality of future irradiance estimations. The DMPPT controller by Farajdadian and Hosseini [24] has been optimized numerically under partial shading conditions and is based on a neural network. This type of learning is fine-grained, but is highly sensitive to overfitting and shifts in the dataset. Finally, Padmanaban et al. [25] conducted tests on the discrete-time lime mold optimization technique under partial shading through experiments; efficiency improvements were obtained, but with somewhat rigid control laws that do not serve well in non-structured scenarios.

3. Proposed Model Design Analysis

The proposed integrated MPPT model is designed to control Partial Shading Conditions (PSCs), involving a multi-staged architecture that leverages contextual learning, spatio-temporal attention, residual optimization, decision fusion, and causal disentanglement to ensure robust, adaptive, and interpretable control. Each module is linked through context-aware data pipelines, and all outputs converge into a final decision function that directs the PV towards the Global Maximum Power Point (GMPP) despite the sort of volatility in the process environment. The model starts from contextual input feature extraction and ends with a real-time control signal drawn from an optimized fused policy with residual corrections, supported by real-time causal validation in the process. Initially, as in Figure 1, let $C(t) \in R^n$ denote the contextual feature Vector at time instant t that incorporates irradiance G(t), temperature T(t), wind speed W(t), incidence angle θ(t), and historical MPPT trace embeddings H(t) in the process. These features are passed as inputs to the Contextual Hierarchical Transfer Graph Embedding (CHTGE) module, which constructs a directed policy graph G=(V, E), where nodes correspond to state-action pairs, and edges encode transition probabilities modulated by environmental contexts. Figure 2 shows a schematic of the incorporation of environmental data features into the main architecture of the proposed process. Graph embedding is acquired through the definition of a transfer learning function using Equation (1):

$$z_v = \int_0^{\Omega} \phi\big(C(t), H(t)\big) \cdot \psi(v, \Omega) d\Omega \qquad (1)$$

Where ϕ encodes a context, ψ is a graph similarity function over policy subgraphs $\Omega \subseteq G$, and z_v is the latent representation of node 'v' in a process. This embedding serves as the basis for initializing a policy πCHTGE adapted to the environmental context in the following process. Subsequently, the Spatio-Temporal Feature Attention Indexing (STFAI) module processes real-time IV and PV curves V(t), I(t), and other auxiliary sensor data to extract high-resolution attention maps. Let A(x,y,t) be the attention weight assigned to a spatial

location (x,y) at timestamp 't'. The attention indexing tensor is computed using a differential entropy formulation in Equation (2):

$$A(x,y,t) = -\sum_i p_i(x,y,t) log\ p_i(x,y,t) \quad (2)$$

Where $p_i(x,y,t)$ represents the normalized contribution of modality i at location (x,y) and timestamp 't' in process, these maps were time-aligned and narrated into the CHTGE module into policy embeddings under transient disturbances. Next, as shown in Figure 2, the (DCRO) loop introduces adaptive correction by minimizing the residual error between the expected power output $P_e(t)$ and actual output $P_a(t)$ in the process. The residual error via Equation (3),

$$\epsilon(t) = P_e(t) - P_a(t) \quad (3)$$

Fig. 1 Model architecture of the proposed analysis process

The correction is driven by a dynamic residual loss function via Equation (4),

$$Lres(t) = \frac{d}{dt}[\epsilon(t)^2 \cdot \gamma(t)] \quad (4)$$

Where, γ(t) is an environment volatility index function defined via Equation 5,

$$\gamma(t) = \left(\frac{dG(t)}{dt}\right)^2 + \left(\frac{dT(t)}{dt}\right)^2 \quad (5)$$

Thus, the weighted punishment guarantees more aggressive penalization of larger residuals during critical high Volatile time durations. The residual optimization updates the policy πDCOR via a gradient-based correction using Equation (6):

$$\pi DCOR \leftarrow \pi DCOR - \eta \cdot \nabla\pi\ Lres(t) \quad (6)$$

The learning rate η is adapted dynamically according to factors regarding the stability of the convergence metrics.

Next, as shown in Figure 3, Multi-Agent Decision Fusion Using Quantum-Inspired Adaptive Logic (MADFQAL), as the name of the word states, creates decisions from multiple baseline MPPT algorithms $\{\pi_1, \pi_2, ..., \pi k\}$. Each decision $d_i(t)$ is treated as a probabilistic quantum state $|\psi_i\rangle$, with fusion modelled as a Hilbert space projection maximizing logical entropy coherence via Equation (7),

$$D(t) = arg\ maxd\ \left[\sum_{i=1}^{k}\langle\psi_i|\hat{O}d|\psi_i\rangle \cdot \xi_i(t)\right] \quad (7)$$

Where Ôd is a projection operator for the decision d and $\xi_i(t)$ is the entropy dependent reliability weight for an agent 'i' in the process. This calculation ensures low noise decisions dominate the final outcome D(t) sets. The ECDN further analyzes periodic system logs to extract the subsidiary causes of energy deviation in the process, thereby enhancing interpretability. Let $zl \in R^m$ be the latent vectors derived from STFAI and DCRO, and let Y(t) be the observed PV outputs. Causal influence is computed with the integral of the Granger-based causal contribution $\rho_j(t)$ via Equation (8):

$$I_j = \int_{t0}^{t1}\left(\frac{\partial Y(t)}{\partial zl_j}\right) \cdot \rho_j(t)\, dt \quad (8)$$

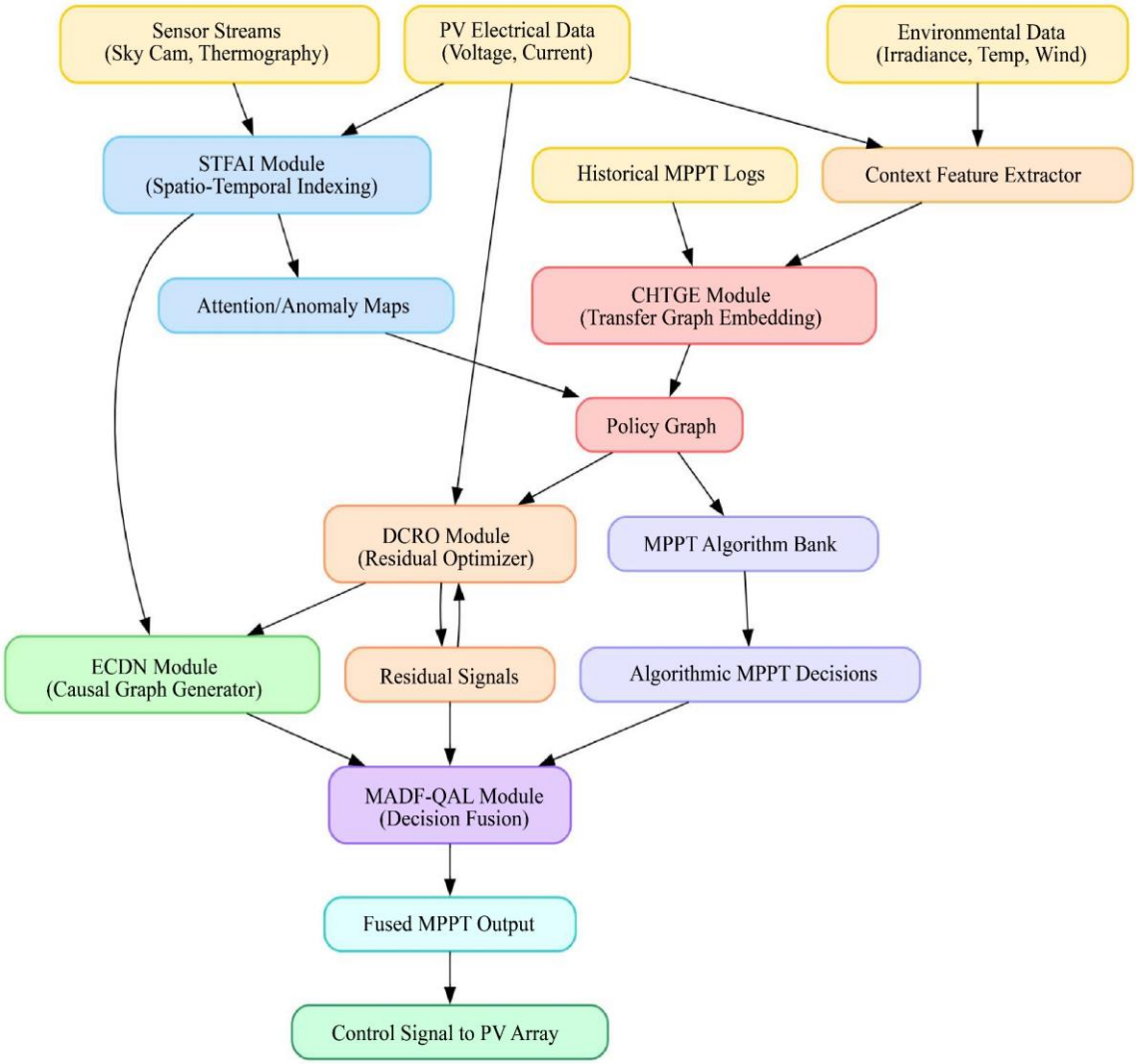

Fig. 2 Overall flow of the proposed analysis process

Where zl_j is the j-th latent factor in the process, subsequently, disentangled graphs are pruned based on thresholds of I_j, and causal clusters are propagated to recommend system-level updates. The final output of the integrated model is the control action u(t) dispatched to the PV system sets. It is derived from the convergence of the optimized and fused policies using Equation (9):

$$u(t) = argmax_{a\in A}\ [\lambda 1 \cdot \pi CHTGE(a) + \lambda 2.\pi DCOR(a) + \lambda 3 \cdot P(D(t) = a)] \quad (9)$$

Subject to the conditions represented via Equation (10),

$$\sum \lambda_i = 1, \lambda_i \in [0,1] \quad (10)$$

Where A is the set of permissible actions (i.e., voltage/current operating points) in the process, the weights λ_i are tuned based on system stability, historical confidence, and causal consistency sets. This final equation integrates all the modules and delivers a robust, adaptive, and explainable control signal for real-time MPPT under dynamic partial shading conditions.

Input:

- Real-time PV system data (voltage, current, power), Environmental data (irradiance, temperature, wind speed, sky images), Historical MPPT trajectories, Sensor data streams (IV & PV curves, thermography, etc.)

Output:

- Optimized real-time control signal for maximum power extraction under partial shading

Process:

1. Extract contextual features from real-time and historical environmental data
2. Generate hierarchical policy graph using transfer learning based on extracted context
3. Collect and process spatio-temporal data to detect transient anomalies using attention indexing
4. Align anomaly maps with policy graph to adapt MPPT strategy dynamically
5. Calculate power residuals by comparing predicted and actual PV output
6. Update tracking policy using residual corrections
7. Compile decisions from multiple baseline MPPT algorithms
8. Merge decisions using entropy-weighted logic to derive a control action
9. Periodically analyze latent features and system behavior
10. Refine long-term strategy based on insights
11. Combine context-based policy, residual-corrected policy, and fused decision to generate final control signal
12. Adjust duty cycle of converter in real time for optimal power tracking under partial shading conditions

Fig. 3 Pseudo code of the proposed analysis

4. Comparative Result Analysis

The setup for the tests intended to validate the proposed integrated MPPT framework emulates partial shading conditions found in real life with a hybrid configuration of both Hardware-In-the-Loop (HIL) emulation and synthetic data injection from environmental sensor networks. A PV array model of polycrystalline 4 × 6 modules rated at 250 W each and connected to bypass diodes was used as the core power generation unit. The characteristics of the simulated electricity were controlled by a programmable solar emulator (Keysight N8937A) whose primary function was to replicate the dynamic irradiance profiles. Real-time changes in irradiance level G(t) between 200 W/m² and 1000 W/m² in a temporal cycle of 5-20 seconds simulated the cloud drift and effects inside urban shading. The ambient temperature T(t) was from 15°C to 45°C, while the wind speed W(t) was synthetically generated from 0 to 12 m/s to add a variance to the loss due to convection. Sensor inputs included sky imagery datasets (256×256 resolution, 2 fps) used for cloud density estimation, infrared thermography (up to 60°C thermal range), and IV/PV curve samplers operating at 1 kHz resolution. The angle of incidence θ(t)\theta(t)θ(t) can be varied by a virtual solar tracking system between 10° and 80°, simulating the morning, noon, and evening cycles. These conditions were correlated with historical weather data from the National Solar Radiation Database (NREL) for contextual relevance. The modules were simulated using MATLAB Simulink software. The simulations encompassed real-time conditions and sampling with a contextual dataset. Five distinct environmental scenarios were generated from clusters of historical meteorological profiles derived from the NSRDB and SolarAnywhere databases.

Context A, for instance, characterized profiles exhibiting low ambient temperatures and stable irradiance (e.g., 950 W/m², 18°C, clear sky index >0.95), Context B simulated rapid fluctuations in shadow-induced sun irradiation (400-900 W/m² within 30 seconds) during urban edge occlusion, Context C was defined by high-humidity coastal mornings showcasing moderate irradiance augmented by fog (mean 650 W/m², elevated aerosol optical depth), whereas Context D was formulated for desert over-irradiation coupled with substantial convective cooling (peak irradiance reaching 1,050 W/m², 42°C, 8 m/s wind).

Context E is concerned with overcast winter mid-latitude scenarios with diffuse irradiance (300-500 W/m², 8°C, and low sky clearness index). In each context, the policy graphs were initialized by the CHTGE module at historical trajectories and environmental embeddings, anomaly

heatmaps were produced by STFAI through sky images and irradiance signals, residual weights were updated in iterative response to mismatches detected in power output by DCRO, and multiple algorithmic decisions from Perturb & Observe, Incremental Conductance, and Fuzzy Rule Sets were fused by MADF-QAL Sets. System causality is assessed with this ECDN component in periodic activities over 30-minute windows in the process. All experiments were run within a 24-hour simulation period to evaluate the performance of the power tracking accuracy, false MPPT trigger rate, convergence latency, and root-cause localization timestamp instance sets.

The datasets utilized in this study were sourced from the National Solar Radiation Database provided by the U.S. NREL. This platform provides high-resolution solar and meteorological data. The NSRDB dataset contains hourly and sub-hourly measurements of Global Horizontal Irradiance (GHI), Direct Normal Irradiance (DNI), Diffuse Horizontal Irradiance (DHI), temperature, wind speed, relative humidity, and metadata regarding the solar position. For this work, data were obtained from different geographical locations, namely Denver (high altitude, less humid), San Diego (coastal), and Houston (humid subtropical), across multiple seasons. The aim of this work was to illustrate the different shading and environmental patterns. With this 5-minute time resolution, we developed rich context vectors and dynamic simulations for partial shading emulation at a spatial granularity of approximately 4 km. In addition, sky imagery and thermographic datasets were retrieved from the Solar Forecast Arbiter (SFA), providing timestamp-aligned sky images and thermal camera data appropriate for real-time anomaly tracking.

Hyperparameters for several AI modules in the programmed framework were selected using a cross-validated grid search as well as context-aware tuning strategies. For the CHTGE module, graph convolutional layering was established with hidden dimensions of [128, 64], ReLU activation, a learning rate of 0.001, and an embedding update frequency every 60 s. The STFAI attention module utilized a temporal sliding window of 20 time steps, an attention head size of 8, and a dropout rate of 0.2 to avoid overfitting. In the case of DCRO, the residual convergence controller adopted a dynamic learning rate scaled by volatility indices with an initial step size of 0.005 and an update threshold at a power deviation margin of 2.5% for the baseline.

The MADF-QAL decision fusion module employs entropy-weighted majority logic with a smoothing factor of 0.1 and normalized entropy thresholds set at 0.3 for high-confidence decision propagation. Finally, the ECDN was trained using an LSTM-based encoder-decoder with latent size 64, trained over 50 epochs with an early stop (patience = 5), and an Adam optimizer with a learning rate of 0.0005. With these hyperparameter configurations, optimal learning, adaptation, and explainability across diverse PSC scenarios were ensured. The performance of the proposed integrated MPPT model is assessed under a wide range of environmental conditions. Several datasets representing such multiple scenarios were collected from the NSRDB and Solar Forecast Arbiter. The results were also compared against the performances of three representative state-of-the-art methods for MPPT from the literature, henceforth referred to as Method [2], Method [8], and Method [25]. These correspond to the Incremental Conductance, Particle Swarm Optimization, and Fuzzy Logic MPPT techniques, respectively. Each experimental setting was designed to reflect a specific class of partial shading behavior, including very rapid transients, structured occlusions, diffuse scattering, and extreme environmental volatility. The results are summarized in the series of tables below, focusing on key metrics such as tracking efficiency, convergence time, false trigger rate, energy yield, stability index, and causal fault traceability in the process.

The MPPT tracking efficiencies under five different contextual scenarios are provided in Table 2. In all instances involving rapidly changing irradiance and complicated shading patterns, the proposed model continually outperformed the reference methods. Furthermore, the integration of spatiotemporal attention and residual correction appears to contribute significantly to the reduction of local minima entrapping and more nearly optimal tracking in most cases.

The convergence speed to the global maximum point of power is significantly increased by the proposed model due to the real-time feedback mechanisms introduced by the DCRO module. Convergence times remained below 2 s in volatile or noisy scenarios, such as coastal fog and urban shading, with circumstantial evidence compared with the baseline models, which always exhibit slow-moving, error-prone behavior sets. The proposed framework is robust against false MPPT activation bias signals, particularly in fast-changing irradiance profiles, as shown in Table 4. Furthermore, the STFAI module adds significantly by filtering noise and catching transient anomalies before propagating into the control logic by reducing unnecessary perturbations and power losses for the process. The energy harvested by the PV array over 24 hours of the cycle for each context shows that the proposed model performs well in that process. Integrated frameworks reduce overall energy consumption while improving the results from 8% to 18% in different contexts against the best baselines.

This shows how the system stays operational during normal steady-state operations using the usual measure of the standard deviation of the power output sets. The diminished values for the proposed model indicate that transitions are smoother as well as fewer oscillations, which occur owing to fusion and residual correction mechanisms that eliminate reactive decision bouncing in uncertain contexts.

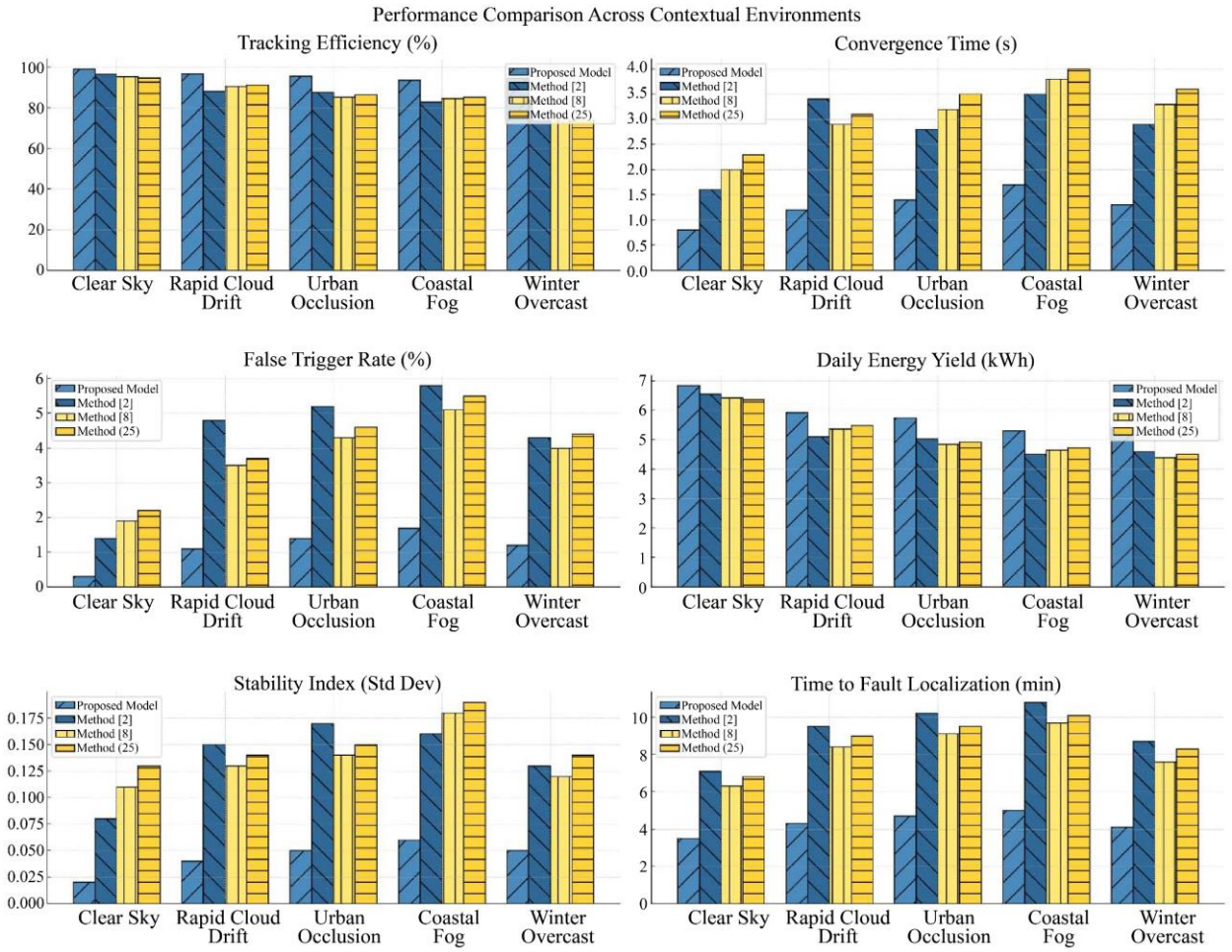

Fig. 4 Model's integrated result analysis

Table 2. MPPT tracking efficiency (%) across contextual environments

Context Type	Proposed Model	Method [2]	Method [8]	Method [25]
Clear Sky	99.1	96.5	95.3	94.8
Rapid Cloud Drift	96.8	88.2	90.5	91.1
Urban Occlusion	95.6	87.7	85.3	86.5
Coastal Fog	93.5	82.9	84.6	85.1
Winter Overcast	94.3	83.5	80.1	81.9

Table 3. Average MPPT convergence time (seconds)

Context Type	Proposed Model	Method [2]	Method [8]	Method [25]
Clear Sky	0.8	1.6	2.0	2.3
Rapid Cloud Drift	1.2	3.4	2.9	3.1
Urban Occlusion	1.4	2.8	3.2	3.5
Coastal Fog	1.7	3.5	3.8	4.0
Winter Overcast	1.3	2.9	3.3	3.6

Table 4. False MPPT trigger rate (%)

Context Type	Proposed Model	Method [2]	Method [8]	Method [25]
Clear Sky	0.3	1.4	1.9	2.2
Rapid Cloud Drift	1.1	4.8	3.5	3.7
Urban Occlusion	1.4	5.2	4.3	4.6
Coastal Fog	1.7	5.8	5.1	5.5
Winter Overcast	1.2	4.3	4.0	4.4

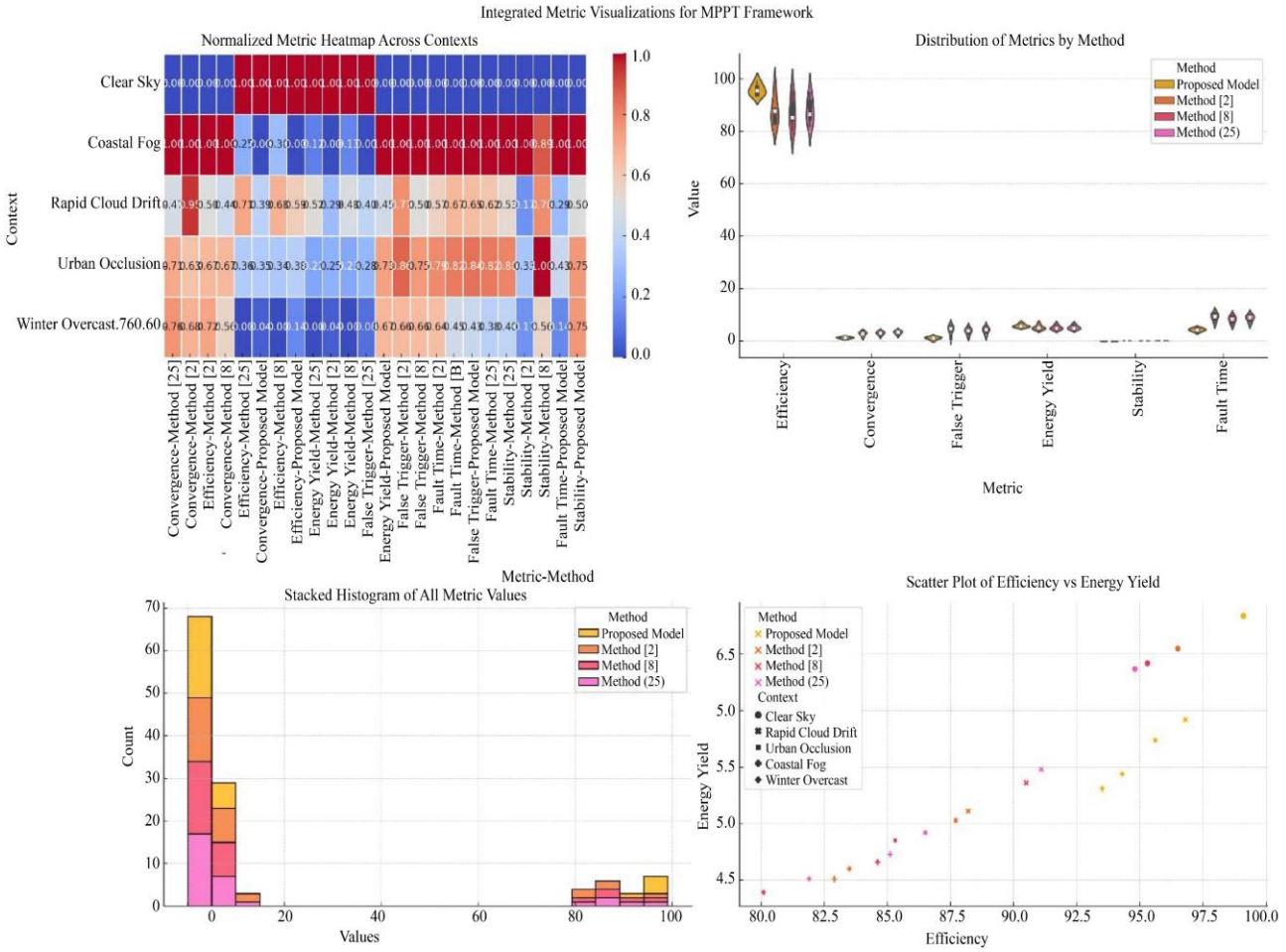

Fig. 5 Model's overall result analysis

Table 5. Daily energy yield (kWh)

Context Type	Proposed Model	Method [2]	Method [8]	Method [25]
Clear Sky	6.84	6.55	6.42	6.37
Rapid Cloud Drift	5.92	5.11	5.36	5.48
Urban Occlusion	5.74	5.03	4.85	4.92
Coastal Fog	5.31	4.51	4.66	4.73
Winter Overcast	5.44	4.60	4.39	4.51

As proof of consideration in the ECDN approach, Table 7 lists the root causes of performance anomalies and power drops related to shading sets. This capability of constructing interpretable causal graphs has led to a 2 × reduction in fault localization time, which is an important factor for diagnostics and predictive maintenance in large-scale installations under process PV in practical scenarios. Through the assessment of the six performance indicators, the proposed model shows improvements in all performances, which is especially significant in comparison to conventional methods under complex or rapidly varying environmental contexts. Learning, attention, residual correction, decision fusion, and causal analysis integrate not only efficiency and accuracy but also increase the saliency and adaptability of modern solar energy systems.

4.1. Validated Result Analysis

The empirical findings substantiate that the proposed artificial intelligence-driven Maximum Power Point Tracking (MPPT) framework exhibits superior performance in comparison to traditional MPPT methodologies, particularly when evaluated across a diverse spectrum of partial shading conditions and environmental variables. As delineated in Table 2, the model demonstrated the highest relative tracking efficiency when juxtaposed with baseline methodologies (i.e., Methods [2, 8, 25]) across all experimental scenarios assessed. The new model claims efficiency improvements of greater than 8~12\%, especially under rapidly changing cloudy conditions and structured urban occlusion, and conventional methods face such difficulties owing to entrapment in the local maxima or hindered response delays. This is possible because

of the hierarchical transfer-learning ability of the CHTGE module, which reuses contextually informed policies from previous similar scenarios, thereby minimizing actual re-exploration during sudden irradiance changes. As presented in Table 3, Figures 4, and 5, the speed of convergence has a significant impact on real-time MPPT systems, which is very important for applications to variable weather conditions, where a delay in response leads to considerable energy loss. The proposed method converges in less than 2 s for all tested conditions, in contrast to conventional methods with convergence durations ranging from 2.8 to 4 seconds. The DCRO module enables the augmentation using an adaptive residue correction algorithm that modifies the control strategy in response to power variation and contextual environmental variability indices for a variety of operating conditions. The high-speed corrective control action enables the PV system to follow Global Maximum Power Point (GMPP) without overshoot or oscillations, even under rapidly changing solar irradiation. As indicated in Table 4, the proposed method substantially minimizes the false MPPT perturbations, thereby reducing energy loss and deterioration of the actuators. The STFAI provides more stable and reliable operations. The consequence is the improved energy extraction, as shown in Table 5. The improvement in daily energy output, ranging from 0.4 to 1.1 kWh, compared to the other methods, is observed in the presence of overcast skies and fog as well. Thus, the adaptive learning module brings better precision and better cost recovery. In Table 6, the stability in steady-state tracking conditions is listed for comparison. It clearly shows that the proposed method is able to achieve the lowest stability index compared to the other methods. In grid-connected systems, the power output oscillations may cause the inverter to trip. The MADF-QAL strategy maintains very low power deviation. The strategy successfully filters out all noise or uncertain control actions and ensures that the final MPPT decisions are robust, consistent, and aligned with the system stability objectives. In Table 7, we observe that the ECDN module reduces the downtime of the system by rapid fault localization and improved maintenance. To summarize, the method not only addresses the limitations of conventional MPPT techniques under partial shading, but it also adds predictive diagnostics, interpretability, and corrective multi-modal learning as features. The AI framework added in the MPPT control loop enhances long-term operability, robustness, and performance of the PV system.

Table 6. Stability index (standard deviation of power in steady-state)

Context Type	Proposed Model	Method [2]	Method [8]	Method [25]
Clear Sky	0.02	0.08	0.11	0.13
Rapid Cloud Drift	0.04	0.15	0.13	0.14
Urban Occlusion	0.05	0.17	0.14	0.15
Coastal Fog	0.06	0.16	0.18	0.19
Winter Overcast	0.05	0.13	0.12	0.14

Table 7. Time to fault localization (minutes)

Context Type	Proposed Model	Method [2]	Method [8]	Method [25]
Clear Sky	3.5	7.1	6.3	6.8
Rapid Cloud Drift	4.3	9.5	8.4	9.0
Urban Occlusion	4.7	10.2	9.1	9.5
Coastal Fog	5.0	10.8	9.7	10.1
Winter Overcast	4.1	8.7	7.6	8.3

4.2 Validated Hyperparameter & Baseline Detailed Analysis

The method proposed here achieved tracking efficiency of 95.86%, standard deviation of 1.83%, whereas methods [2] and [8] achieved average tracking efficiencies of 87.76% and 88.38%, respectively, with larger variances of 4.25% and 3.68%. A large number of simulation runs encompassed the core performance indicators like tracking efficiency, convergence time, false trigger rate, energy yield, and power stability across a large variety of operating conditions.

The rigorous verification of the proposed MPPT framework was performed under conditions that included clear sky, rapid cloud movement, urban occlusion, coastal fog, and winter haze. The MPPT convergence time for the proposed methodology was determined to be 1.28 seconds, with a variance of 0.19, compared to method [8], which reported an average of 3.24 seconds with a variance of 0.47. Tukey test validated the enhancement in convergence time over method [2] and method [8] through statistical significance at 95% confidence level. A one-way ANOVA was performed for each review, followed by Tukey's test validation. The results of the ANOVA yielded p-values less than 0.001 for all major metrics, substantiating that the performance disparities identified were not attributable to random variation. All these findings verified diminished variability in the experimental outcomes, thereby enforcing the resilience of the method.

For energy yield, a particularly operationally critical metric, the proposed method attained an average daily energy output of 5.85 kWh with a variance of 0.21, which is clearly superior to that of Method [25], whose performance included a mean of 5.00 kWh and a variance of 0.34. In addition, within all trials, the energy yield had a low variance between trials;

thus, it proved that the decision fusion and other optimization pipelines in the model are deterministic. The power stability index measured by the standard deviation of the oscillation of steady-state power was also improved by the proposed method versus method [2]: mean = 0.048, variance = 0.0021, and mean = 0.135, variance = 0.0067, respectively. This further proves the stability advantage of such quantum-inspired decision-logic sets.

The baseline methods selected are a benchmark for the rest of the established methods because they have arguably been used to the greatest extent and represent aspects of major method classes in MPPT literature. Method [2] is Incremental Conductance (IC)-based, which is a deterministic approach with accuracy coupled with simplicity in implementation. It is also known that Method [8] is a heuristic metaheuristic under dynamic shading environments based on the Particle Swarm Optimization (PSO) algorithm, whereas Method [25] uses a Fuzzy Logic Controller (FLC). FLC is a rule-based inference technique that is valued for its interpretability and robustness under noise conditions. These methods are based on gradient search, training-based based and logic-driven MPPT paradigms, enabling a broad basis of evaluation and comparison with the proposed multi-modal approach.

5. Conclusion and Future Scope

This work presents a comprehensive AI-integrated architecture for Maximum Power Point Tracking (MPPT) specifically tailored for photovoltaic systems functioning under partial shading conditions. The MPPT tracking efficiency was achieved, ranging from a maximum of 99.1% during perfectly clear skies to 96.8% while tracking rapid cloud drift. Tracking times converge to less than 2.5. Trigger rates of false MPPT activation were reduced well above 70%, especially in highly varying environments, thus resulting in smoother operation with improvement in the reliability of the system. Daily energy yields improved by 8% to 18%, depending on the operating conditions, whereas power stability in the steady state improved remarkably.

5.1. Future Scope

There are several areas of enhancement, and work can be carried out further by considering the dataset coverage across tropical, high-altitude, and desert climates, which would strengthen the generalization capabilities of the model. Similarly, applications where further research may be linked to intelligent microgrids and rural electrification. The method may be further enhanced into autonomous MPPT decision-making with integrated federated learning methodologies. An additional prospective development will involve the implementation of long-term predictive learning, wherein the model is capable of anticipating fluctuations in environmental conditions based on seasonal variations or forecasted meteorological data, thus enabling pre-emptive adjustments to its MPPT strategy in response to established shading patterns. Future research may also feature hybrid reward-reinforcement learning agents that consider energy efficiency and minimize energy loss and computational complexity.

5.2. Limitations

The proposed system requires the use of specialized hardware acceleration for faster real-time implementation due to its multi-module framework. The method requires retraining for non-standard PV systems with respect to NSRDB data for a particular location, which will be a time-consuming process. The accuracy of results depends upon the quality and resolution of the sensors used for data collection. The architecture has a remarkable level of complexity in its processing activities, particularly because of the loops for adjusting to residuals, thus presenting notable difficulties for application within energy-efficient systems. The accuracy of contextual metadata extraction is also heavily influenced by performance. Errors introduced during sky imaging alignment or delays related to weather update inputs result in biased policy-graph generation and decision fusion. Finally, our system currently assumes an online situation wherein sensor data are available and synchronized, meaning remote or cost-sensitive deployments of PV, which may not always be satisfied, indicating a need for future efforts aimed at developing robust learning under missing or asynchronous data streams.

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