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An Epistemological Analysis of Metaheuristic MPPT Performance for Photovoltaic Systems under Partial Shading Conditions

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Abstract

Metaheuristic-based maximum power point tracking algorithms are widely used in photovoltaic systems to address nonlinear and multi-peak characteristics under partial shading conditions. However, many reported performance claims rely mainly on numerical simulation and therefore require cautious interpretation. This study presents a simulation-based comparative and epistemological analysis of Particle Swarm Optimization and Differential Evolution for photovoltaic maximum power point tracking. Both algorithms are implemented in an identical buck converter-based photovoltaic framework to ensure fair comparison. Performance is evaluated under uniform irradiance and partial shading conditions using convergence time and tracked power as evaluation metrics. The results show that under uniform irradiance, both algorithms reliably converge to the maximum power point with similar steady-state accuracy, while Particle Swarm Optimization converges faster. Under partial shading conditions, Particle Swarm Optimization consistently tracks the global maximum power point, whereas Differential Evolution shows occasional convergence failure or suboptimal tracking. From an epistemological standpoint, these findings constitute coherent and pragmatically useful model-based knowledge, while remaining provisional due to the absence of experimental validation.

Keywords: MPPT; Metaheuristic; Epistemological; Partial Shading; Photovoltaic

1. Introduction

Solar photovoltaic (PV) generation has become a cornerstone of the energy transition due to its renewability, modularity, and steadily improving techno-economic performance. Yet PV output is inherently sensitive to irradiance and temperature variations, which continuously shift the maximum power point (MPP) along the I-V and P-V characteristics. Consequently, maximum power point tracking (MPPT) control is indispensable for harvesting the highest feasible energy yield under changing operating conditions [1], [2].

In real deployments, PV arrays frequently experience partial shading conditions (PSC) caused by clouds, nearby objects (trees/buildings), soiling, or non-uniform module orientation. PSC introduces multiple local maxima in the P-V curve (often driven by mismatch and bypass-diode activation) so conventional MPPT schemes such as perturb and observe (P&O), incremental conductance (INC), and hill-climbing variants may lock onto a local peak rather than the global MPP, leading to non-trivial power losses [3]s.

To address the multi-peak nature of PSC, metaheuristic optimization-based MPPT has gained substantial traction. Algorithms such as particle swarm optimization (PSO), differential evolution (DE), and grey wolf optimizer (GWO) are commonly framed as global search mechanisms that balance exploration and exploitation in nonlinear solution spaces and reduce the risk of local entrapment [4]. Recent comparative and survey studies further highlight that reported performance depends strongly on parameter tuning, objective-function design, irradiance test profiles, converter architecture, and sensing/measurement assumptions [4], [5].

Nevertheless, a large share of performance claims (tracking efficiency, convergence speed, steady-state oscillation, and re-tracking under fast transients) are still established mainly through numerical simulation (e.g., MATLAB/Simulink) using idealized PV and converter models. A growing body of recent work therefore emphasizes experimental validation (including hardware-in-the-loop and PV emulation) to assess robustness against sensor limitations, switching non-idealities, noise, and load dynamics [6], [7]. At the same time, new global MPPT proposals continue to emerge, increasing the need for consistent evaluation protocols [8]. Benchmarking practices are also evolving to account for computational cost and implementation complexity, not merely tracking accuracy, as an integral part of engineering relevance [9].

These methodological choices have a clear epistemological dimension: under what conditions do simulation outcomes count as reliable knowledge about real-world MPPT performance? From a falsificationist and model-based epistemological perspective, scientific claims derived from simulation should remain testable and, in principle, refutable through empirical evidence. In contemporary engineering research, simulations frequently operate ahead of direct experimental validation, providing model-based knowledge that supports design decisions while simultaneously introducing epistemic risks related to model bias, idealized assumptions, and limited calibration data [10]. Consequently, simulation-based MPPT studies should be interpreted not as definitive empirical proof, but as conditional knowledge claims whose validity depends on modeling coherence, correspondence with physical principles, and robustness across operating scenarios [11].

Against this background, this article develops an epistemological analysis of metaheuristic MPPT performance for PV systems operating under PSC. Rather than focusing solely on which algorithm appears fastest or most efficient in simulation, we interrogate the justification of performance claims through (i) internal coherence of the modeling and algorithm implementation, (ii) empirical correspondence via validation strategies (experiments, HIL, or field data), and (iii) robustness to irradiance profiles, parameter uncertainty, and measurement perturbations. We also propose reporting and benchmarking recommendations intended to improve transparency, replicability, and the epistemic strength of simulation-centric MPPT studies [1], [4], [9].

The remainder of the paper is structured as follows. The Methodology section describes the PV simulation design and MPPT implementations; the Results and Discussion section presents performance comparisons and their epistemological implications; and the Conclusion section summarizes key findings and outlines directions for future work.

2. Methods

2.1 Photovoltaic System Simulation Design

The simulation framework employed in this study is illustrated in **Figure 1**. It consists of a photovoltaic (PV) module, a DC–DC buck converter, and a metaheuristic-based MPPT control block. The PV module generates output current ipv and voltage vpv, which serve as inputs to the MPPT controller. The controller produces a reference PV voltage v∗pv, which is compared with the measured PV voltage vpv. The resulting error is processed by a PI controller and subsequently fed to a PWM generator that regulates the switching signal of the buck converter. The converter output is connected to an RL load. This configuration enables a controlled and repeatable evaluation of different MPPT algorithms under varying irradiance levels and partial shading conditions.

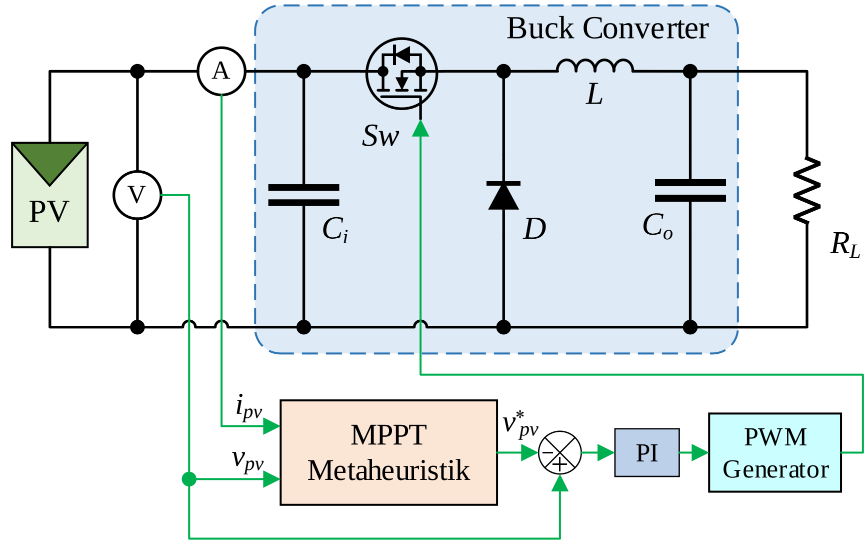

Figure 1. Buck Converter-Based Metaheuristic MPPT for PV Systems

Partial shading conditions are modeled by assigning non-uniform irradiance values to PV submodules, ranging from 1000 W/m2 to 500 W/m2. This setup produces multi-peak P–V characteristics, thereby requiring the MPPT algorithms to identify the global maximum power point (GMPP) rather than converging to local optima. Time-varying irradiance profiles are applied to reflect realistic environmental dynamics and to assess the re-tracking capability of each algorithm.

The DC–DC buck converter serves as the interface between the PV array and the load. The inductor (L) and capacitor (C) values are selected to satisfy a current ripple limit of 20% of the average inductor current and a voltage ripple constraint of 1% of the output voltage. Duty-cycle regulation is exclusively governed by the MPPT controller, which is implemented as a dedicated subsystem for each algorithm under study.

2.2 Implementation of Metaheuristic MPPT Algorithms

This study evaluates two representative metaheuristic algorithms: Particle Swarm Optimization (PSO) and Differential Evolution (DE). These algorithms are selected because they represent two dominant optimization paradigms in MPPT research. PSO is based on swarm intelligence and collective learning through velocity updating, while DE relies on evolutionary mutation and crossover mechanisms. Their widespread adoption in MPPT literature makes them suitable reference algorithms for examining not only numerical performance, but also the epistemic justification of simulation-based performance claims under partial shading conditions.

Particle Swarm Optimization (PSO)

In PSO, each particle represents a candidate duty-cycle value. Particle positions and velocities are iteratively updated based on individual best and global best experiences. The algorithm parameters are set as follows: population size of 6 particles, acceleration coefficients $c1 = c2 = 1.5$, and inertia weight $w = 0.7$. These values are selected to balance exploration and exploitation while maintaining numerical stability.

Differential Evolution (DE)

DE employs mutation and crossover mechanisms to generate candidate solutions. The scaling factor is set to $F = 0.7$, and the crossover rate (CR) is fixed at 0.9. DE is well known for its robustness in nonlinear and multi-modal optimization problems, making it suitable for MPPT under partial shading conditions.

Both algorithms are implemented using MATLAB script functions integrated with the Simulink-based converter model. Each simulation is executed for a duration of 5 s with a fixed-step solver and a time step of $2\times10-6$ s to ensure numerical accuracy and stable switching-level behavior.

2.3 Evaluation Procedure and Performance Metrics

The performance of the MPPT algorithms is assessed using two primary indicators: (a) Convergence time (tc), defined as the time required for the algorithm to reach 99% of the global maximum power; and (b) GMPP tracking accuracy, which measures the ability of the algorithm to maintain operation at the global maximum power point under steady-state and dynamic shading conditions.

These metrics are selected to capture both the transient and steady-state performance of the MPPT strategies, which are critical for practical PV energy harvesting applications.

2.4 Epistemological Perspective in Simulation Validation

From an epistemological standpoint, simulation-based research raises fundamental questions regarding the status and validity of the knowledge produced. In this study, the PV model, converter parameters, and algorithmic formulations constitute epistemic representations of a real physical system rather than direct empirical observations.

The epistemic validity of the simulation results is therefore grounded in three interrelated criteria. First, internal coherence refers to the logical and mathematical consistency among the PV model, power converter, and MPPT algorithms. All subsystems are constructed based on established physical laws and widely accepted modeling practices, ensuring theoretical consistency.

Second, correspondence with physical principles concerns the extent to which the simulation reflects known photovoltaic behavior, such as irradiance-dependent I–V characteristics and power conversion dynamics. While the present study does not include experimental validation, the models are designed to remain faithful to first-principle constraints.

Third, pragmatic usefulness evaluates whether the simulation outcomes provide reliable and repeatable insights across different partial shading scenarios.

From this perspective, simulation results are not treated as definitive empirical proof, but as idealized, model-based knowledge that supports hypothesis generation and comparative analysis.

Accordingly, the findings of this study should be interpreted as epistemically valid within the domain of simulation (coherent and pragmatically informative) yet provisional with respect to real-world deployment. Experimental testing is therefore identified as a necessary future step to extend the epistemic status of these results from model-based inference toward empirically validated engineering knowledge.

3.Results and Discussion

This section presents and discusses the simulation results of the proposed metaheuristic-based MPPT strategies (PSO and DE) under two operating scenarios: uniform irradiance and partial shading conditions (PSC). Beyond numerical comparison, the discussion is framed within an epistemological perspective to evaluate the strength, limits, and justification of simulation-based performance claims.

3.1 System Parameters and Baseline Conditions

The buck converter parameters used in all simulations are summarized in Tabel 1. The inductance and capacitance values were selected to satisfy current and voltage ripple constraints commonly adopted in MPPT studies, ensuring stable converter operation and minimizing bias introduced by excessive switching ripple. A switching frequency of 5 kHz was chosen to balance dynamic response and computational burden.

Tabel 1. Buck converter parameters

Parameters	Value
Converter inductance value L	2 mH
Converter capacitance value C	220 uF
Switching frequency f_{sw}	5 kHz
Load resistance R_L	2 Ω

Under these fixed hardware parameters, the MPPT algorithms were evaluated independently, ensuring that observed performance differences can be attributed primarily to algorithmic behavior rather than converter design variations. This controlled setup strengthens the internal coherence of the simulation framework.

3.2 Scenario 1: Uniform Irradiance Conditions

Figure 2 illustrates the P–V characteristic of the PV system under uniform irradiance, where a single global maximum power point (GMPP) is present. The theoretical maximum power under this condition is approximately 159.83 W.

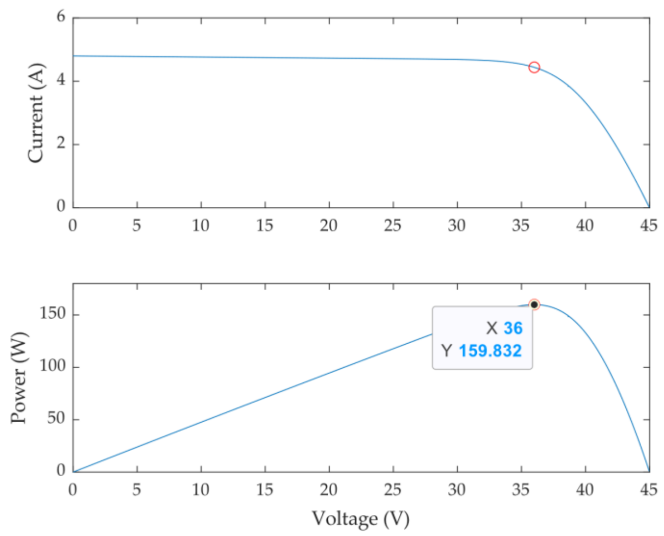

Figure 2. Characteristics of the PV System under Uniform Irradiance

Figure 3. shows representative tracking responses of the MPPT algorithms during one iteration. Quantitative results across ten independent runs are summarized in **Tabel 2**. Both PSO and DE consistently converged to the GMPP in all trials, indicating reliable global convergence in unimodal conditions.

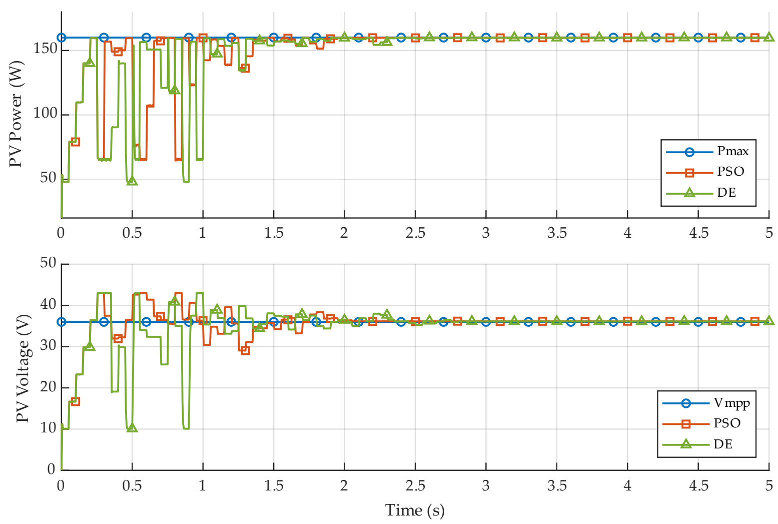

Figure 3. MPPT Tracking Response under Uniform Irradiance

From a performance standpoint, PSO achieved a lower average convergence time (2.22 s) compared to DE (3.3 s), while both algorithms reached nearly identical steady-state power levels (159.69 W for PSO and 159.78 W for DE). These results suggest that, in smooth and unimodal search spaces, both metaheuristic approaches are epistemically equivalent in terms of solution correctness, with PSO exhibiting a modest advantage in convergence speed.

Epistemologically, this scenario primarily supports correspondence-based justification: the simulated results align well with the known physical behavior of PV systems under uniform irradiance, where a single MPP exists and can be reliably tracked by global optimization methods. However, because the problem is relatively simple, this scenario offers limited discriminatory power between advanced metaheuristic algorithms.

Tabel 2. MPPT Performance Comparison under Uniform Irradiance Conditions

Iterasi	PSO			DE		
	t_c (s)	P_{pv} (W)	Status	t_c (s)	P_{pv} (W)	Status
1	2.05	159.7	Converged	2.8	159.8	Converged
2	2.55	159.8	Converged	3.05	159.8	Converged
3	2.05	159.7	Converged	3.05	159.8	Converged
4	2.8	159.7	Converged	3.05	159.8	Converged
5	1.55	159.5	Converged	2.8	159.8	Converged
6	2.8	159.8	Converged	3.3	159.8	Converged
7	2.3	159.8	Converged	3.05	159.8	Converged
8	1.55	159.5	Converged	4.05	159.7	Converged
9	2.55	1597	Converged	3.55	159.7	Converged
10	2.05	159.7	Converged	4.3	159.8	Converged
Avg.	**2.22**	**159.69**	**-**	**3.3**	**159.78**	**-**

3.3 Scenario 2: Partial Shading Conditions

Because both PSO and DE are inherently stochastic optimization algorithms, performance evaluation under partial shading conditions is conducted over ten independent simulation runs. This approach is necessary to capture variability in convergence behavior and to avoid conclusions based on single-run artifacts that may not reflect typical algorithm performance. The second scenario introduces partial shading, resulting in a multi-peak P–V curve as shown in Figure 4. Under this condition, the theoretical GMPP is approximately 88.22 W, and the MPPT task becomes substantially more challenging due to the presence of local maxima.

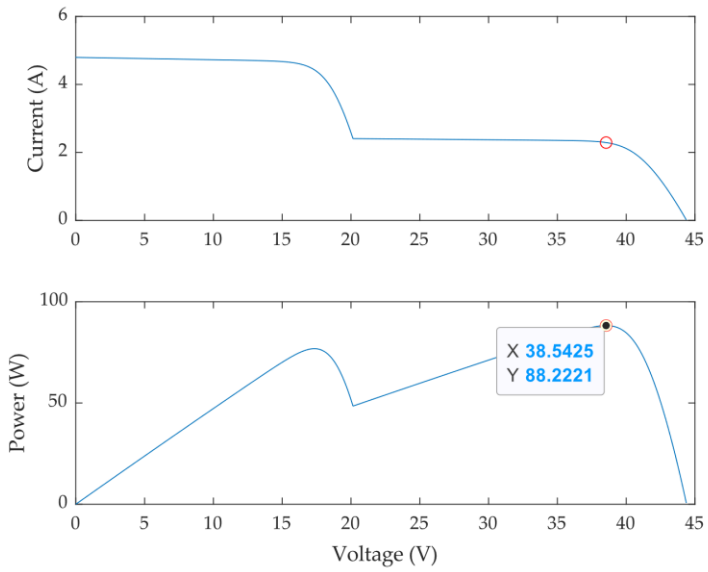

Figure 4. Characteristics of the PV System under Partial Shading Conditions

Figure 5. presents a representative tracking response under partial shading, while Table 3 summarizes the results over ten independent runs. PSO demonstrates strong robustness, converging to the GMPP in all iterations with an average convergence time of 2.25 s and an average tracked power equal to the theoretical maximum.

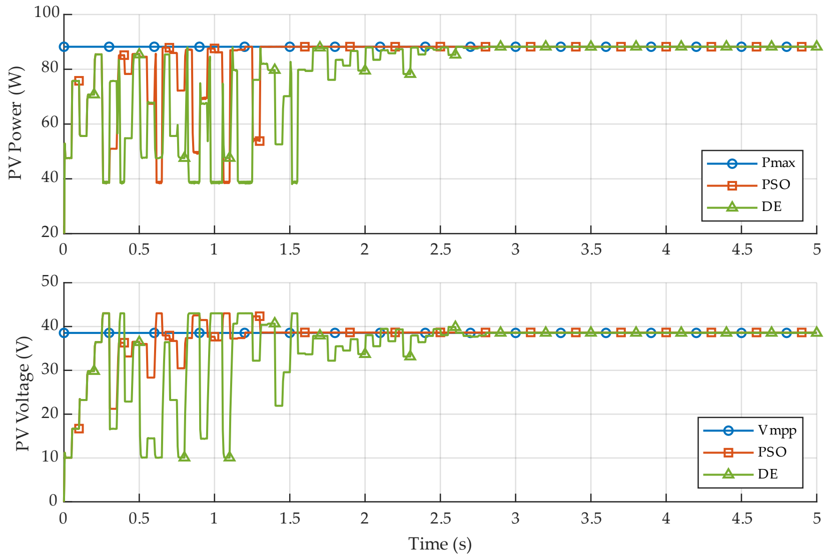

Figure 5. MPPT Tracking Response under Partial Shading Conditions

In contrast, DE exhibits less consistent behavior. Although DE successfully converges to the GMPP in several iterations, multiple runs result in failed convergence or timeout, with tracked power values significantly below the theoretical maximum (e.g., 65.5 W and 84.8 W). Consequently, the average convergence time of DE increases to 4.335 s, and the average tracked power drops to 85.53 W.

Tabel 3. MPPT performance comparison under partial shading conditions

Iterasi	PSO			DE		
	t_c (s)	P_{pv} (W)	Status	t_c (s)	P_{pv} (W)	Status
1	2,55	88,2	Converged	5	87,6	Failed/Timeout
2	2,05	88,2	Converged	3,8	88,2	Converged
3	1,3	88,2	Converged	2,8	88,2	Converged
4	2,55	88,2	Converged	4,8	88,2	Converged
5	2,8	88,2	Converged	5	65,5	Failed/Timeout
6	1,8	88,2	Converged	4,55	88,2	Converged
7	2,8	88,2	Converged	4,55	88,2	Converged
8	2,8	88,2	Converged	4,3	88,2	Converged
9	1,8	88,2	Converged	3,55	88,2	Converged
10	2,05	88,2	Converged	5	84,8	Failed/Timeout
Avg.	**2,25**	**88,2**	**-**	**4,335**	**85,53**	**-**

These findings indicate that PSO offers superior robustness under PSC within the adopted simulation configuration. From an epistemological perspective, this difference highlights the role of procedural knowledge embedded in algorithm dynamics. PSO's velocity-update mechanism enables more effective exploration–exploitation balance in multi-modal landscapes, whereas DE's mutation and crossover operations appear more sensitive to parameter settings and stochastic initialization.

3.4 Epistemological Interpretation of Simulation Results

While the numerical results suggest that PSO outperforms DE under partial shading, it is critical to interpret these findings within their epistemic context. The results satisfy internal coherence: the PV model, converter dynamics, and MPPT algorithms are mathematically consistent and implemented under identical conditions. Moreover, the observed behaviors are plausible given known characteristics of the algorithms and the physics of PSC-induced multi-peak P–V curves.

However, the justification remains primarily pragmatic rather than fully empirical. The absence of experimental validation implies that these results should be understood as model-based knowledge claims rather than definitive statements about real-world performance. Factors such as sensor noise, quantization effects, converter non-idealities, and computational delays (often decisive in practical MPPT deployment) are idealized or omitted in the present simulations.

While the simulation results indicate superior robustness of PSO compared to DE under partial shading conditions, these findings must be interpreted within their epistemic limits. The observed performance differences are internally coherent and physically plausible within the adopted modeling framework, yet they remain contingent upon idealized assumptions, parameter selections, and numerical representations. As such, claims of algorithmic superiority should be regarded as conditional and model-dependent rather than universally valid. Experimental validation is therefore required to extend these model-based insights toward empirically grounded engineering knowledge.

4. Conclusion

This study presented a simulation-based comparative analysis of Particle Swarm Optimization and Differential Evolution for maximum power point tracking in photovoltaic systems under uniform irradiance and partial shading conditions using an identical buck converter-based framework. Numerically, both algorithms reliably track the maximum power point under uniform irradiance with comparable steady-state accuracy, while Particle Swarm Optimization achieves faster convergence on average. Under partial shading conditions, Particle Swarm

Optimization demonstrates superior robustness by consistently converging to the global maximum power point, whereas Differential Evolution exhibits sensitivity to stochastic effects and parameter interactions, resulting in occasional convergence failure or suboptimal tracking. Epistemologically, these results constitute coherent and pragmatically useful model-based knowledge, yet remain provisional in the absence of experimental validation.

Under partial shading conditions, Particle Swarm Optimization demonstrates superior robustness by consistently converging to the global maximum power point across all test runs. Differential Evolution, in contrast, exhibits sensitivity to stochastic effects and parameter interactions, leading to occasional convergence failure or suboptimal tracking. These findings indicate that the effectiveness of metaheuristic MPPT algorithms in multi peak operating conditions is strongly influenced by their exploration and exploitation mechanisms.

From an epistemological perspective, the results constitute coherent and pragmatically useful model based knowledge but remain provisional due to the absence of experimental validation. Simulation is therefore positioned as a comparative and hypothesis generating tool rather than definitive empirical evidence. Future work should focus on experimental verification and the inclusion of practical non idealities to strengthen the reliability and real world applicability of the proposed MPPT conclusions.

Authors' Declaration

Authors' contributions and responsibilities - The authors made substantial contributions to the conception and design of the study. The authors took responsibility for data analysis, interpretation, and discussion of results. The authors read and approved the final manuscript.

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Availability of data and materials - All data is available from the authors.

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