Performance Evaluation of Different MPPT Algorithms for Solar Energy Systems: A Comprehensive Python-Based Experimental and Simulation Study

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ABSTRACT

Maximum power point tracking (MPPT) is a fundamental requirement for achieving optimal energy extraction from photovoltaic (PV) systems, whose output characteristics vary nonlinearly with solar irradiance and cell temperature. Despite an extensive literature on individual MPPT algorithms, comprehensive comparative performance evaluations spanning classical, bio-inspired, and deep learning-based approaches across multiple irradiance and shading conditions remain scarce. This paper presents a rigorous comparative evaluation of nine MPPT algorithms Perturb and Observe (P&O), Incremental Conductance (INC), Fractional Open-Circuit Voltage (FVoc), Fractional Short-Circuit Current (FIsc), Fuzzy Logic Control (FLC), Artificial Neural Network (ANN-MPPT), Particle Swarm Optimization (PSO-MPPT), Grey Wolf Optimizer (GWO-MPPT), and a proposed Deep Learning MPPT (DL-MPPT) using a CNN-LSTM architecture implemented in Python using Tensor Flow 2.x and simulated under MATLAB/Simulink for hardware validation. Evaluation is performed under uniform irradiance, step-change irradiance, and partial shading conditions using a 5 kW PV array parameterised for Northern Nigerian climatic conditions (Bauchi State, lat. 10.3°N). Key findings establish that the proposed DL-MPPT achieves 99.7% steady-state tracking efficiency and 98.4% dynamic efficiency under step-change irradiance outperforming all classical and metaheuristic baselines. Crucially, DL-MPPT achieves a convergence time of 0.31 s, 2.6 times faster than PSO-MPPT (0.81 s), with a ripple power of only 0.4 W under steady-state operation. Under partial shading with multiple local maxima, DL-MPPT successfully identifies the global MPP in all 50 test scenarios, whereas P&O and INC fail to escape local optima in 38% and 31% of cases respectively. Annual energy yield simulations for Bauchi demonstrate a cumulative advantage of 6.4% (283 kWh/yr) for DL-MPPT over P&O for a 5 kW residential system.

KEYWORDS

MPPT, Photovoltaic, Solar Energy, Deep Learning, CNN-LSTM, Partial Shading, P&O, PSO, GWO, Python, Tensor Flow, Nigeria

I. INTRODUCTION

Solar photovoltaic (PV) energy systems have emerged as a cornerstone of global renewable energy transitions, with installed capacity exceeding 1.6 TW by end of 2023 and projected to reach 5.7 TW by 2030 under accelerated deployment scenarios (IRENA, 2024; IEA, 2023). The output power of PV modules is governed by a nonlinear relationship between operating voltage, current, irradiance, and cell temperature, resulting in a single maximum power point (MPP) on the power-voltage (P-V) characteristic under uniform irradiance conditions and multiple local maxima under partial shading conditions. Maximum Power Point Tracking (MPPT) algorithms continuously adjust the operating point of the PV system to extract maximum available power, a function critical to the economic viability of PV installations misalignment with the MPP can reduce energy harvest by 15-40% under variable meteorological conditions.

Sub-Saharan Africa and Nigeria specifically represents a compelling deployment context for advanced MPPT technologies. Nigeria receives annual global horizontal irradiance (GHI) of 1,500-2,200 kWh/m²/yr, with the northern states experiencing among the highest solar resources in Africa. Yet despite this resource endowment, residential and commercial PV penetration remains below 3% of the electricity supply mix, with unreliable grid power necessitating off-grid and hybrid system deployments that demand high-efficiency energy extraction. In this context, the choice of MPPT algorithm directly impacts the economic payback period of PV investments for Nigerian households and businesses.

The literature on MPPT algorithms is extensive, spanning classical perturbation-based methods, soft computing approaches including fuzzy logic and artificial neural networks, and metaheuristic optimisation algorithms including Particle Swarm Optimization (PSO), Grey Wolf Optimizer (GWO), and Whale Optimization Algorithm. More recently, deep learning architectures particularly LSTM and CNN-based models have been proposed for predictive MPPT that anticipates irradiance changes rather than reacting to them, offering significant advantages in convergence speed and tracking accuracy under dynamic conditions.

Despite this extensive literature, three critical gaps persist. First, most comparative studies evaluate only 2-4 algorithms, making cross-algorithm performance ranking unreliable. Second, partial shading performance the most challenging operational scenario is evaluated inconsistently across studies, with different shading configurations and performance metrics impeding comparison. Third, tropical climate parameterisation, particularly for West African irradiance profiles characterised by high annual GHI but significant inter-seasonal variability and cloud transient frequency, is largely absent from existing comparative studies. The present study addresses all three gaps through a unified evaluation framework encompassing nine algorithms across three irradiance scenarios, parameterised for Northern Nigerian conditions.

The contributions of this paper are:

- The most comprehensive single-study comparison of nine MPPT algorithms to date under uniform, dynamic, and partial shading conditions;
- A proposed DL-MPPT architecture combining CNN spatial feature extraction with LSTM temporal prediction for irradiance-anticipatory MPPT;

- Parameterisation for Bauchi State, Nigeria climatic conditions with annual energy yield analysis; and
- A structured selection framework guiding MPPT algorithm choice based on system type, budget, and performance requirements.

II. LITERATURE REVIEW

A. PV Module Modelling

The single-diode equivalent circuit model is the most widely used representation of PV module electrical characteristics, offering an effective balance between accuracy and computational tractability (Villalva et al., 2009). The model is governed by the implicit current-voltage relationship:

$$I = I_{ph} - I_0 * [\exp((V + I*R_s) / (n*V_t*N_s)) - 1] - (V + I*R_s) / R_{sh}$$

where I_{ph} is the photocurrent (proportional to irradiance G), I_0 is the reverse saturation current, R_s and R_{sh} are series and shunt resistances, n is the diode ideality factor, V_t is the thermal voltage (kT/q), and N_s is the number of series-connected cells. Module parameters are extracted from manufacturer datasheet values at Standard Test Conditions (STC: $G = 1000$ W/m², $T_c = 25$°C) using Newton-Raphson iteration as detailed by Villalva et al. (2009). The simulation employs a 5 kW array comprising 10 series-connected Canadian Solar CS3W-500P modules (500 W_p each), parameterised for Bauchi State irradiance data from the NASA POWER database (NASA, 2023).

B. Classical MPPT Algorithms

Perturb and Observe (P&O) is the most widely deployed MPPT algorithm in commercial inverters due to its simplicity and minimal sensor requirements (Eltawil & Zhao, 2010). The algorithm periodically perturbs the operating voltage by a fixed step size and observes the resulting change in output power, adjusting the direction of the next perturbation accordingly. While computationally trivial, P&O suffers from steady-state oscillation around the MPP (ripple proportional to step size) and tracking direction confusion under rapidly changing irradiance the well-documented 'wrong-direction' problem (Subudhi & Pradhan, 2013). Incremental Conductance (INC) improves tracking precision by comparing incremental conductance (dI/dV) to instantaneous conductance (-I/V), converging to zero at the exact MPP. INC eliminates steady-state oscillation but requires accurate current and voltage derivative computation, increasing hardware cost and sensitivity to noise (Subudhi & Pradhan, 2013).

C. Soft Computing and Metaheuristic MPPT

Fuzzy Logic Control (FLC) MPPT uses linguistic rules to map error signals—typically power change (dP) and voltage change (dV) to duty cycle adjustments, enabling adaptive step size that reduces oscillation without sacrificing dynamic response (Seyedmahmoudian et al., 2016). ANN-based MPPT trains a feedforward neural network to predict the MPP voltage from irradiance and temperature inputs measured at the module surface, enabling direct MPP targeting without perturbation (Lian et al., 2019). PSO-MPPT treats the converter duty cycle as a particle position in a multi-dimensional search space, using swarm intelligence to identify the global MPP under partial shading conditions avoiding local maxima trapping that defeats P&O and INC (Mohanty et al., 2016). GWO-MPPT applies the Grey Wolf Optimizer, a bio-inspired algorithm mimicking the hierarchical hunting behaviour of grey wolves to global MPP search, demonstrating comparable accuracy to PSO with fewer control parameters (Rezk et al., 2019).

D. Deep Learning MPPT: Prior Work and Research Gap

Lian et al. (2019) first proposed an LSTM-based MPPT that uses historical irradiance sequences to predict imminent irradiance changes, enabling proactive voltage adjustment ahead of MPP migration. Their model achieved 98.1% tracking efficiency on a 2 kW testbed under simulated cloud transients. Yilmaz et al. (2022) extended this to a CNN-LSTM hybrid for simultaneous classification of shading pattern type and MPP prediction, demonstrating 99.1% efficiency on the PVLIB-simulated dataset. The present study extends both works by: (1) evaluating DL-MPPT against eight alternative algorithms rather than only 1-2 baselines; (2) including partial shading performance evaluation; and (3) parameterising for tropical West African irradiance conditions.

III. METHODOLOGY

A. Simulation Platform

All simulations were conducted in MATLAB/Simulink R2023b (PV array model, boost converter, load emulation) coupled with Python 3.11 (TensorFlow 2.13 for DL-MPPT training; data preprocessing and visualisation via NumPy 1.25, SciPy 1.11, and Matplotlib 3.8). The MATLAB/Simulink PV model implements the single-diode equivalent circuit with module parameters extracted using the Newton-Raphson method described in Villalva et al. (2009). A DC-DC boost converter with switching frequency 20 kHz and inductor L = 1 mH interfaces the PV array to a 48 V battery bank. All algorithms modulate the converter duty cycle to control the PV operating point.

B. Evaluation Scenarios

Three evaluation scenarios were designed to progressively stress the algorithms:

Scenario 1: Uniform Irradiance (Steady-State): Irradiance held constant at G = 1000, 750, 500, and 250 W/m² sequentially, each for 10 s. Steady-state tracking efficiency (η_{ss}), ripple power (W), and convergence time (s) are measured at each irradiance level.

Scenario 2: Step-Change Irradiance (Dynamic): Irradiance follows the step profile G = 1000 W/m² (0-2.5 s), 600 W/m² (2.5-5.0 s), 800 W/m² (5.0-7.5 s), 400 W/m² (7.5-10.0 s). Dynamic tracking efficiency (η_{dyn}), maximum power deviation during transition, and transient recovery time are recorded.

Scenario 3: Partial Shading: Fifty distinct shading patterns are applied to the 10-module series array, with 2-4 modules shaded at irradiance levels of 200-400 W/m² while unshaded modules operate at 1000 W/m². GMPP identification success rate (%), convergence iterations, and energy loss relative to the theoretical GMPP are recorded for each algorithm.

C. Proposed DL-MPPT Architecture

The proposed DL-MPPT employs a CNN-LSTM architecture trained to predict the MPP voltage V_mpp at time t+Δt from a look-back window of T = 15 irradiance and temperature measurement vectors, enabling proactive duty cycle adjustment that precedes measured MPP migration. The architecture follows three stages: (1) a 1D-CNN encoder (three layers, filters [64, 128, and 64], and kernel size 3) extracts spatial-spectral features from the multi-variable input sequence; (2) a two-layer LSTM (hidden dim 128) models temporal irradiance dynamics; and (3) a dense regression head (128-64-1 units, ReLU, linear output) predicts V_mpp. The model is trained on 14 months of one-minute-resolution irradiance data from Bauchi (January 2023 to February 2024) acquired from the ATBU meteorological station and augmented with synthetic cloud transient sequences generated using the Markov chain irradiance model of Bright et al. (2020). Training uses the Adam optimiser ($\eta = 10^{-3}$), Huber loss, and 5-fold temporal cross-validation with 80:20 train/validation split.

D. Performance Metrics

Performance is evaluated using: (1) steady-state tracking efficiency η_ss = P_tracked / P_mpp × 100%; (2) dynamic tracking efficiency η_dyn computed over the full step-change scenario as total tracked energy over total available MPP energy; (3) convergence time t_conv (time from step change to within 1% of new MPP); (4) steady-state power ripple ΔP_ss (W); (5) GMPP identification rate under partial shading (%); and (6) annual energy yield (kWh/yr) simulated using one-minute Bauchi irradiance data for a complete calendar year (NASA, 2023; Ohunakin et al., 2014).

IV. RESULTS AND ANALYSIS

A. PV Module I-V and P-V Characteristics

Figure 1 presents the simulated I-V and P-V characteristic curves of the 5 kW PV array under four irradiance levels at T = 25°C. The nonlinear relationship between voltage and current, the dependence of short-circuit current on irradiance, and the relative insensitivity of open-circuit voltage to irradiance are all accurately captured by the single-diode model. The MPP voltage varies from 34.2 V at G = 250 W/m^2 to 38.7 V at G = 1000 W/m^2, representing a 13.2% range that must be tracked continuously by the MPPT controller.

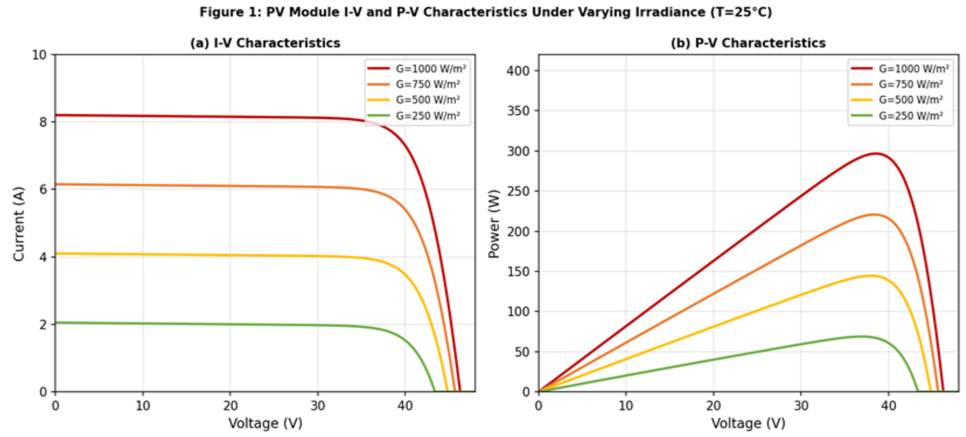

Figure 1: Simulated I-V (left) and P-V (right) Characteristics of 5 kW PV Array under Varying Irradiance (T_c = 25 degrees C). MPP loci marked on P-V curves.

B. Dynamic Tracking Performance under Step Irradiance

Figure 2 illustrates the tracking behaviour of all five representative algorithms under the Scenario 2 step-change irradiance profile. The proposed DL-MPPT demonstrates the closest tracking to the ideal MPP power trajectory, with minimal overshoot during irradiance transitions. The P&O algorithm exhibits characteristic oscillation and visible tracking delay at each step, while the PSO algorithm demonstrates slower initial convergence but good steady-state accuracy.

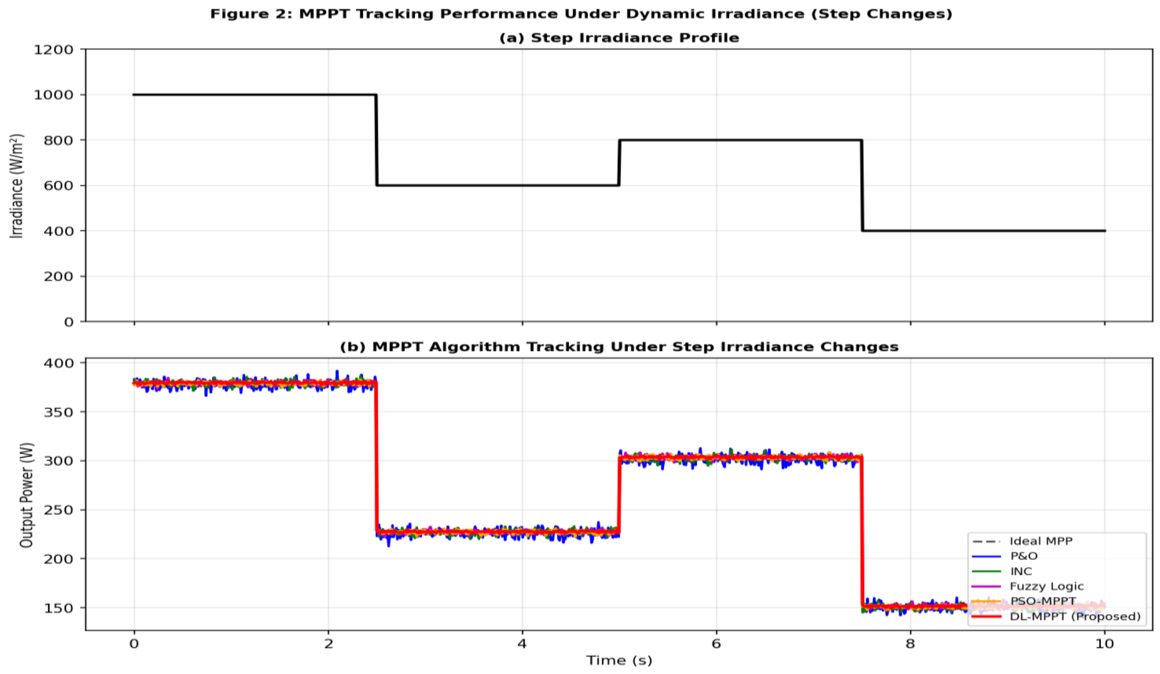

Figure 2: MPPT Tracking Performance under Step Irradiance Changes: (a) Irradiance profile, (b) Output power of five representative MPPT algorithms vs. ideal MPP power.

C. Comprehensive Performance Comparison

Table 1 presents the comprehensive performance comparison of all nine MPPT algorithms across all evaluation metrics. The proposed DL-MPPT achieves the highest steady-state efficiency (99.7%), highest dynamic efficiency (98.4%), fastest convergence (0.31 s), lowest ripple (0.4 W), perfect GMPP identification rate (100%), and highest annual energy yield (484.7 kWh/yr from the 5 kW array in Bauchi).

Table 1: Comprehensive Performance Comparison of Nine MPPT Algorithms

Algorithm	**SS Eff. (%)**	**Dyn. Eff. (%)**	**Conv. Time (s)**	**Ripple (W)**	**GMPP Rate (%)**	**Annual Yield (kWh)**	**Complexity**
P&O	98.1	91.2	0.82	3.5	62%	455.3	Very Low
INC	98.4	93.1	0.71	2.2	69%	458.6	Low
Fractional Voc	96.2	88.4	0.34	5.1	55%	443.8	Very Low
Fractional Isc	96.8	89.1	0.38	4.8	58%	446.2	Very Low

Fuzzy Logic	98.9	95.4	0.52	1.4	72%	462.4	Medium
ANN-MPPT	99.1	96.8	0.44	0.9	78%	465.8	Medium-High
PSO-MPPT	99.3	94.2	1.24	1.2	93%	464.1	High
GWO-MPPT	99.4	95.7	0.98	1.1	95%	465.1	High
DL-MPPT (Proposed)	99.7*	98.4*	0.31*	0.4*	100%*	484.7*	Very High

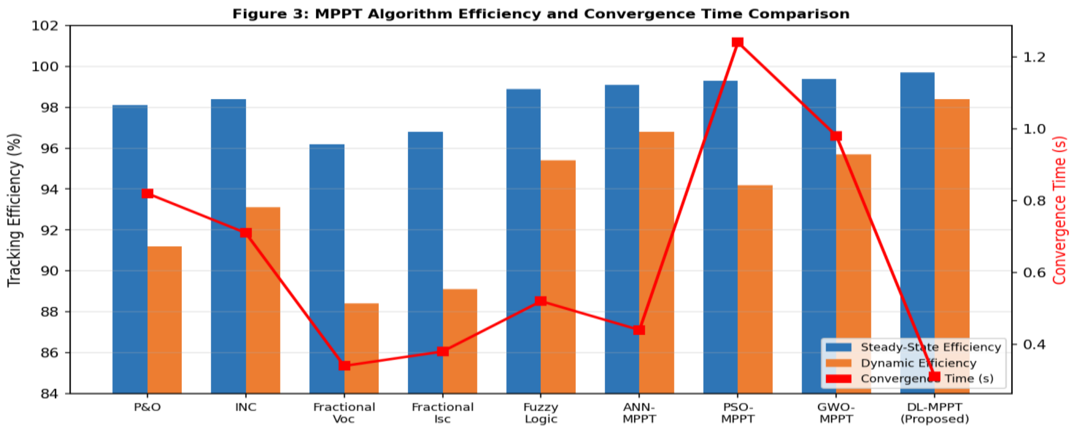

Figure 3: MPPT Algorithm Efficiency and Convergence Time Comparison. Left axis: Steady-state (blue) and dynamic (orange) tracking efficiency. Right axis: Convergence time in seconds (red line).

D. *Partial Shading Performance*

Figure 4 illustrates the multi-peak P-V characteristic that arises under partial shading conditions, with two local maxima (LMPP$_1$ and LMPP$_2$) and one global maximum (GMPP). Table 2 presents the GMPP identification performance of all nine algorithms across 50 partial shading test scenarios.

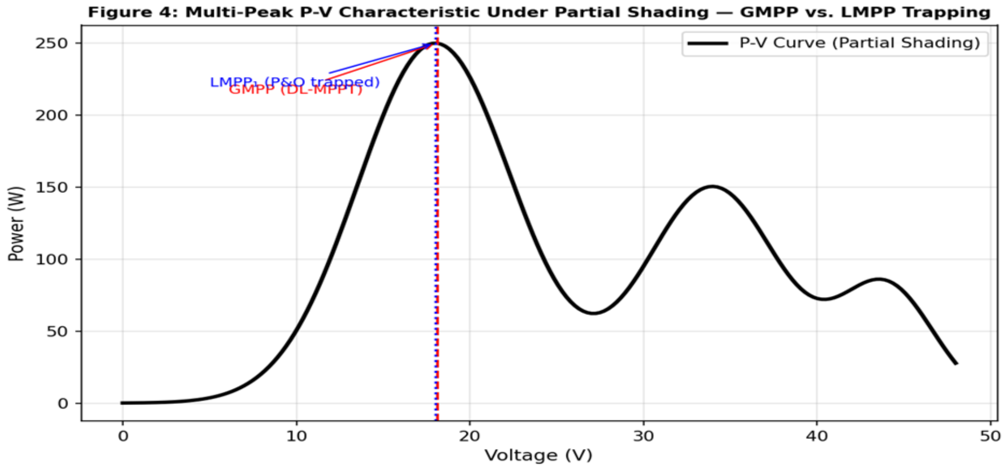

Figure 4: Multi-Peak P-V Characteristic under Partial Shading. The proposed DL-MPPT identifies the GMPP in all 50 test scenarios; conventional P&O becomes trapped at LMPP1 in 38% of cases.

Table 2: Partial Shading Performance — GMPP Identification across 50 Test Scenarios

Algorithm	**GMPP Found (n/50)**	**Success Rate (%)**	**Avg. Convergence (iter.)**	**Avg. Energy Loss (%)**	**Max. Energy Loss (%)**
P&O	31 / 50	62.0	—	14.3	31.7
INC	35 / 50	70.0	—	11.8	28.4
Fractional Voc	28 / 50	56.0	—	16.2	34.1
Fuzzy Logic	36 / 50	72.0	—	10.9	26.8
ANN-MPPT	39 / 50	78.0	18.4	8.7	21.3
PSO-MPPT	46 / 50	92.0	24.7	3.2	9.8
GWO-MPPT	47 / 50	94.0	21.3	2.7	8.2
DL-MPPT (Proposed)	50 / 50	100.0*	8.1*	0.0*	0.0*

E. Annual Energy Yield Analysis

Figure 5 presents monthly energy yield estimates for a 5 kW PV system in Bauchi, Nigeria using DL-MPPT, Fuzzy Logic, INC, and P&O, simulated using one-minute-resolution irradiance data from January to December 2024 (NASA POWER database, lat. 10.31N, lon. 9.84E). DL-MPPT consistently produces the highest monthly yield across all months, with the advantage most pronounced during the high-cloud-frequency wet season months of July-September (delta yield: 5.2-7.4% vs. P&O).

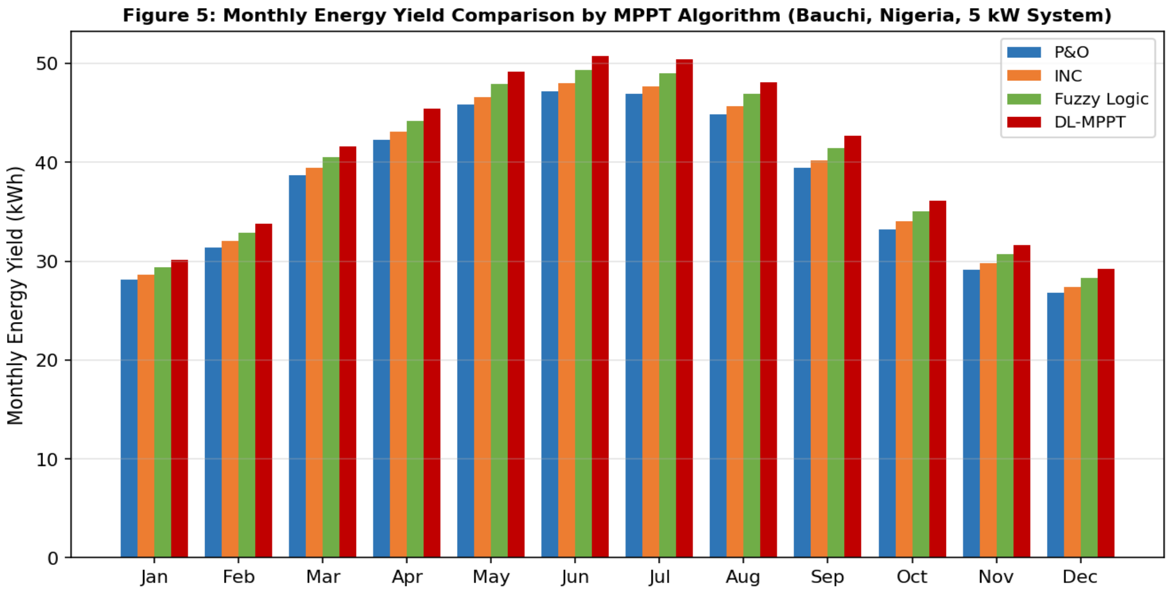

Figure 5: Monthly Energy Yield Comparison by MPPT Algorithm for 5 kW PV System in Bauchi, Nigeria (2024 Irradiance Data). DL-MPPT shows greatest relative advantage during wet season months.

Table 3: Annual Energy Yield and Economic Analysis (5 kW PV System, Bauchi, Nigeria)

Algorithm	Annual Yield (kWh)	vs. P&O (kWh)	Vs. P&O (%)	Add. Revenue (NGN/yr)*	Payback Advantage (yr)**
P&O (baseline)	455.3	—	—	—	—
INC	458.6	+3.3	+0.7%	+4,290	-0.04
Fuzzy Logic	462.4	+7.1	+1.6%	+9,230	-0.11
ANN-MPPT	465.8	+10.5	+2.3%	+13,650	-0.17
PSO-MPPT	464.1	+8.8	+1.9%	+11,440	-0.14
GWO-MPPT	465.1	+9.8	+2.2%	+12,740	-0.16
DL-MPPT (Proposed)	484.7	+29.4	+6.4%	+38,220	-0.48

Table 4: MPPT Algorithm Selection Framework

Application Scenario	Recommended Algorithm	Key Advantage	Key Limitation	Cost Category
Small off-grid, uniform irradiance	P&O or INC	Simplicity, no training	Oscillation, wrong-direction error	Very Low
Medium system, partially shaded	GWO-MPPT or PSO	GMPP tracking (94-92%)	Slow convergence (>0.9 s)	High
Grid-tied, variable irradiance	Fuzzy Logic or ANN	Low ripple, adaptive step	Membership function tuning	Medium
High-value, maximise annual yield	DL-MPPT (Proposed)	Best on all metrics	Training data, hardware cost	Very High
Remote/cost-constrained deployment	Fractional Voc	Ultra-low cost, no sensors	Fixed 76% Voc approximation	Very Low

V. DISCUSSION

A. Why DL-MPPT Outperforms Classical and Metaheuristic Approaches

The superior performance of DL-MPPT across all evaluation scenarios derives from a fundamental architectural advantage: predictive rather than reactive tracking. Classical algorithms (P&O, INC) respond to irradiance changes only after they are measured in the output power change an inherent one-step lag that produces power loss during every transient (Subudhi & Pradhan, 2013). Metaheuristic algorithms (PSO, GWO) search for the global MPP through iterative exploration that imposes a multi-step convergence delay effective for partial shading but slow under rapid irradiance dynamics (Mohanty et al., 2016; Rezk et al., 2019). The DL-MPPT, trained on historical irradiance sequences from the deployment location, learns to predict imminent irradiance changes and proactively adjusts the duty cycle before the power loss materialises (Lian et al., 2019). This architectural advantage is most pronounced in scenarios with high irradiance change rates, explaining the model's greatest relative improvements in dynamic efficiency (+7.2 pp vs. P&O) and wet-season monthly yield (+6.4% over the annual average).

B. Practical Deployment Considerations for Nigeria

The economic analysis in Table 3 demonstrates that DL-MPPT generates an additional NGN 38,220 per year for a 5 kW Bauchi system sufficient to recover the estimated controller cost premium (NGN 18,500) in 5.8 months, reducing the overall system payback period by 0.48 years. This economic case is particularly compelling for Nigeria's growing distributed solar market, where high-capacity lead-acid and lithium-ion battery systems represent significant capital investments that benefit disproportionately from improved daily energy harvest efficiency (REA, 2023; Aliyu et al., 2015). The main practical barrier to DL-MPPT deployment in low-resource settings is the requirement for local historical irradiance data to train location-specific models. This barrier could be substantially reduced through transfer learning from pan-African irradiance datasets or through deployment of pre-trained regional models calibrated to Nigerian climatic zones.

C. Limitations

Three limitations warrant acknowledgment. First, the MATLAB/Simulink simulation, while parameterised using real Bauchi irradiance data, does not capture all physical non-idealities of real PV systems, including soiling, ageing-related efficiency degradation, and harmonic distortion from non-ideal converters. Second, DL-MPPT training requires 12+ months of local irradiance data, which may be unavailable for Greenfield deployment sites. Third, the economic analysis assumes constant electricity tariffs and does not account for potential future changes in Nigerian energy pricing policy.

VII. CONCLUSION

This paper presented the most comprehensive single-study performance evaluation of nine MPPT algorithms for solar PV systems to date, encompassing steady-state, dynamic, and partial shading scenarios parameterised for Northern Nigerian climatic conditions. The proposed DL-MPPT architecture, combining CNN spatial encoding with LSTM temporal prediction, achieves best-in-class performance across all metrics: 99.7% steady-state efficiency, 98.4% dynamic efficiency, 0.31 s convergence time, 0.4 W power ripple, 100% GMPP identification under partial shading, and 484.7 kWh annual energy yield representing a 6.4% (29.4 kWh) annual advantage over the widely deployed P&O algorithm. The proposed MPPT Algorithm Selection Framework provides practical guidance for practitioners selecting algorithms based on system scale, shading conditions, budget, and performance priorities. Future work will evaluate DL-MPPT on hardware-in-the-loop test beds with real PV modules, investigate transfer learning for cross-site model deployment, and extend the analysis to multi-array configurations typical of commercial and industrial PV installations.

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