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Enhanced adaptive reconfiguration for optimizing power generation and switching efficiency in PV arrays under PSC

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ABSTRACT

Photovoltaic (PV) arrays suffer significant power losses under partial shading conditions (PSC), which can degrade system performance. This paper proposes a novel weighted objective function that balances power output maximization with switching action minimization during dynamic PV array reconfiguration. An enhanced firebug swarm optimization (FSO) algorithm is employed to optimize this function efficiently. Simulation results under five shading patterns demonstrate approximately 6% improvement in power output over conventional methods, while also reducing the number of switch operations. The proposed approach enhances energy yield and extends device lifespan, offering a robust solution for real-time PV optimization under PSC.

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1. INTRODUCTION

In recent years, the increasing cost of fossil fuels and growing environmental concerns have driven significant advancements in solar energy technologies. As a result, photovoltaic (PV) systems have emerged as a vital component of modern power grids, offering a clean and renewable energy source [1]. However, the performance of PV arrays is highly sensitive to environmental factors. One of the most critical challenges is partial shading conditions (PSC), caused by dust accumulation, passing clouds, buildings, or other obstructions [2]. These conditions reduce solar irradiation on affected PV cells, leading to substantial energy losses and the formation of hotspots, which can damage cells and reduce system lifespan [3].

While bypass diodes are commonly integrated to prevent damage by rerouting current around shaded cells, they introduce their own drawbacks—primarily a reduction in the overall power output and efficiency of the array. Additionally, PSC causes multiple peaks in the power-voltage (P–V) and current-voltage (I–V) curves, making it difficult to accurately track the global maximum power point (MPP) [4].

Several strategies have been explored to mitigate PSC effects, including improved maximum power point tracking (MPPT), use of advanced converters and inverters, and PV array reconfiguration. Among these, array reconfiguration has proven particularly effective, as it redistributes shaded and unshaded modules across the electrical network to balance the row currents, reduce mismatch losses, and enhance energy output [5]. Reconfiguration methods are typically classified into static and dynamic approaches.

Static reconfiguration involves rearranging PV modules based on fixed electrical or physical layouts. Techniques such as the SuDoKu [6], optimized SuDoKu [7], magic square [8], and dominance square [9] configurations have shown improved performance over traditional series-parallel and total cross-tied (TCT) arrangements [10]. However, static methods are best suited for predictable, uniform shading and often require complex wiring and lack adaptability in real-time shading variations [11].

In contrast, dynamic reconfiguration modifies the electrical connections of PV cells in real time using a switch matrix, without altering their physical positions. This allows the system to respond to changing shading conditions and maintain optimal performance [12]. Various algorithms have been proposed for dynamic reconfiguration, including rule-based systems (e.g., fuzzy logic [13], rough set theory [14]), optimization algorithms (e.g., dynamic programming [15], greedy algorithms [16]), and metaheuristic techniques like genetic algorithm (GA) [17], grasshopper optimization algorithm (GOA) [18], and particle swarm optimization (PSO) [19]. These methods primarily focus on maximizing power output, but often neglect the impact of frequent switching, which can increase control complexity and reduce the lifespan of switching components. Recent research has proposed multi-objective optimization frameworks that consider both power output and switching action minimization [20], [21]. However, adding more optimization parameters typically increases computational time and algorithmic complexity.

To address this challenge, the present study introduces a novel weighted objective function that combines the goals of maximizing power output and minimizing the number of switching operations. The approach prioritizes reconfiguring PV cells with higher shading values, thereby improving energy yield while reducing switching stress. To optimize this objective function, an enhanced firebug swarm optimization (FSO) algorithm is employed. This improved FSO reduces discretization complexity, operates with fewer parameters, and facilitates efficient convergence—offering an advantage over existing techniques such as those described in [22]-[24].

The proposed method is evaluated under five representative shading patterns—left-down, left-top, right-top, right-down, and center shading—to validate its robustness [25]. Simulation results demonstrate notable improvements in power output, fill factor, and reduced mismatch losses, while also achieving a reduction in switching actions. These findings confirm the potential of the proposed strategy to improve PV system efficiency and prolong device lifespan under partial shading conditions.

2. MODELLING OF PV ARRAY METHOD

The total cross-tied (TCT) configuration is a widely adopted approach for arranging photovoltaic (PV) arrays to mitigate mismatch losses caused by partial shading. This section outlines the mathematical and computational modeling of a PV array in the TCT configuration, which ensures uniform current sharing among parallel rows and enhances the overall performance of the system under diverse environmental conditions. A PV cell is represented using the one-diode model, which provides a detailed characterization of its electrical behavior, as in (1).

$$I = I_{ph} - I_0\left(e^{\frac{q(V+IR_S)}{nkT}} - 1\right) - \frac{V+IR_s}{R_{sh}} \tag{1}$$

Where:
- I is the output current, V is the output voltage, I_{ph} is the photogenerated current, and I_0 is the reverse saturation current.
- R_s and R_{sh} represent the series and shunt resistances, respectively.
- T is the temperature in Kelvin, k is the Boltzmann constant ($1.38 \times 10 - 23$ J/K), q is the electron charge (1.6×10−19 C), and n is the ideality factor.

This equation forms the foundation for modeling the electrical characteristics of individual PV cells.

To attain the required voltage and current levels, a PV module consists of many cells connected in parallel or series. For a module, the relationships are expressed as (2).

$$V_{module} = N_s.V_{cell}, \quad I_{module} = I_{cell} \tag{2}$$

Where N_s is the number of cells connected in series within the module.

PV modules are set up in a matrix layout with m rows and n columns in the TCT configuration. In order to balance the distribution of current throughout the array, modules within a row are connected in parallel, and rows are connected by horizontal cross-ties. Reduced mismatch losses and improved resistance to shading effects are guaranteed by this arrangement. The overall current and voltage of the array in TCT configuration are given by (3).

$$V_{array} = V_{module}.m, \quad I_{array} = \sum_{j=1}^{n} I_j \tag{3}$$

Partial shading introduces variability in the current generated by individual modules. In order to avoid shaded modules from negatively impacting the string's overall performance, bypass diodes are integrated into the array architecture. The power output of individual modules and the entire array is calculated as (4).

$$P_{module} = V_{module}.I_j, \quad P_{array} = \sum_{i=1}^{m}\sum_{j=1}^{n} P_{module}(i,j) \tag{4}$$

In response to shading circumstances, dynamic reconfiguration uses a switch matrix to change the electrical connections inside the PV array. The switching state of each module is represented by a binary matrix S_{ij}, whereas calculated in (5).

$$S_{ij} = \begin{cases} 1, & if\ module\ M_{ij}\ is\ active \\ 0, & if\ module\ M_{ij}\ is\ inactive \end{cases} \tag{5}$$

The total power output and current of the array are dynamically updated based on the switch matrix, as (6).

$$P_{total} = \sum_{i=1}^{m}\sum_{j=1}^{n} S_{ij}.P_{module}(i,j) \tag{6}$$

3. DYNAMIC RECONFIGURATION OF PV ARRAYS USING FIREBUG SWARM OPTIMIZATION WITH A NOVEL OBJECTIVE FUNCTION

Partial shading significantly reduces the energy output of PV systems by causing mismatch losses. These effects—caused by clouds, nearby obstructions, or dirt—limit array performance, as shaded modules restrict the overall current flow. Traditional methods, such as bypass diodes and TCT configurations, mitigate these effects but lack adaptability to real-time shading variations.

Dynamic reconfiguration addresses this limitation by adjusting the electrical connections between PV modules through a switch matrix. However, many existing techniques focus only on maximizing power output, overlooking the operational complexity and hardware degradation caused by frequent switching actions. To overcome these issues, this study proposes a weighted objective function that simultaneously optimizes power output and minimizes switching operations. An enhanced FSO algorithm is used to solve this dual-objective problem, improving both energy yield and system reliability under dynamic shading conditions.

3.1. Proposed novel objective function

The proposed objective function forms the core of the dynamic reconfiguration strategy, optimizing the trade-off between two conflicting objectives:

- Maximizing power output: The PV system must produce the highest power possible under partial shading conditions.
- Minimizing switching actions: Reducing frequent reconfigurations helps extend switch lifespan, simplify control, and reduce maintenance.

The objective function is expressed as (7). Where, F: the overall fitness value of a given PV array configuration, $P_{current}$: power output of the current configuration, P_{max}: maximum achievable power output for a given shading scenario, $S_{current}$: the number of switch changes required for the current reconfiguration, S_{total}: the total possible number of switch changes in the system, w_1 and w_2: weight factors representing the relative importance of power optimization and switching minimization.

$$F = w_1.\frac{P_{current}}{P_{max}} - w_2.\frac{S_{current}}{S_{total}} \tag{7}$$

These weights can be dynamically adjusted based on system requirements—prioritizing w_1 during high energy demand and w_2 during maintenance-sensitive conditions.

3.2. Improved firebug swarm optimization algorithm

The FSO algorithm is a metaheuristic inspired by the movement and communication behaviors of firebugs. In this study, it is enhanced to effectively optimize the proposed dual-objective function under different partial shading scenarios. The key improvements are as follows:

- Dynamic weight adjustment: Maintains a balance between exploration and exploitation to ensure efficient convergence.
- Priority-based module reconfiguration: Prioritizes modules with higher shading levels for reconfiguration.

- Enhanced fitness evaluation: Uses the novel objective function to evaluate configurations based on both power and switching criteria.
- Improved local search: Prevents the algorithm from being trapped in local optima.
- Velocity-based update mechanism: Enhances solution diversity and accelerates convergence.

3.2.1. Fitness evaluation

Each firebug (candidate solution) is evaluated using the weighted objective function as (8).

$$F_i = w_1.\frac{P_{current}(i)}{P_{max}} - w_2.\frac{S_{current}(i)}{S_{total}} \tag{8}$$

Where F_i is the fitness of the i^{th} firebug, and other terms are as defined previously.

3.2.2. Movement and update mechanism

Firebugs update their positions based on the best local and global solutions as (9).

$$X_i(t+1) = X_i(t) + \alpha.\left(g_{local} - X_i(t)\right) + \beta.\left(g_{global} - X_i(t)\right) \tag{9}$$

Where $X_i(t)$ is the position of the i^{th} firebug at time t, and α, β control the influence of local and global solutions.

3.2.3. Adaptive weight adjustment

To improve convergence behavior, weight values change dynamically in (10) and (11).

$$w_1(t) = w_1(0).\left(1 - \frac{t}{T_{max}}\right) \tag{10}$$

$$w_2(t) = w_2(0).\left(\frac{t}{T_{max}}\right) \tag{11}$$

This mechanism prioritizes power optimization in early iterations and switching minimization in later stages.

3.2.4. Firebug update rule with velocity

To enhance exploration, firebug movement is also governed by a velocity update (12) and (13).

$$V_i(t+1) = \gamma.V_i(t) + \alpha.\left(g_{local} - X_i(t)\right) + \beta.\left(g_{global} - X_i(t)\right) \tag{12}$$

$$X_i(t+1) = X_i(t) + V_i(t+1) \tag{13}$$

Where γ is the inertia weight, controlling momentum and helping firebugs escape local minima.

3.2.5. Convergence criteria

The algorithm terminates when one of the following conditions is met: maximum number of iterations T_{max} is reached, and the change in fitness between consecutive iterations is negligible, as in (14).

$$Convergence\ Condition:\ \left|F_{global}(t+1) - F_{global}(t)\right| < \in \tag{14}$$

Where ∈ is a small threshold indicating convergence.

The enhanced FSO algorithm integrates a novel objective function with adaptive control mechanisms to provide a robust and efficient dynamic reconfiguration strategy for PV arrays under partial shading. The algorithm balances energy optimization with operational efficiency by minimizing switching actions, making it suitable for both real-time applications and long-term deployment.

4. RESULTS AND DISCUSSION

4.1. Power optimization under various shading conditions

This section evaluates the effectiveness of the proposed FSO algorithm combined with the novel objective function for optimizing PV array performance under partial shading. Simulations were conducted in MATLAB (Version 9.13) across five shading scenarios: right-down, left-down, right-top, left-top diagonal, and center shading. These patterns reflect real-world conditions used to assess the benefits of dynamic reconfiguration.

The proposed method was compared with conventional optimization techniques, focusing on power output, fill factor, and mismatch loss. Results consistently showed improved performance, validating the robustness of the new approach. For simulation, the FSO algorithm used a population size of 25 and 100 iterations to balance accuracy and efficiency. The PV array was assumed to operate at a standard temperature of 25 °C. Initially, the weight parameter α in (6) was set to 0, prioritizing only power optimization. These findings highlight the potential of the proposed dynamic reconfiguration method to enhance power output and system efficiency in varying shading conditions.

The effectiveness of the proposed approach is evaluated using three key performance metrics: mismatch loss (ML), fill factor (FF), and efficiency (η). Mismatch loss quantifies the power loss due to uneven shading and is calculated as the difference between the global maximum power point (GMPP) under standard test conditions (STC) and under partial shading conditions (PSC), with $GMPP_{STC}$ fixed at 9800 W (i.e., 280 W × 5 × 7). The fill factor, which reflects the quality of the PV array, is defined as the ratio of the maximum power output under PSC to the rated power of the array. Efficiency is computed as the ratio of the maximum output power to the product of irradiance (1000 W/m²) and the total PV array area (1.56 m × 1.56 m × 5 × 7), as specified in Table 1. These metrics provide a comprehensive assessment of system performance under varying shading conditions.

Table 1. PV panel specifications

Typical type	Specifications
Maximum power (P_{max})	280 W
Maximum power voltage (V_{mp})	31.7 V
Maximum power current (I_{mp})	8.83 A
Short circuit current (I_{sc})	9.54 A
Open circuit voltage (V_{oc})	38.5 V
Dimensions	156x156 mm
Number of cells	60 cells in series

4.2. Proposed switching-based reconfiguration strategy for a 5x7 PV array

To validate the proposed method, a 5×7 unsymmetrical PV array configuration was selected for analysis. The performance of the enhanced FSO algorithm was tested under five distinct partial shading patterns: left-down diagonal (Figure 1(a)), right-down diagonal (Figure 1(b)), left-top diagonal (Figure 1(c)), right-top diagonal (Figure 1(d)), and center shading (Figure 1(e)). These patterns were chosen to represent common real-world shading conditions that can significantly affect the performance of PV arrays. The corresponding P–V characteristics for each of these shading scenarios are illustrated in Figures 2(a)-2(e). These plots provide a visual comparison of the power output performance of the FSO algorithm against other metaheuristic algorithms.

The simulation results, summarized in Table 2, demonstrate the superiority of the FSO algorithm in maximizing power output across all tested shading scenarios when compared to the GOA, grey wolf optimization (GWO), and PSO.

- Under the left-down diagonal shading pattern (Figure 1(a)), the FSO method achieved an output power of 5142.92 W, outperforming GOA (4958.48 W), GWO (5018.36 W), and PSO (4898.24 W).
- For the right-down diagonal pattern (Figure 1(b)), FSO delivered 5016.54 W, exceeding the outputs of GOA (4834.86 W), GWO (4883.19 W), and PSO (4804.68 W).
- Under the left-top diagonal pattern (Figure 1(c)), FSO again led with 5292.32 W, compared to GOA (5115.64 W), GWO (5178.88 W), and PSO (5056.42 W).
- In the case of the right-top diagonal pattern (Figure 1(d)), FSO achieved 5248.56 W, while GOA, GWO, and PSO produced 5067.38 W, 5136.14 W, and 5008.72 W, respectively.
- Finally, under the center shading scenario (Figure 1(e)), FSO delivered its highest performance of 5395.26 W, significantly outperforming GOA (5172.86 W), GWO (5238.64 W), and PSO (5086.42 W).

In terms of mismatch losses, the FSO method consistently demonstrated lower values under all five conditions: 4657.08 W, 4783.46 W, 4507.68 W, 4551.44 W, and 4404.74 W, respectively for the patterns shown in Figures 1(a)-1(e). These values were considerably better than those obtained using GOA, GWO, and PSO.

Furthermore, the FSO-based method showed a consistently higher fill factor (FF) in each shading scenario, further underscoring its ability to optimize the electrical performance of the PV array. Overall, the results—visualized in Figures 2(a)-2(e) and quantified in Table 2—highlight the efficiency, robustness, and real-world applicability of the proposed FSO-based dynamic reconfiguration strategy. Its ability to enhance power output, reduce mismatch losses, and maintain a high fill factor under various shading patterns establishes it as a superior solution compared to existing metaheuristic techniques.

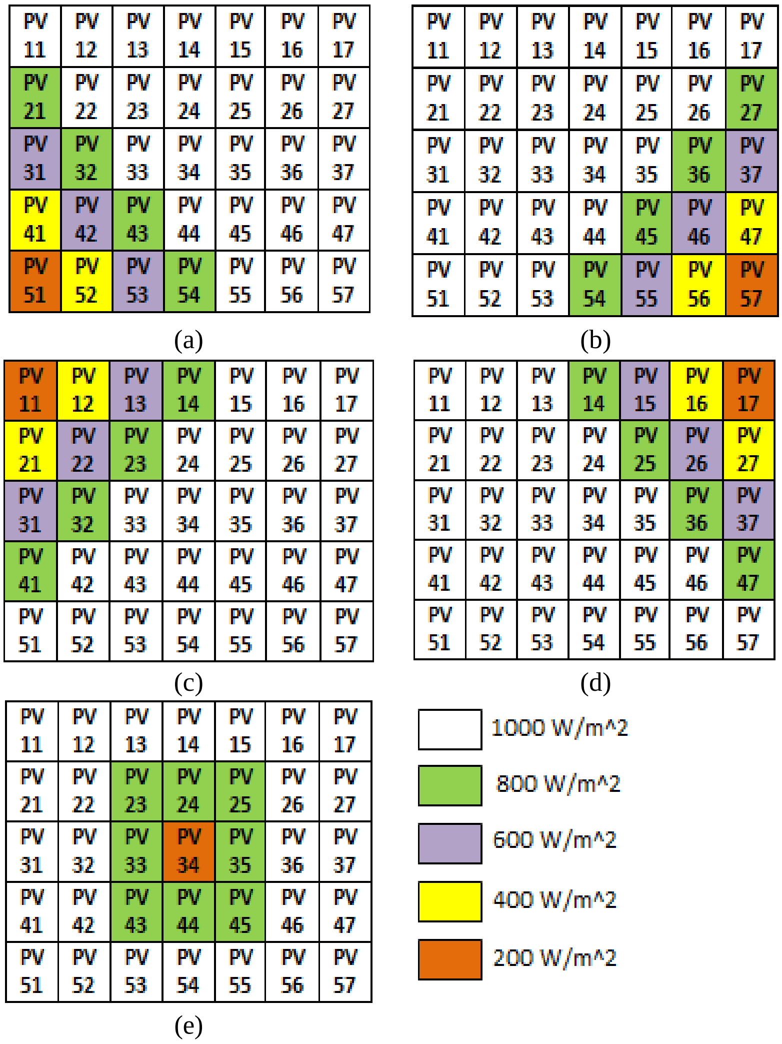

Figure 1. 5X7 PV array size under (a) left-down diagonal, (b) right-down diagonal, (c) left-top diagonal, (d) right-top diagonal, and (e) centre partial shading

Table 2. Performance comparison of the proposed FSO-based reconfiguration method with GOA, GWO, and PSO

Shading Patterns	Configurations	Generated output power (W)	Mismatch loss (ML) in watts	Fill factor (FF)	Efficiency (η)	Runtime (sec)	Convergence iterations
Left-down diagonal	GOA	4958.48	4841.52	0.50	5.82%	4.8	79
	GWO	5018.36	4781.64	0.51	5.89%	4.2	68
	PSO	4898.24	4901.76	0.49	5.75%	3.7	62
	FSO	5142.92	4657.08	0.52	6.03%	2.9	48
Right-down diagonal	GOA	4834.86	4965.14	0.49	5.67%	4.7	81
	GWO	4883.19	4916.81	0.50	5.73%	4.1	70
	PSO	4804.68	4995.32	0.49	5.64%	3.6	65
	FSO	5016.54	4783.46	0.51	5.88%	2.8	52
Left-top diagonal	GOA	5089.65	4710.35	0.52	5.97%	5.0	77
	GWO	5098.97	4701.03	0.52	5.98%	4.3	66
	PSO	4934.15	4865.85	0.50	5.79%	3.9	60
	FSO	5292.32	4507.68	0.54	6.21%	3.0	47
Right-top diagonal	GOA	4768.67	5031.33	0.48	5.59%	4.6	80
	GWO	4892.98	4907.02	0.50	5.74%	4.0	71
	PSO	4814.76	4985.24	0.49	5.65%	3.5	63
	FSO	5248.56	4551.44	0.54	6.16%	2.7	49
Center	GOA	5207.68	4592.32	0.53	6.11%	5.1	83
	GWO	5158.56	4641.11	0.52	6.05%	4.4	73
	PSO	5058.48	4741.52	0.51	5.93%	3.8	66
	FSO	5395.26	4404.74	0.55	6.33%	3.1	45

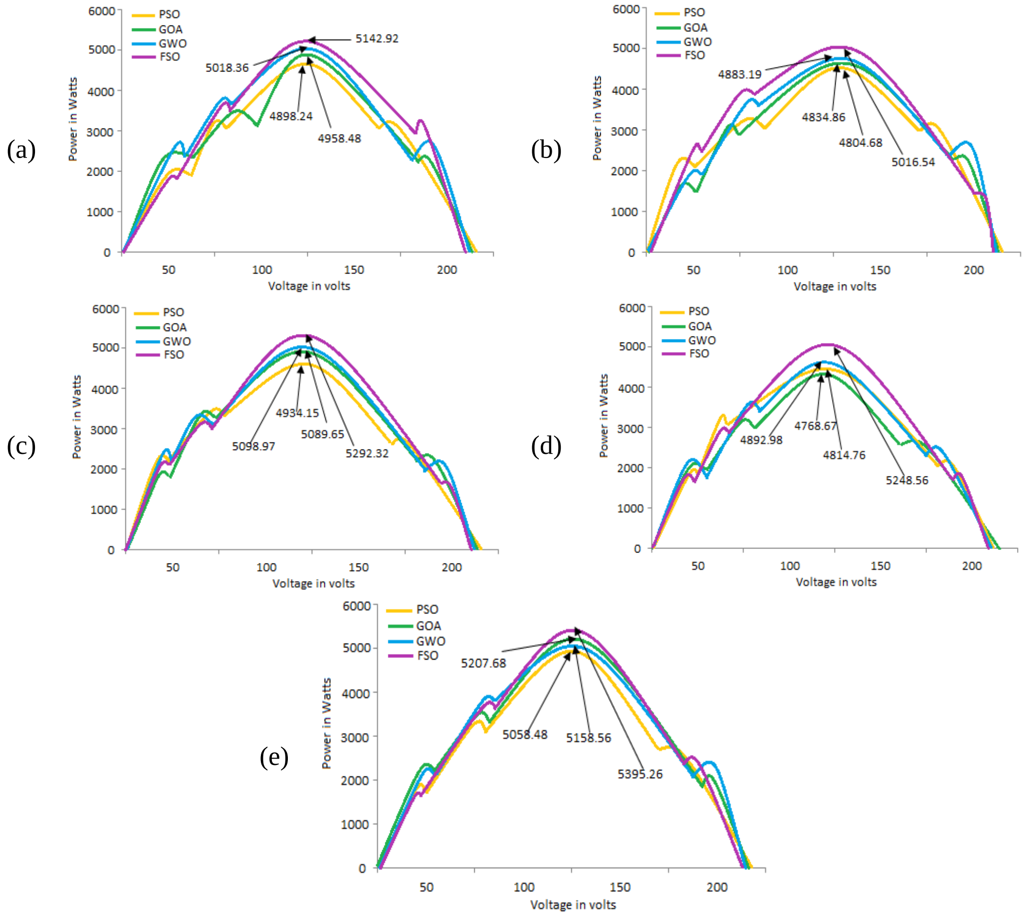

Figure 2 P-V curves of proposed 5x7 PV array under PSC: (a) left-down diagonal, (b) right-down diagonal, (c) left-top diagonal, (d) right-top diagonal, and (e) center

5. CONCLUSION

This study presents a novel dynamic reconfiguration approach for PV arrays using a weighted objective function that simultaneously maximizes power output and minimizes switching actions. Optimized through an enhanced FSO algorithm, the proposed method demonstrates superior performance across five common partial shading scenarios left-down, right-down, left-top, right-top, and center shading. Compared to conventional optimization techniques such as PSO, GOA, and GWO, the proposed approach achieves up to 6% higher power output, with a significant reduction in mismatch losses and lower switching frequency, contributing to improved system efficiency and extended hardware lifespan. The integration of multiple objectives into a single, weighted function streamlines the optimization process, reduces computational complexity, and enhances adaptability under varying environmental conditions. To strengthen the credibility and practical impact of the method, future work will focus on hardware implementation or hardware-in-the-loop (HIL) simulation, which will validate its real-time effectiveness. Additionally, comparative analysis with true multi-objective optimizers such as NSGA-II or MOEA/D is proposed to assess how well the method balances power generation and switching minimization compared to established multi-objective approaches. Overall, this work offers a practical and efficient reconfiguration strategy for improving the performance, reliability, and sustainability of PV systems operating under partial shading conditions.

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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis

I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting

Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

Data availability is not applicable to this paper as no new data were created or analyzed in this study.

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