A Novel Hybrid Approach for Global Maximum Power Point Tracking in Standalone PV Systems

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ABSTRACT

The efficiency of Photo-Voltaic (PV) systems is highly dependent on their ability to accurately track the Global Maximum Power Point (GMPP) under varying environmental conditions. Traditional Maximum Power Point Tracking (MPPT) methods often struggle with issues such as slow tracking speed, susceptibility to local maxima, and the need for complex parameter tuning, particularly in dynamically changing environments with Partial Shading Conditions (PSCs) and rapid irradiation changes. To address these challenges, this study introduces a hybrid approach that combines a modified Rao algorithm with the Perturb and Observe (P&O) method. The modified Rao algorithm was employed in the initial tracking stages to quickly locate the global vicinity, benefiting from its simplicity and the absence of algorithm-specific parameters, whereas the P&O method ensured precise tracking in the final stages. The performance of the proposed method was assessed on a PV array subjected to PSCs and compared with several well-known MPPT algorithms, such as Gray Wolf Optimization (GWO), JayaDE, and the Slime Mould Algorithm (SMO). The proposed approach was implemented and analyzed using the MATLAB/Simulink software.

Keywords-solar PV system; partial shading; maximum power point tracking; modified Rao algorithm; global maximum power point

I. INTRODUCTION

In the contemporary global energy landscape, a transformative shift is underway, driven by the urgent need to combat climate change, decrease greenhouse gas emissions, and move towards sustainable energy sources. Historically, conventional energy sources, particularly fossil fuels such as oil, coal, and natural gas, have served as the cornerstone of global energy production. Nevertheless, their widespread utilization has led to significant environmental degradation, air pollution, and geopolitical tensions related to resource extraction and distribution. In response to these challenges, there is increasing momentum towards adopting renewable energy sources as viable alternatives to conventional fuels. Among these alternatives, solar Photo-Voltaic (PV) technology has emerged as a particularly promising solution due to its abundance, scalability, and environmental benefits. Solar PV systems directly harness sunlight to generate electricity via the photovoltaic effect, offering a clean, renewable, and virtually inexhaustible energy source. The efficiency and performance of PV systems are heavily influenced by various environmental factors including changes in irradiation, temperature, and partial shading. Partial shading occurs when some areas of a PV array receive less sunlight because of obstructions such as nearby objects, clouds, or foliage. This leads to uneven irradiance across PV modules, causing mismatches in the voltage and current outputs. Traditional Maximum Power Point Tracking (MPPT) methods, including Perturb and Observe (P&O), Incremental Conductance (IC) [1], and hill climbing, are widely employed to optimize the operating point of PV systems under fluctuating temperature and irradiation conditions. However, these techniques often struggle to accurately track the Maximum Power Point (MPP) when partial shading occurs. Consequently, the overall energy yield and efficiency of PV systems can be significantly reduced [2]. This limitation has accelerated interest in advanced soft computing methods for this problem. These techniques include particle swarm optimization, genetic algorithms, fuzzy logic control, and artificial neural networks, and offer robust solutions for handling the nonlinear and dynamic nature of PV systems [3-9]. These methods are designed to handle uncertainties and approximate solutions, making them suitable for the complex optimization problems inherent in MPPT. Additionally, the hybrid MPPT techniques discussed in [10] and [11] combine the strengths of multiple algorithms to enhance the overall performance and robustness of MPPT in standalone solar PV systems. These techniques often integrate conventional algorithms with metaheuristic approaches or employ hybrid control strategies to improve the tracking efficiency and adaptability to changing environmental conditions. However, challenges, such as the complexity of the system design and parameter tuning, remain.

Although numerous MPPT methods have been explored in the existing literature, this study attempts to tackle the research problem by introducing a hybrid approach. This approach combines the modified Rao and P&O algorithms. Both algorithms have individually shown promise for MPPT due to their simplicity, effectiveness, and computational efficiency. The proposed hybrid approach aims to address the limitations reported in the literature by leveraging the inherent benefits of the Rao algorithm and the P&O methods for enhanced MPP tracking.

II. PV SYSTEM

This section will go over the modelling of PV modules, the role of DC-DC converters, and the significance of Maximum MPPT controllers in maximizing power output. The modeled system is depicted in Figure 1.

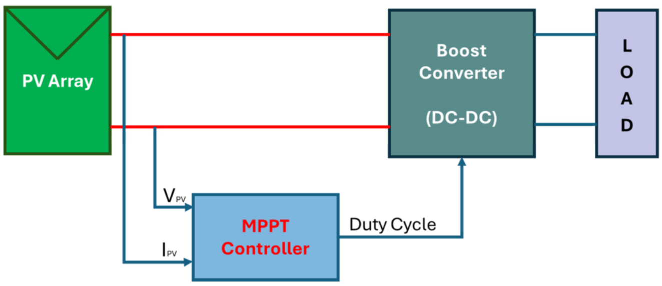

Fig. 1. General overview of the modeled PV system.

A. PV Module Modelling

Interconnected solar cells form PV modules, which serve as the basic building blocks of PV systems. These cells use the photovoltaic effect to transform sunlight into electrical energy. Modelling PV modules involves characterizing their electrical behavior in response to changes in environmental factors such as temperature and irradiation. To understand the properties of photovoltaic modules, the most popular model is the single-diode model, which details the I-V and P-V characteristics. This model considers parameters such as the open-circuit voltage (V_{oc}), short-circuit current (I_{sc}), diode ideality factor (n), and series and parallel resistances (R_s and R_p). By accurately modeling PV modules, we can predict their performance and optimize PV system design and operation.

The output current of the PV module is expressed as follows [12]:

$$I_L = I_{ph}N_p - I_{sd}N_p\left(e^{\left\{\frac{q\left\{V_L+\frac{I_L R_S N_S}{N_p}\right\}}{nN_S kT}\right\}} - 1\right) - \frac{V_L+\frac{I_L R_S N_S}{N_p}}{\frac{R_{sh}N_S}{N_p}} \quad (1)$$

where N_s is the number of series cells and N_p is the number of parallel cells.

B. DC-DC Converter

DC-DC converters serve an essential role in PV systems by efficiently converting the DC output voltage produced by PV modules to the required voltage level for the connected load or battery bank. However, a load or battery bank often requires a specific voltage level for an effective operation. This is where DC-DC converters are essential. They adjust the voltage either up or down or regulate it to meet the requirements of the load or battery bank, thereby ensuring efficient power transfer and utilization. These converters operate on different principles depending on their configuration (boost, buck, or buck-boost).

However, in terms of MPPT operation, the main goal is to adjust the output voltage of the converter to match the voltage at the MPP of the PV modules. This is accomplished through control algorithms that continually monitor the PV module voltage and maintain the duty cycle or switching frequency of the converter for optimal power transfer. In our modeled system, a boost converter is utilized.

C. MPPT Controller

MPPT controllers are integral components of PV systems and are tasked with enhancing the power output by continually adapting the operational parameters of the PV modules to align with the MPP. These controllers ensure that the PV systems operate at peak efficiency under changing environmental conditions, including variations in temperature and irradiance. To achieve this objective, a range of MPPT techniques such as P&O, IC., and various metaheuristic algorithms, can be employed. Modeling MPPT controllers involves assessing their tracking efficiency, response time, and stability to identify the most appropriate technique for a specific PV system. This paper proposes a hybrid MPPT method aimed at maximizing the energy capture and optimizing the PV system performance under diverse operating conditions.

III. PARTIAL SHADING CONDITIONS

Partial shading occurs when one or multiple photovoltaic modules within a complex PV array are obstructed by dust, trees, structural interference from surrounding buildings, or poles. These shaded modules are unable to generate power and instead function as loads, thereby generating heat. In the worst-case scenario, the current in the string may drop to zero, leading to a complete loss of power due to more shaded modules. In PV power systems, partial shading is an inevitable complication that drastically affects the overall system efficiency, leading to multiple peaks with several local peaks and one global peak in the I-V and P-V curves. In contrast, PV arrays operating under uniform illumination exhibit only one peak, as illustrated in Figures 2 and 3. Thus, identifying this peak presents a major challenge when designing an effective MPPT for a PV system. Conventional techniques like the P&O

might inadvertently converge on a local peak of the curve, potentially leading to energy wastage in the PV system. To address this issue, Artificial Intelligence (AI) has been integrated into MPPT systems [6]. AI-based MPPT methods include particle swarm optimization [4, 5], artificial bee colony optimization [13], and grey wolf optimization [14]. These approaches circumvent the limitations of traditional methods, which may converge at the local maximum points. Through global search strategies, such as those employed by AI-based techniques, the MPP of the PV system can be accurately traced, even under partial shading conditions. However, these methods still face challenges regarding performance metrics such as tracking time, accuracy, cost, and potential influence on the stability of the PV system. Recognizing the various issues encountered when directly applying AI-based MPPT to PV systems, researchers have sought to enhance tracking effectiveness by refining existing AI techniques.

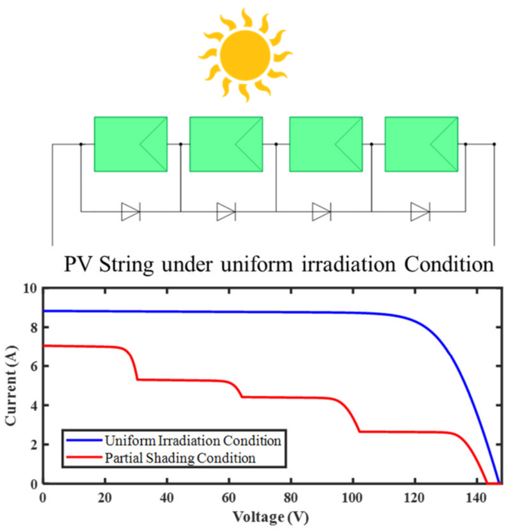

Fig. 2. I-V curves of PV under uniform irradiation (blue) and partial shading conditions (red).

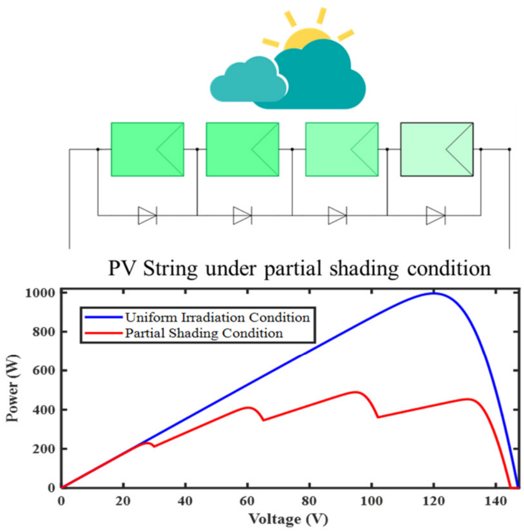

Fig. 3. P-V curves of PV under uniform irradiation (blue) and partial shading conditions (red).

IV. PROPOSED MPPT METHOD

A. Rao Optimization Algorithm

The Rao optimization algorithm is a novel search algorithm developed by Rao in 2019 [15] that does not rely on metaphors. This algorithm is based on random interactions between candidate solutions and the best and worst solutions identified throughout the optimization process. This method does not require any algorithm-specific control settings; it simply requires standard control parameters such as population size and number of iterations.

Let $f(x)$ be the objective function. At each iteration i, let there be m design variables, n candidate solutions (i.e., population size, k=1,2,…,n). The best candidate achieves the best value of $f(x)$ among all candidate solutions, whereas the worst candidate achieves the worst value of $f(x)$ among all candidate solutions. If $X_{j,k,i}$ represent the jth variable for the kth candidate through the ith iteration, this value is updated according to (2):

$$X'_{j,k,i} = X_{j,k,i} + r_{1,j,i}\left(X_{j,best,i} - X_{j,worst,i}\right) \tag{2}$$

$$X'_{j,k,i} = X_{j,k,i} + r_{1,j,i}\left(X_{j,best,i} - X_{j,worst,i}\right) + r_{2,j,i}\left(X_{j,best,i} - X_{j,k,i}\right) \tag{3}$$

where r_1 and r_2 are a random generation between $U[0,1]$

Equation (3) is the modified equation to update the candidate solution.

B. Modified Rao Algorithm based MPPT

To implement the modified Rao algorithm for MPPT, firstly the candidate solutions D_i (design variable considered as duty cycle D) are randomly distributed in the search space. These solutions are then iteratively updated by taking in to account the best and worst solutions. The mathematical equation for updating the candidate solutions is as follows:

$$D'_{i,k} = D_{i,k} + \text{rand1} * \left(D_{best,k} - D_{worst,k}\right) + \text{rand2} * \left(D_{best,k} - D_{i,k}\right) \tag{4}$$

$$P(D'_i) > P(D_i) \tag{5}$$

In this context, $P(D)$ represents the instantaneous power at the duty cycle D_i , $D_{i,k}$ is the ith candidate solution's previous value in the kth iteration, where, k is the number of iterations (k = 1, 2, …, n), $D'_{i,k}$ is the updated value of $D_{i,k}$, rand1 and rand2 are random numbers generated between [0, 1], $D_{best,k}$ is the best value of the candidate solution during kth iteration and $D_{worst,k}$ is the worst values of the candidate solutions during the kth iteration.

The process for implementing the proposed approach to track the global maximum point is illustrated in the flowchart in Figure 4.

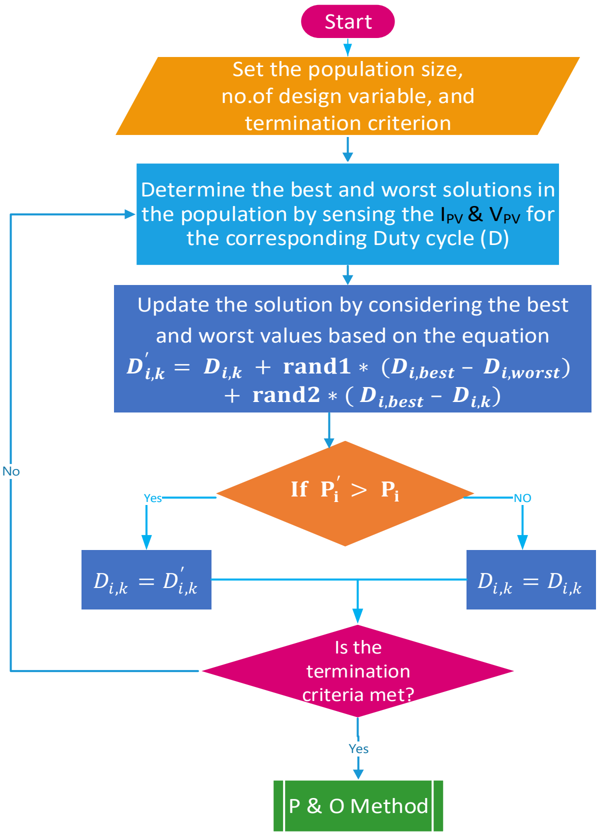

Fig. 4. Flowchart of the proposed method.

The following steps outline this process:

Step 1. Parameter initialization: Generate the initial vector of candidate solutions for eight duty cycles, each within the range [0.1, 0.8]. The particles are initialized at the rightmost, middle, and leftmost positions to ensure the coverage of all search space intervals during the global maximum point exploration phase.

Step 2. Fitness evaluation: Obtain the fitness value of the duty cycles by sensing the current and voltage, and then calculate the PV system's power for each duty cycle.

Step 3. Selection: Of all the solutions, the best and worst solutions are identified.

Step 4. Updating the candidate solutions: The position of the duty cycles in each iteration (kth) is adjusted according to (4).

Step 5. Comparison: If the updated candidate's fitness surpasses the prior fitness of that candidate, then choose the updated candidate for the next iteration; otherwise, retain the previous solution.

Step 6. Termination: If the criteria for termination are satisfied, save the best solution; otherwise, repeat steps 2 to 5.

Step 7. It was observed that when only the modified Rao algorithm was considered as the MPPT technique and run several times, the operating power settled near the Global MPP (GMPP) instead of exactly at the GMPP. In step 4, the algorithm for updating the solutions mostly relies on random numbers r_1 and r_2; this stochastic process leads to settling near the GMPP instead of exactly at the GMPP. Hence, the P&O method is applied once the best solution is obtained after the completion of the termination criteria (in this method, the maximum iterations are considered as termination criteria). The P&O method can quickly settle to near GMPP. The flowchart of the P&O algorithm is illustrated in Figure 5.

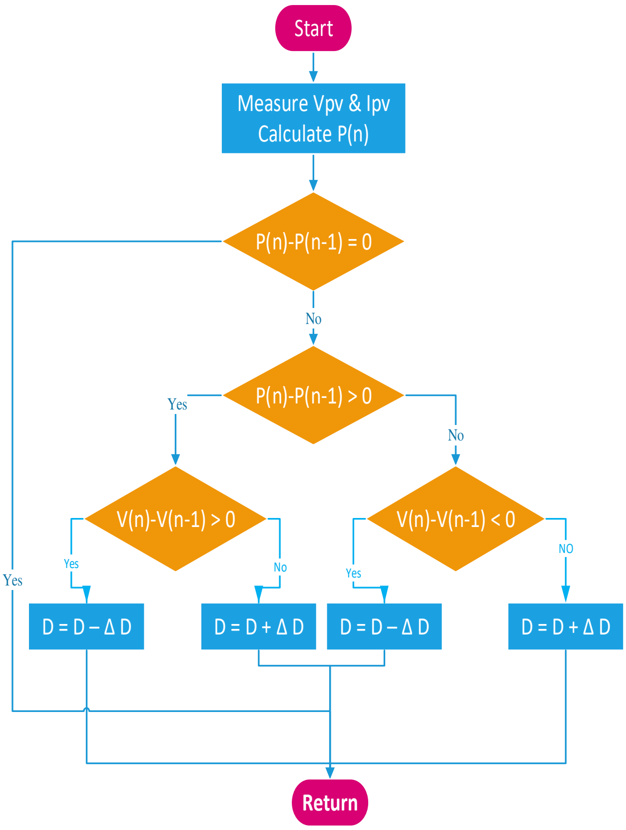

Fig. 5. Flowchart of the P&O algorithm.

V. RESULTS AND DISCUSSION

To validate the effectiveness of the proposed approach, numerical simulations were conducted for GMPP tracking under various shading patterns, considering both steady and dynamic weather conditions. Specifically, the performance of the proposed approach was compared to three standard algorithms: Grey Wolf Optimization (GWO) [14], JayaDE [16], and Slime Mould Optimization (SMO) [17]. This comparison was carried out across various scenarios to thoroughly assess the effectiveness of the proposed algorithm.

A. Simulation Setup

To validate the proposed approach, the system depicted in Figure 1 was modelled and simulated under various conditions. The simulation model comprised a photovoltaic system with four series-connected modules and a boost converter supplying a resistive load. The maximum power of the PV array under nominal conditions (25°C and 1000 W/m²) was 996 W. The specifications of the solar panels are listed in Table I. Simulations were performed using MATLAB to ensure a precise representation of the PV system behavior. The evaluation encompassed three key scenarios to thoroughly assess the performance of the algorithms.

TABLE I. PV MODULE SPECIFICATIONS

PV panel Nominal Power rating	249 W
Open circuit voltage	36.8 V
Voltage at Max Power	30 V
Short circuit current	8.83 A
Current at Max Power	8.3 A

B. Scenario 1: Rapidly Changing Irradiance

This scenario reflects the ideal operating conditions under which the PV system is exposed to uniform sunlight without any shading effects. In addition, step changes in irradiation were considered. This scenario served as a baseline for evaluating the algorithm performance under rapidly changing irradiation conditions.

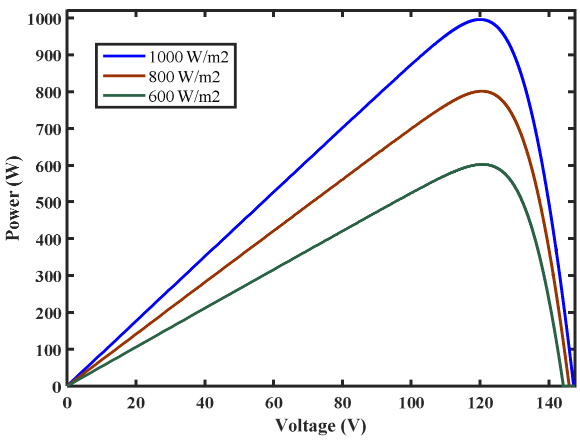

Fig. 6. P-V curves under different irradiation conditions.

The irradiance is uniform and changes abruptly from 1000 W/m^2 to 800 W/m^2, and then to 600 W/m^2 after 0.5 s and 1 s, respectively. The PV curves for this scenario are shown in Figure 6. The resulting tracking curves are shown in Figure 7.

During tracking, the proposed approach converges after 0.068 s and stabilizes at 0.12 s with an MPP of 995.8 W. The GWO converges after 0.19 s and stabilizes at 0.23 s with an MPP of 994.5 W. The JayaDE algorithm converges after 0.06 s and stabilizes at 0.09 s with an MPP of 957.1 W, while the SMO converges after 0.08 s and stabilizes at 0.101 s with an MPP of 982.18 W.

As shown in Figure 7, the proposed approach outperformed the other approaches in this scenario. Both the JayaDE and SMO methods failed to track the MPP effectively under rapid changes in irradiance. Compared to GWO, the proposed approach tracked the MPP more quickly and demonstrated better tracking efficiency than GWO, JayaDE, and SMO.

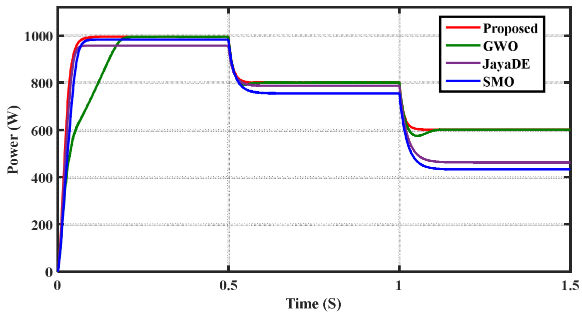

Fig. 7. Power tracking curves under rapidly changing irradiation.

C. Scenario 2: Partial Shading Conditions

This scenario examined four distinct partial-shading patterns to simulate real-world conditions. These patterns vary in complexity, representing different degrees and configurations of shading across solar panels. To clearly distinguish the effects of partial shading on the PV system, the temperature was maintained at 25 °C. The irradiance profiles for all four Shading Patterns (SP) are listed in Table II. Figure 8 shows the P-V curves for the considered patterns, where two or more peaks are visible: local MPPs and a single GMPP.

TABLE II. INPUT IRRADIATION PATTERNS

Shading Patterns	**Irradiance of PV Modules in W/m^2**			
	Module 1	**Module 2**	**Module 3**	**Module 4**
SP1	800	500	1000	1000
SP2	600	300	800	500
SP3	400	800	600	1000
SP4	600	600	900	900

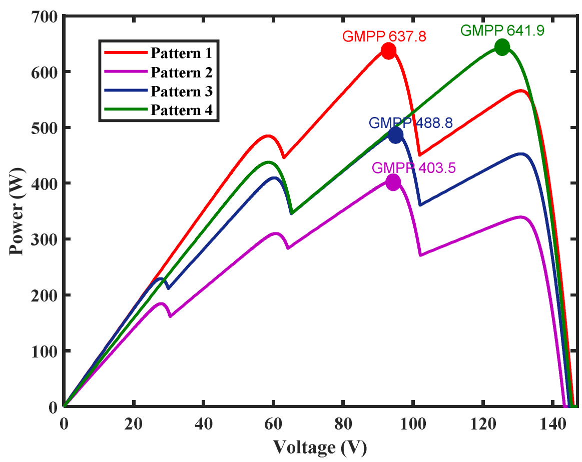

Fig. 8. P-V curves under different partial shading conditions.

Figures 9–12 show the simulation results for the PV system's MPPT control under these four shading patterns. According to Figure 8, the ideal GMPPs for SP1-4 are 637.8, 403.5, 488.8, and 641.9 W, respectively. The stability, precision, and tracking time of the four MPPT controllers are shown in Figures 9–12, respectively.

The proposed approach reached the GMPP in 0.11 s, 0.09 s, 0.12 s, and 0.1 s for SP1-4, respectively, while the other algorithms took approximately 0.14 s to 0.28 s. Moreover, the response curves of the proposed approach stabilized near the GMPP with minimal oscillations after a short adjustment period. Thus, the proposed approach demonstrated superior tracking accuracy and speed compared to other algorithms. Although the tracking time indicates the convergence speed of the MPPT, it is also important to highlight the tracking precision of the proposed controller. The tracking efficiency of the MPPT controller, η, is defined as follows:

$$\eta = \frac{P_{out}}{P_{GMPP}} \times 100\% \qquad (6)$$

where, P_{out} is the output power of PV system under MPPT control, P_{GMPP} is the theoretical power at GMPP of the PV system under specific shading conditions. Table III summarizes the results for scenario 2 and shows the higher efficiency of the proposed algorithm.

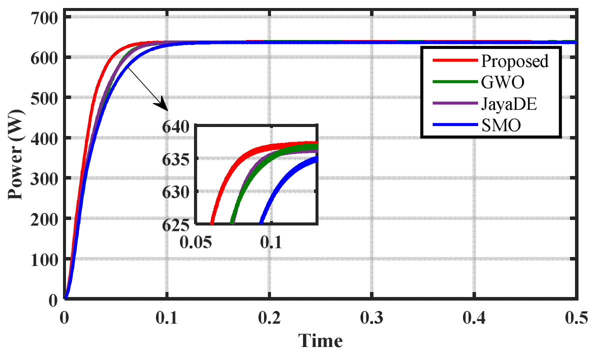

Fig. 9. Power tracking curves under the SP1 partial shading conditions.

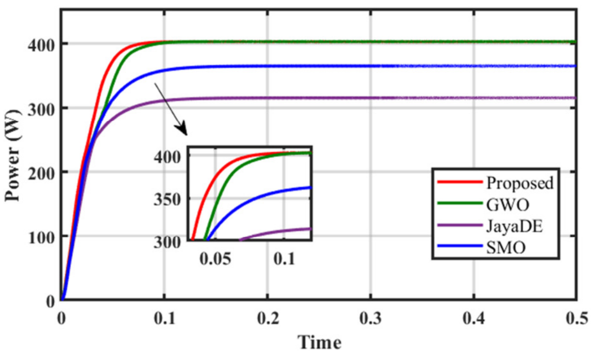

Fig. 10. Power tracking curves under the SP2 partial shading conditions.

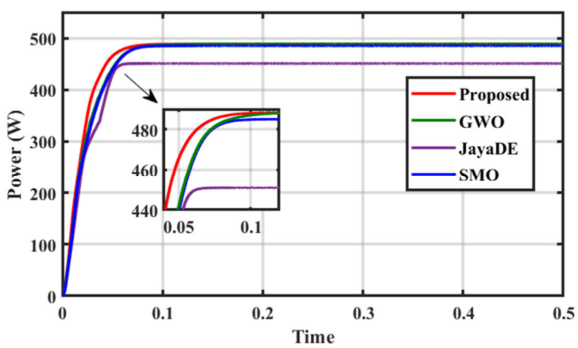

Fig. 11. Power tracking curves under the SP3 partial shading conditions.

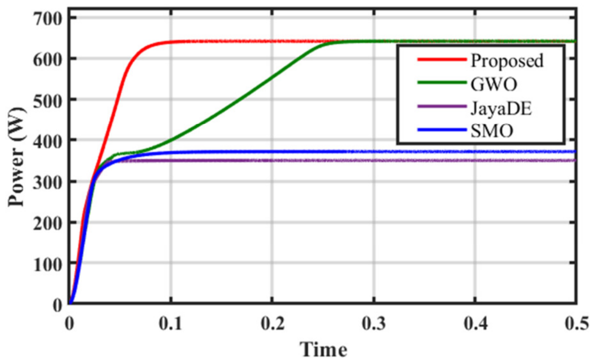

Fig. 12. Power tracking curves under the SP4partial shading conditions.

TABLE III. COMPARATIVE ANALYSIS OF MPPT METHODS

Partial SP	MPPT tracking method	Maximum power from P-V curve (W)	Tracking power (W)	Converge time (s)	Time to stabilize at GMPP (s)	Efficiency (%)
1	GWO	637.8	636.94	0.1	0.14	99.86
	JayaDE		636.24	0.1	0.15	99.75
	SMO		635.86	0.12	0.16	99.69
	Proposed		637.43	0.08	0.11	**99.94**
2	GWO	403.5	402.932	0.06	0.12	99.85
	JayaDE		315.462	0.032	14	78.17
	SMO		364.453	0.045	0.15	90.32
	Proposed		402.841	0.05	0.09	**99.83**
3	GWO	488.8	488.6	0.07	0.25	99.95
	JayaDE		450.8	0.06	0.065	92.22
	SMO		485.3	0.07	0.11	99.28
	Proposed		488.6	0.06	0.12	**99.95**
4	GWO	641.9	641.03	0.25	0.28	99.85
	JayaDE		350.06	0.02	0.12	54.53
	SMO		370.21	0.023	0.12	57.67
	Proposed		641.46	0.06	0.1	**99.92**

D. Scenario 3: Dynamic Partial Shading

In this scenario, the PV system was exposed to dynamically changing shading conditions to simulate the unpredictable nature of the shading produced by passing clouds or objects. The algorithms were tested for their responsiveness and ability to dynamically change the operating point to maximize power output.

During the simulation, SP1 was applied for the first 0.6 s, followed by SP3 for the next 0.6 s. As shown in Figure 13, under SP1, the proposed algorithm converged to a GMPP of 637.43 W, GWO tracked a GMPP of 636.94 W, JayaDE tracked a GMPP of 636.24 W, and SMO converged at 635.86 W. However, after 0.6 s the SP2 was applied and the proposed approach successfully located the GMPP of 488.6 W, while the other algorithms failed to locate the GMPP and got stuck at local maxima.

As the output power of the PV system is the most significant variable for illustrating the performance of the MPPT controller, only the power responses are presented here. Similarly, the simulation examined the system performance by dynamically changing SP2 to SP4. The corresponding performance variations of the PV system under these environments are presented in Figure 14. Additionally, the approach was tested by changing the shading pattern in two steps, from SP1 to SP2, and then to SP3, with the corresponding power responses shown in Figure 15.

Figures 13-15 confirm that the proposed approach outperforms the other algorithms, even under abruptly changing shading conditions. It consistently achieved the shortest tracking time and operated near the GMPP, whereas the other algorithms failed to do so when the shading pattern changed dynamically.

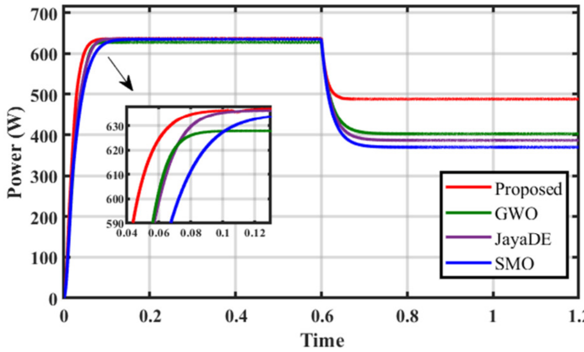

Fig. 13. Power tracking curves under abruptly changing from SP1 to SP3.

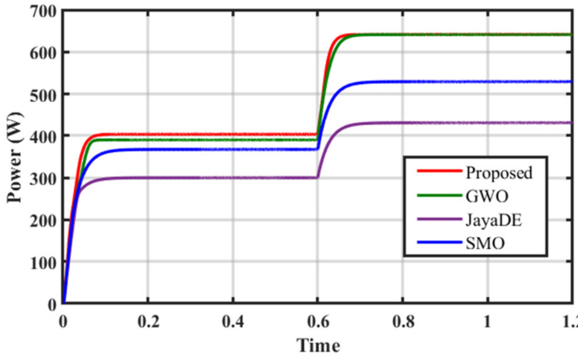

Fig. 14. Power tracking curves under abruptly changing from SP2 to SP4.

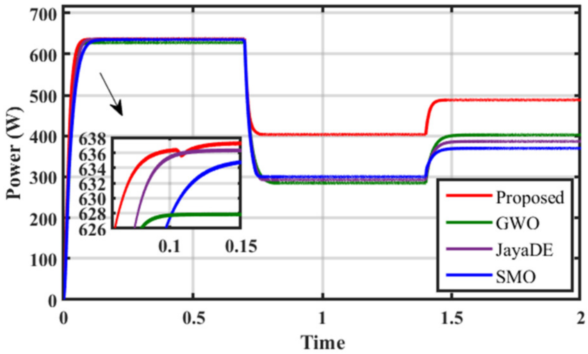

Fig. 15. Power tracking curves under abruptly changing from SP1 to SP2 and to SP3.

VI. CONCLUSIONS

This work presents a novel hybrid approach for Global Maximum Power Point (GMPP) tracking in Photo-Voltaic (PV) systems that combines the strengths of a modified Rao algorithm with the Perturb and Observe (P&O) method. The proposed approach effectively addresses the challenges posed by dynamic and complex weather conditions such as rapid irradiation changes and partial shading. By leveraging the Rao algorithm during the initial stages, the system rapidly identifies the vicinity of the global maximum, whereas the P&O method ensures precise tracking in the final stages. A significant advantage of the modified Rao algorithm is its simplicity, as it does not require any algorithm-specific parameters, unlike many other optimization techniques. This reduces the complexity associated with parameter tuning and makes the algorithm easier to implement across various scenarios. In contrast, algorithms such as Grey Wolf Optimization (GWO), JayaDE, and Slime Mould Optimization (SMO) often require careful parameter selection to achieve optimal performance, which can be a limitation in dynamically changing environments. This inherent simplicity and robustness make the modified Rao algorithm a particularly effective choice for GMPP tracking in PV systems. The comparative analysis with existing MPPT methods: GWO, JayaDE, and SMO demonstrates that the proposed hybrid method achieves superior tracking efficiency and reduced tracking time. This leads to greater energy extraction from the PV system, making it a promising solution for real-world applications where efficiency and reliability are paramount. Future work may explore further optimizations and the application of this hybrid approach to larger and more complex PV systems to validate its scalability and robustness.

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