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Maximum power point tracking technique based on the grey wolf optimization-perturb and observe hybrid algorithm for photovoltaic systems under partial shading conditions

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ABSTRACT

Photovoltaic panels represent the most abundant source of renewable energy and the cleanest form of electrical energy derived from the sun. However, partial shading can lead to the appearance of multiple local maximum power points (LMPP) in the power-voltage (P-V) characteristics of solar panels. This situation traps classical power maximization algorithms, such as perturb and observe (P&O) or incremental conductance, as these algorithms tend to deviate from the global maximum power point (GMPP), resulting in reduced electrical energy production. To overcome this major challenge in the electrical industry, we propose in this study a hybrid grey wolf optimization-perturb and observe hybrid (GWO-P&O) algorithm, designed to converge towards the global maximum power without being trapped in local peaks. To demonstrate its effectiveness, the proposed algorithm was simulated in MATLAB/Simulink under various complex and uniform partial shading conditions. Furthermore, a comparative study was conducted with the P&O and GWO algorithms to evaluate precision, tracking, response time, and efficiency. The simulation results revealed superior performance for the proposed technique, particularly in terms of constant tracking of the global peak, with efficiencies of 99.95% and 99.98% in the best cases, faster response times (ranging from 0.07 to 0.04 s), and minimal, almost negligible oscillations around the GMPP.

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1. INTRODUCTION

In developing countries, there is an increasing demand for new energy sources while simultaneously combating climate change primarily caused by fossil fuel energy sources. Renewable energies, continually replenished by nature, represent a major alternative to the increasingly significant consumption of electrical energy, with photovoltaic (PV) energy being one of the most significant sources on Earth. PV energy involves converting solar energy into electricity using solar panels composed of multiple photovoltaic cells arranged in series and/or parallel configurations. Due to their declining production costs, increased reliability, and enhanced durability, the share of photovoltaic panels in global energy production has significantly increased in recent years. This growth has been further fueled by government incentives and policies favoring renewable energies. Photovoltaic panels are employed for a variety of applications, ranging from powering individual homes and small businesses to large-scale power plant projects. According to a report published in 2020 by the International Renewable Energy Agency (IRENA), photovoltaic solar panels were the primary source of renewable energy for small-scale electricity production projects, such as off-grid power systems. In 2019, they had an installed capacity of over 150 GW [1]. Solar photovoltaic energy optimization is an active research field that utilizes optimization techniques to ensure that each solar panel operates at its maximum power level regardless of variations in environmental conditions. Therefore, maximum power point tracking (MPPT) is an essential technology for maximizing the efficiency of solar energy systems. It is important to note that environmental conditions such as ambient temperature and irradiation directly influence the electrical production performance of PV systems.

In photovoltaic systems, solar irradiation frequently varies due to weather conditions (such as clouds) or partial obstructions (such as cast shadows). These variations result in the appearance of multiple peaks in the power-voltage curve (PV curve), complicating the tracking of the MPPT. The challenge lies in the MPPT algorithm's ability to distinguish and reach the global maximum power point (GMPP) while avoiding local maximum power points (LMPP), which can lead to significant energy losses if selected by mistake. This issue becomes critical under partial shading conditions, where classical solutions, such as the perturb and observe (P&O), hill climbing (HC), and incremental conductance (INC) methods, although simple and widely used, may show limitations in identifying and tracking the global power [2]. The central problem is as follows: to design an MPPT algorithm that efficiently identifies the global maximum power point while minimizing energy losses, even under complex conditions such as partial shading. In this context, the P&O method is one of the most commonly used approaches for MPPT due to its simplicity and ease of implementation. However, it has some significant limitations, such as slow tracking speed during sudden weather changes and photovoltaic power fluctuations around the maximum power point (MPP), leading to considerable energy losses [3], [4]. Furthermore, the risk of losing the tracking point increases under partial shading conditions or abrupt variations in solar irradiance. To overcome these limitations, researchers in [4]–[6] have proposed using a variable step size instead of a fixed step size to improve the performance of the classical P&O method [7], [8]. However, most of these studies have focused on variations in temperature and irradiance while neglecting the specific challenges associated with partial shading conditions.

Still aiming to solve the problem of global power tracking and minimize power losses under partial shading conditions, numerous metaheuristic techniques have been proposed, collectively known as metaheuristic techniques. These algorithms, based on swarm intelligence, are utilized in modern MPPT controllers [9]. They often draw inspiration from animal behavior, physical phenomena, and evolutionary concepts [10], providing strategies or rules to explore and exploit the search space effectively. This enables them to solve tracking problems across different solar irradiation conditions with high efficiency. Notably, the BAT search algorithm is an optimization technique inspired by the echolocation behavior of natural bats to detect specific prey, as recommended by Oshaba in [11]. Another recent study published in [12] introduces an algorithm that emulates the social behavior of horse herds throughout their lives. Additionally, under partial shading conditions, some methodologies draw inspiration from whale behavior, as mentioned in [13], while others, such as artificial bee colony algorithms for maximum power point tracking [14], have been developed to optimize power extraction in photovoltaic systems. Other notable algorithms include the cuckoo search method, proposed by Hussaian in [15], ant colony optimization [16], the powerful bio-inspired firefly algorithm, published by Titri in [17], the salp swarm algorithm [18], moth-flame optimization [19], grasshopper optimization, as presented in research published in [20]–[22], and particle swarm optimization, proposed in [23], [24]. However, most of these metaheuristic techniques face common challenges in terms of precision, global power tracking, and long response times under partial shading conditions. This is why their practical adoption remains limited. Furthermore, the current research trend has shifted toward hybrid algorithms.

Grey wolf optimization (GWO) is an approach developed by Mirjalili [25], inspired by the organization of wolves and their hunting techniques, particularly in terms of tracking and encircling prey. It is noteworthy that this technique has benefited from hybridization with other algorithms to improve its performance, especially concerning the reduction of oscillations and tracking time. Integration with the fuzzy logic controller (FLC) has significantly reduced output power oscillations [25], However, this necessitates the inclusion of certain approximations achieved through trial and error [26]. Another study published by Laxman in [27] proposes an optimized GWO with fuzzy logic for smooth and efficient tracking. Some researchers have opted for combinations with other metaheuristic techniques, such as particle swarm optimization (PSO), as seen in the works presented in [28], [29], whereas Yadav in [30] recommended hybridization with genetic algorithms. Additionally, the work published by Salim in [31] is notable for proposing power maximization through hybridization of cuckoo search and grey wolf optimizer in partial shading conditions. Furthermore, in terms of time efficiency and stabilization, another hybridization technique known as grey wolf optimizer with differential evolution (GWODE) has been proposed [32], [33]. In addition to the complexity associated with the implementation of these hybrid algorithms, their execution requires considerable computation time [26]. This is why we encourage researchers to explore other types of hybridization, as presented in this study, where we selected the hybridization between a metaheuristic algorithm, GWO, and a classical algorithm widely used in photovoltaic (PV) systems, P&O. The proposed method is both efficient and easy to implement.

The novelty and objective of this study lie in the simulation of a photovoltaic system subjected to various complex partial shading conditions, characterized by multiple local maximum power points. The GWO-P&O hybridization achieves excellent results in tracking global power, avoiding entrapment in local maxima, while offering reduced response time and remarkable efficiency under various atmospheric conditions. A comparative study was conducted in terms of convergence, tracking, oscillation, and response time toward the GMPP, to evaluate the effectiveness of the proposed method compared to the GWO and P&O algorithms under partial or uniform shading conditions. This work explored all possible combinations, transitioning from one irradiation condition to another four times in a single simulation.

The study is organized into several sections as follows: the second section presents the photovoltaic system and explains the partial shading phenomenon. The third section describes the proposed hybrid GWO-P&O method in detail. The fourth section covers the simulation of the photovoltaic system using MATLAB/Simulink and discusses the results, while the fifth section provides the conclusion of the study's findings.

2. PHOTOVOLTAIC SYSTEM

2.1. Mathematical model of a photovoltaic cell

Photovoltaic generators are regarded as voltage-controlled current generators [34]. Several equivalent circuits are utilized for modeling a photovoltaic cell, with the most common being single and double-diode models [35]. The circuit depicted in Figure 1 is employed throughout the remainder of the study for modeling purposes.

$$\mathrm{I} = \mathrm{I_{ph}} - \mathrm{I_d} - \mathrm{I_{sh}} \quad (1)$$

I_{ph} represents the photovoltaic current generated by the illumination, and I_d represents the diode current, which is given by (2):

$$I_d = I_0 \left[exp\left(\frac{q.(V+IR_s)}{a.N_s.K.T}\right) - 1\right] \quad (2)$$

Using Kirchhoff's voltage law (KVL), we have:

$$R_{sh}I_{sh} - R_sI - V = 0 \quad (3)$$

$$I_{sh} = \frac{R_sI+V}{R_{sh}} \quad (4)$$

Finally, the expression for the current generated by the photovoltaic cell is written as (5):

$$I = I_{ph} - I_0 \left[exp\left(\frac{q.(V+IR_s)}{a.N_s.K.T}\right) - 1\right] - \frac{R_sI+V}{R_{sh}} \quad (5)$$

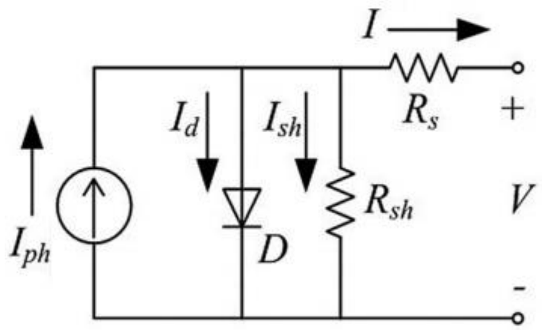

Figure 1. Equivalent representative circuit of a photovoltaic cell

A single photovoltaic cell typically produces a very low power, approximately 2 W, for a voltage of 0.5 V [36]. Due to this reason, cells are arranged in series and parallel configurations to generate sufficient current and voltage for a given operation. Here, N_p represents the number of cells in parallel and N_s denotes the number of cells in series, assuming all cells are identical under the same irradiation and temperature conditions. Equation (5) can then be written as (6):

$$I = N_p\ I_{ph} - N_p\ I_0\ \left[exp\left(\frac{q.\left(\frac{V}{N_s}+\frac{IR_s}{N_p}\right)}{a.N_s.K.T}\right) - 1\right] - \frac{R_sI+\frac{VN_p}{N_s}}{R_{sh}} \tag{6}$$

2.2. Partial shading

The issue of partial shading is a nearly constant problem that must be taken into consideration due to its significant influence on the efficiency of solar panel installations. It occurs when a portion of a solar panel is shaded by phenomena such as clouds, trees, or even dust. This shading has a direct impact on the power curve, causing local power peaks that are less significant than the maximum power point. This often traps conventional maximization techniques like P&O or incremental methods, which converge towards these less significant power points instead of the global maximum power point.

Modeling of partial shading is conducted using MATLAB software with the Simulink diagram shown in Figure 2. Four identical photovoltaic panels are placed in series, with their characteristics determined by Table 1. Each panel is subjected to solar irradiation separately, including uniform irradiation where each panel receives identical irradiation of 1000 W/m². The various power-voltage curves obtained are represented in Figure 3. These LMPP on the power-voltage (P-V) curve make it more difficult to identify the GMPP. The primary function of MPPT algorithms is to monitor the maximum power output of photovoltaic panels and ensure they can deliver a high-power level, even under partial shading conditions.

Conventional algorithms are less effective under partial shading conditions, leading to significant energy losses. However, under uniform operating conditions, the P&O algorithm demonstrates good efficiency in power extraction, as shown by previous research [37]. In contrast GWO used as a metaheuristic technique, can track the global maximum power point under partial shading conditions, where P&O fails, though it presents noticeable oscillations around the optimal power point [38]. To address these challenges, this study proposes hybridizing the GWO with the P&O algorithm to enable rapid and accurate convergence to the GMPP, regardless of environmental conditions, whether under partial or uniform shading. We simulated four types of solar irradiation conditions (SIC), each associated with a specific GMPP. The details of these conditions are summarized in Table 2.

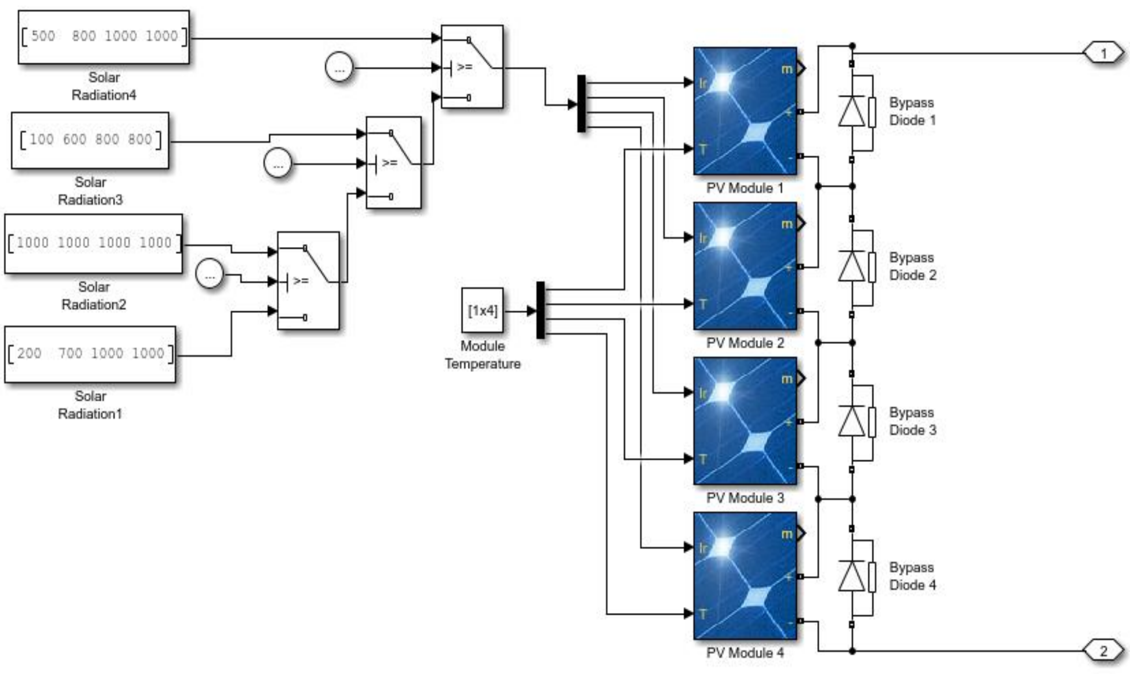

Figure 2. The partial shading under MATLAB/Simulink

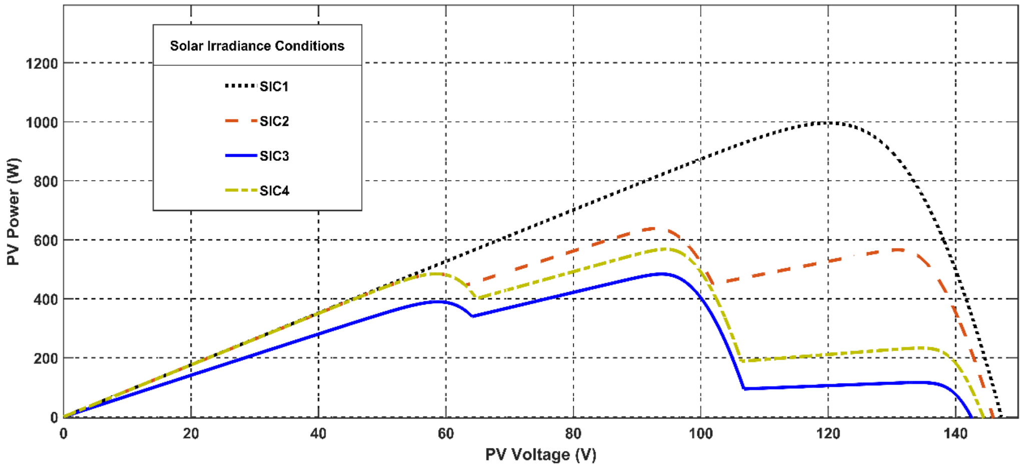

Figure 3. PV Power curve under different irradiation conditions

Table 1. Specific parameters of the photovoltaic module

Parameters	Values
Module type	Data power TP 250 MBZ
Maximum power	249 W
Open circuit voltage	36.8 V
Short circuit current	8.83 A
Voltage at MPP	30 V
Current at MPP	8.3 A
Temperature coefficient of current	0.063805
Cells per module	60

Table 2. Different shading patterns

Solar irradiance conditions	Partial shading conditions	GMPP (W)
SIC1	[1000 1000 1000 1000]	996
SIC2	[500 800 1000 1000]	637.8
SIC3	[100 600 800 800]	483.8
SIC4	[200 700 1000 1000]	567.9

3. PROPOSED GWO-P&O ALGORITHM
3.1. Designing the GWO algorithm

The gray wolf optimizer (GWO) is an optimization algorithm inspired by the social behavior of gray wolves. It relies on social hierarchy and wolf-hunting interactions to solve complex optimization problems. GWO is a meta-heuristic swarm intelligence optimization technique, where intelligence emerges from the collective actions of simple agents [25]. The algorithm mimics prey-seeking, grouping, and hierarchy-updating behaviors observed in wolves. There are four levels of leadership in this organization. Leaders are defined as alpha (α), while sub-leaders are categorized as beta (β), delta (Δ), and omega (ω), depending on their positions within the hierarchy [39]. The hunting process involves pursuing the target, followed by progressively approaching it until it is surrounded. Then, the target is attacked and immobilized, as illustrated in Figure 4.

All wolves iteratively update their positions relative to those higher in the pecking order, resulting in the best solution [40], [41], classified as Alpha, Beta, and Delta wolves, respectively. GWO is renowned for its ability to find effective solutions to difficult problems. The greater the number of iterations, the more optimal the solution becomes. However, this increases the algorithm's execution time. For this reason, the number of iterations in GWO must be carefully determined based on the type and difficulty of the problem to be solved [40].

The behavior of wolves while hunting by circling their prey can be modeled by (7) and (8):

$$E = \left|C.d_p(t) - d(t)\right| \tag{7}$$

$$d(t+1) = d_p(t) - A.E \tag{8}$$

In the equations provided, t represents the current iteration. The vectors $d(t)$ and $d_p(t)$ respectively indicate the position of the gray wolf and the position of the prey. Vectors A and C are two sets of coefficients, and their values are determined by (9)-(11):

$$A = 2.a.r_1 - a(t) \tag{9}$$

$$C = 2.r_2 \tag{10}$$

$$a(t) = 2 - (2.t)/Iter_{max} \tag{11}$$

The random numbers r_1 and r_2 are selected from the interval between zero and one, and they are utilized to update the positions of wolves within the search area. The parameter a decreases linearly from 2 to 0 during iterations, while $Iter_{max}$ represents the maximum number of iterations used in the search algorithm [25], [42].

In this scenario, the prey is surrounded by gray wolves. The members of the pack first follow the instructions of the leader (alpha wolf), then those of the beta wolves, and finally those of the delta wolves. Each wolf adjusts its position to get as close as possible to the prey [30], [43]. The decision steps of the GWO algorithm are presented in Figure 5. This behavior is described by (12)-(14):

$$\begin{cases} E_\alpha = |C_1.d_\alpha(t) - d(t)| \\ E_\beta = |C_2.d_\beta(t) - d(t)| \\ E_\gamma = |C_3.d_\Delta(t) - d(t)| \end{cases} \tag{12}$$

$$\begin{cases} d_1 = d_\alpha(t) - A_1.E_\alpha(t) \\ d_2 = d_\beta(t) - A_2.E_\beta(t) \\ d_3 = d_\Delta(t) - A_3.E_\gamma(t) \end{cases} \tag{13}$$

$$d(t+1) = \frac{d_1+d_2+d_3}{3} \tag{14}$$

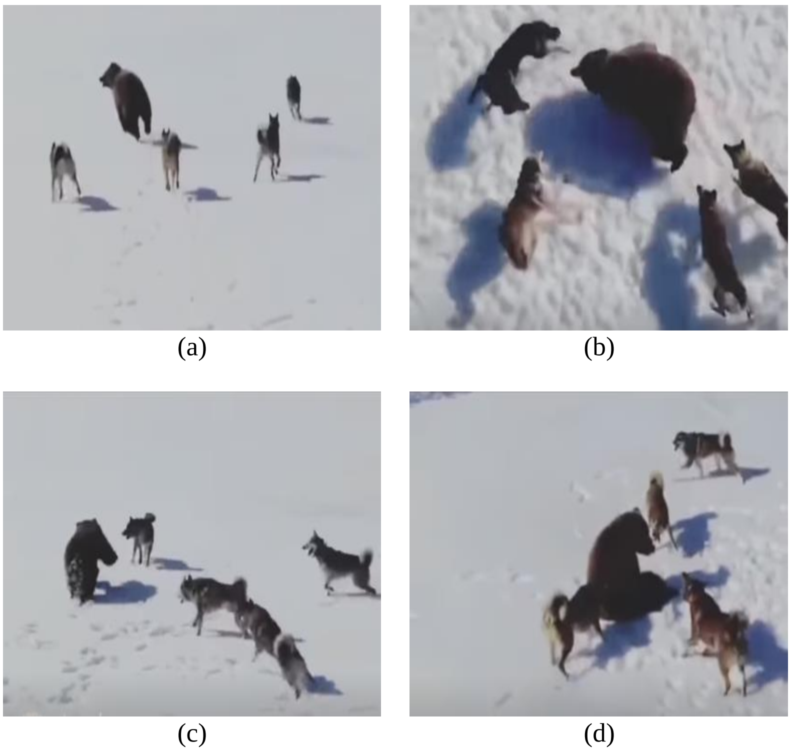

Figure 4. The hunting behavior of gray wolves: (a) target pursuit, (b) approaching the target, (c) encirclement, and (d) the target is attacked, it no longer moves

The algorithm is written in the form of an equation which will have the value of entering the photovoltaic voltage V_{pv} and the photovoltaic current I_{pv}

The first step is the initialization of the magnifier values in the form of a zero matrix, as well as the initialization of different values of the duty cycle $D_c(j)$ with values between 0.1 and 1, where (j) represents the total number of wolves.

Calculation of the objective function that will be named $Fitness = V_{pv} * I_{pv}$ and attribution of the position of the wolves in relation to the fitness value as follows:

$$
\begin{aligned}
&If\ fitnesse < alpha\\
&alpha = fitnesse\ \&\ alpha\_stance = D_{c\alpha}(i)\\
&If\ fitnesse\ < alpha\ \&\ fitness\ > Beta\\
&Beta\ = fitnesse\ \&\ Beta\_stance = D_{c\beta}(i)\\
&If\ fitnesse < alpha\ \&\ fitness < Beta\ \&\ fitnesse > Delta\\
&Delta = fitnesse\ \&\ Delta\_stance = D_{c\Delta}(i)
\end{aligned}
$$

In this section, we calculate the values d_1, d_2, d_3 according to (13) and determine the value of $d(t+1)$ according to (14) for all duty cycle values. This update is done at each iteration to obtain the best value of duty cycle $D_{c\alpha}(i)$ that yields the optimal power value.

At this stage, the P&O algorithm is initiated according to the flowchart (P&O part) to refine and determine the new duty cycle value as follows:

$$
\begin{aligned}
D_{New} &= D_{GWO} + \Delta d\\
D_{New} &= D_{GWO} - \Delta d
\end{aligned}
$$

Figure 5. Decision steps of the GWO algorithm

3.2. P&O algorithm

This method is based on calculating the photovoltaic power $P_{pv}(i)$ by measuring the current $I_{pv}(i)$ and the voltage $V_{pv}(i)$, and comparing it with the previous power value $P_{pv}(i-1)$. The maximum power point is achieved when ΔP. When the difference between the two power values is not zero, the algorithm will attempt to find the optimal point to the left or right of the recent power value [44]. Therefore, the perturbation of the duty cycle ratio ΔD depends on the sign of the last perturbation and the sign of the last power increment [6], which are used to decide the direction of the next perturbation [45] according to the decision flowchart (P&O part). The perturbation must be maintained in the same direction if the power increases, and if the power decreases, the next perturbation should be in the opposite direction.

3.3. MPPT with GWO-P&O combination

The approach is straightforward: first, the GWO method is used to determine the optimal duty cycle $D_{c\alpha}$ to achieve maximum power. This result is then used as a starting point and further refined by the P&O method for greater precision. By combining both methods, local maximum power points are avoided while benefiting from the efficiency and simplicity of the P&O algorithm. Figure 6 illustrates the GMPP that the hybrid algorithm aims to achieve without being trapped in LMPP. It also highlights the challenges encountered under partial shading conditions. The combination process is illustrated in the flowchart of the

GWO-P&O hybridization presented in Figure 7 and explained in detail in the flowchart of the GWO-P&O algorithm in Figure 8.

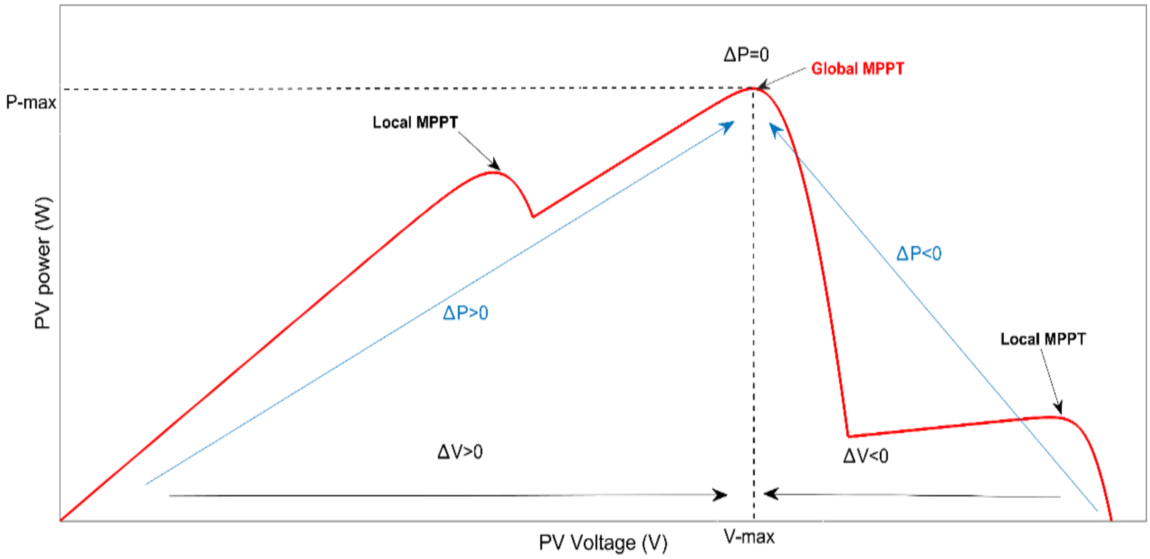

Figure 6. P-V graph of the proposed MPPT technique

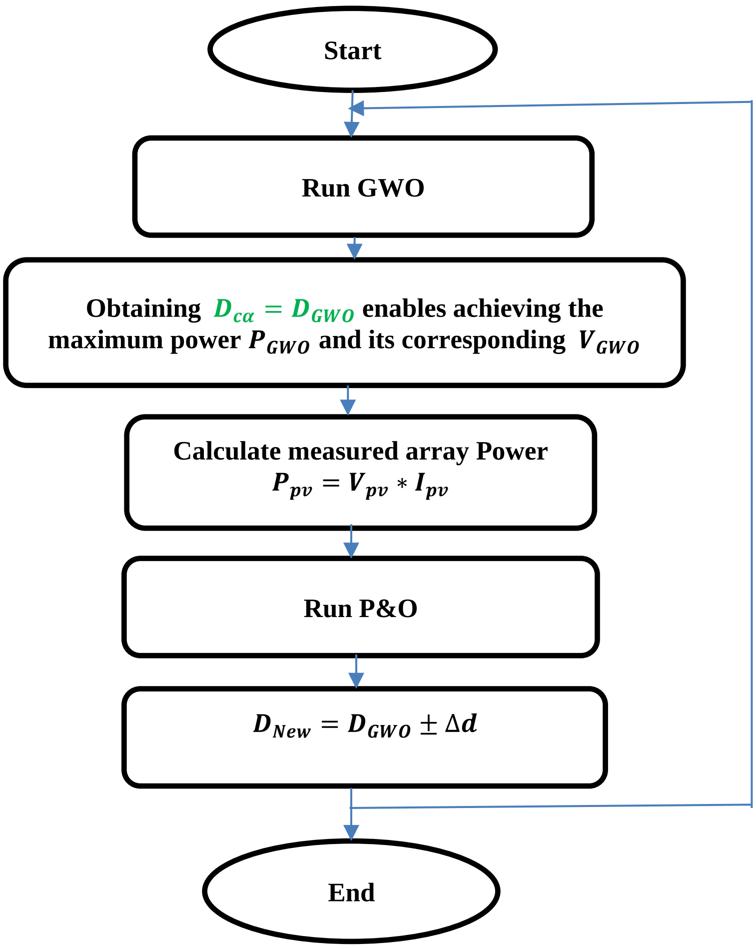

Figure 7. Flowchart of the GWO-P&O hybridization

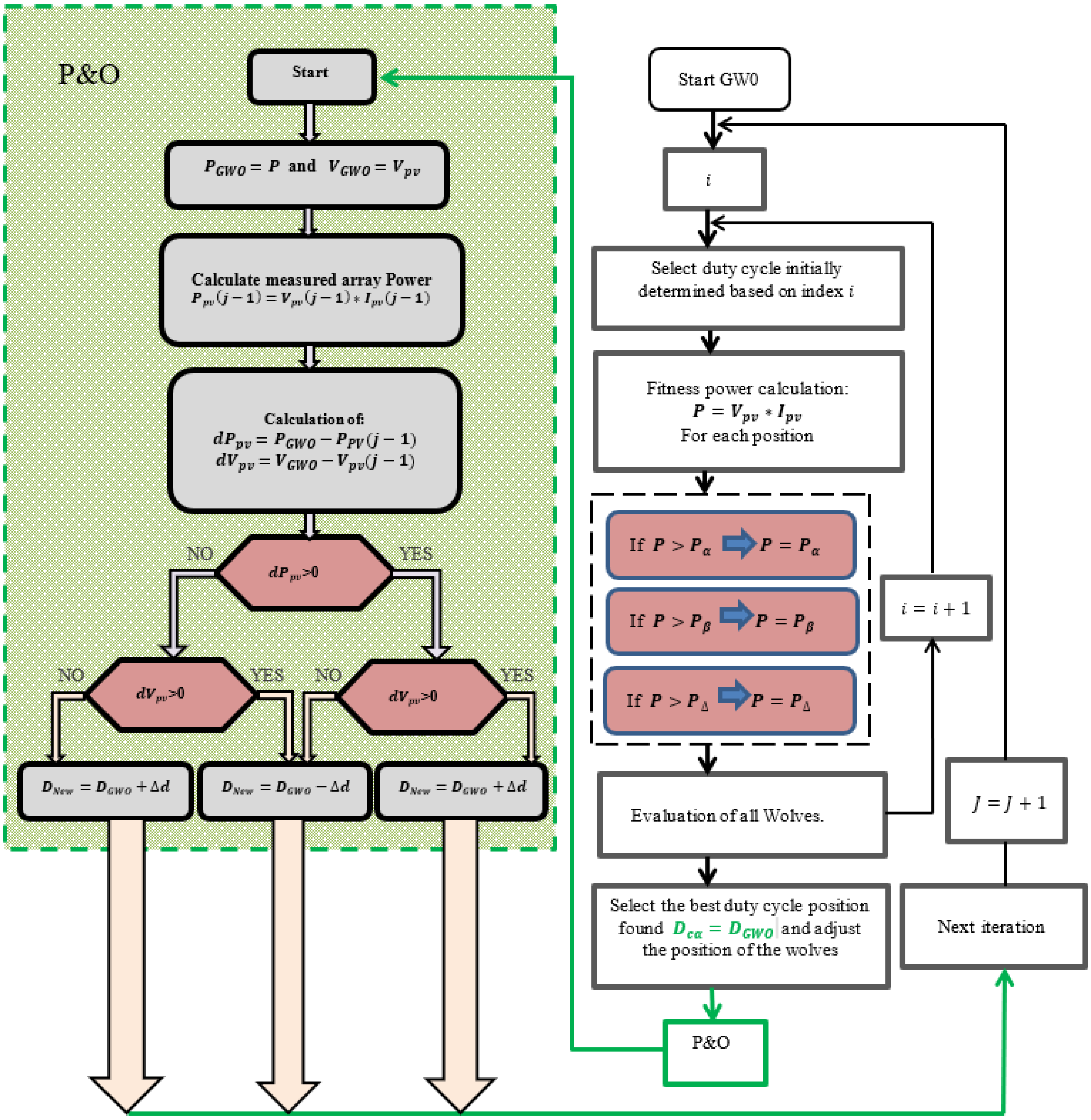

Figure 8. Flowchart of the GWO-P&O algorithm

4. RESULTS AND DISCUSSION

The simulation model of the proposed hybrid power maximization method is illustrated in Figure 9. Four identical photovoltaic (PV) panels are connected in series to form a single array, with their specific characteristics detailed in Table 1. The simulation was conducted under various conditions, including uniform irradiation and partial shading, all summarized in Table 2. Initially, the photovoltaic (PV) panels were subjected to partial shading represented by SIC4. Subsequently, at t = 0.4 s, solar irradiation became uniform across the four groups of panels, with an intensity of 1000 W/m² for each group. At t = 0.8 s, a disturbance introduced partial shading represented by SIC3. Finally, at t = 1.2 s, the system transitioned to irradiation represented by SIC2.

Thus, the solar system under investigation was exposed to several types of environmental conditions, transitioning sequentially from partial shading to uniform irradiation, then to another shading condition, and finally to a shading condition distinct from the previous ones. All these scenarios were simulated using the three methods: P&O, GWO, and the proposed hybrid GWO-P&O, which were previously studied and explained. Figure 10 shows the maximum global power for each solar irradiation condition that the photovoltaic system must achieve as accurately and quickly as possible at each stage of the simulation.

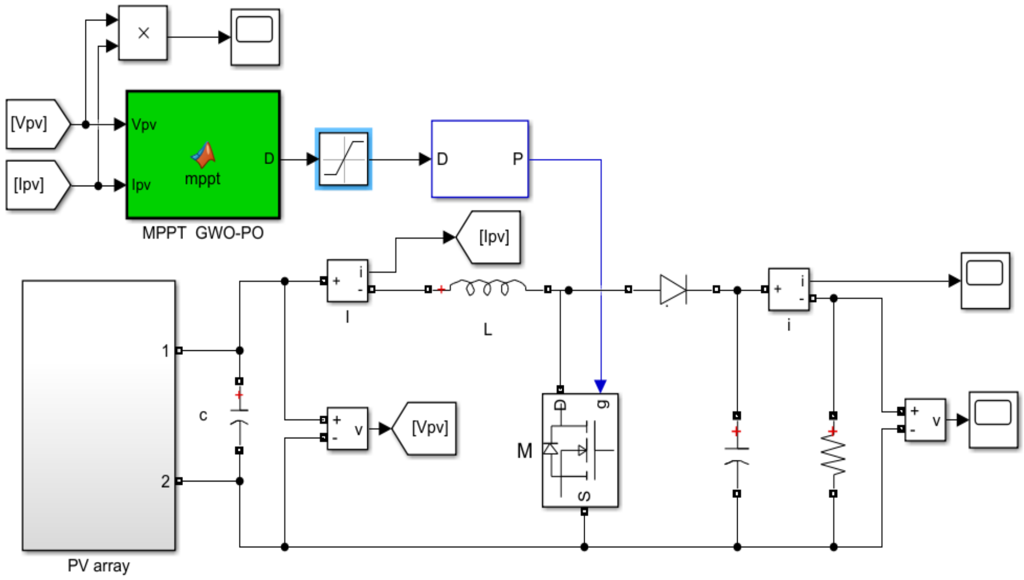

Figure 9. Block diagram of the proposed method in Simulink/MATLAB

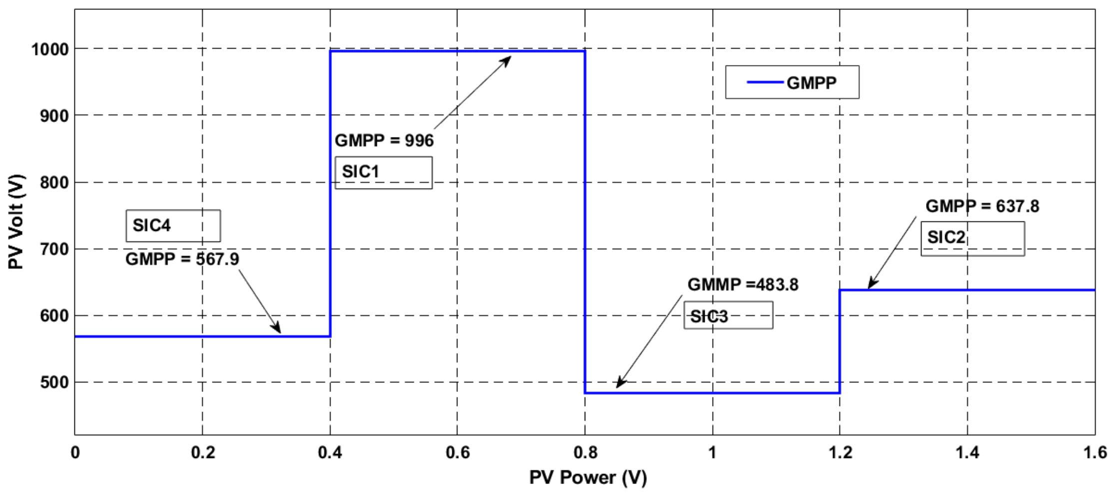

Figure 10. GMPP under different solar irradiation conditions

At the beginning of the simulation, each of the four panels is subjected to a different irradiation, represented by SIC4, as follows: 200, 700, 1000, and 1000 W/m². Figure 11 shows that the GWO algorithm exhibits steady-state oscillations, while the P&O algorithm struggles to track the global maximum power, as clearly illustrated in SIC4 of Figure 12. In contrast, the proposed hybrid algorithm, shown in Figure 13, achieves a response time of 0.07 s and successfully tracks the global maximum power at 567.6 W, with a calculated efficiency of 99.95%, demonstrating superior performance.

At t = 0.4 s, when the irradiation becomes uniform across the four panels at 1000 W/m², represented by SIC1, the GWO-P&O algorithm shows the best response time, 0.04 s, with an efficiency of 99.95%. In contrast, Figure 11 shows that the GWO algorithm has a high response time of 0.24 s. Figure 12 indicates that the P&O algorithm, although supposed to perform well under uniform irradiation conditions, shows a response time of 0.15 s and an efficiency of 99.4%.

At t = 0.8 s, each of the four panels again receives different irradiations: 100, 600, 800, and 800 W/m². Under these conditions (SIC3 sequence), both the P&O and even GWO algorithms, which is a metaheuristic algorithm, fail to track the global maximum power, as shown in Figures 12 and 11, respectively. In contrast, the proposed hybrid algorithm tracks this global power, showing 483.6 W with an efficiency of 99.95% maintained and a response time of 0.07 s, as illustrated in Figure 13 in the SIC3 section.

In the final phase of the simulation, irradiation values of 500, 800, 1000, and 1000 W/m² are applied to the panels at t =1.2 s, as represented by SIC2. Under these conditions, although the GWO and P&O algorithms produce almost equivalent results in terms of tracking the optimal power and response time, with noticeable oscillations for GWO in a steady state, as shown in SIC2, the hybrid algorithm once again outperforms them. It shows a power output of 637.7 W, an efficiency of 99.98%, and a record response time of 0.04 s.

Figures 14 and 15 show the voltage and current associated with the hybrid technique, reflecting the global maximum power extracted at each phase of the simulation. Figure 16 displays the overlay of the powers, providing a better visualization of the comparative study performed between the three algorithms studied in this paper. Finally, Figures 17 to 20 zoom in on the transition zone of the global power of the simulated system when switching from one solar irradiation condition to another, clearly demonstrating the superiority of the proposed GWO-P&O hybrid technique in terms of response time and power tracking.

This comparative study, which takes into account response time, efficiency, and the maximum global power extracted for each algorithm, is summarized in Table 3. Consistent convergence toward the GMPP, reduced tracking time, and high efficiency are observed under all shading conditions, whether partial or uniform, for the proposed method. Where the P&O or GWO methods fail, hybridization surpasses them, resulting in significant energy savings during electricity production. These findings offer practical insights for manufacturers on optimizing and maximizing power output under real-world conditions. However, experimental validation and long-term reliability studies at a photovoltaic site are desirable, taking into account other parameters such as temperature, humidity, and wind speed.

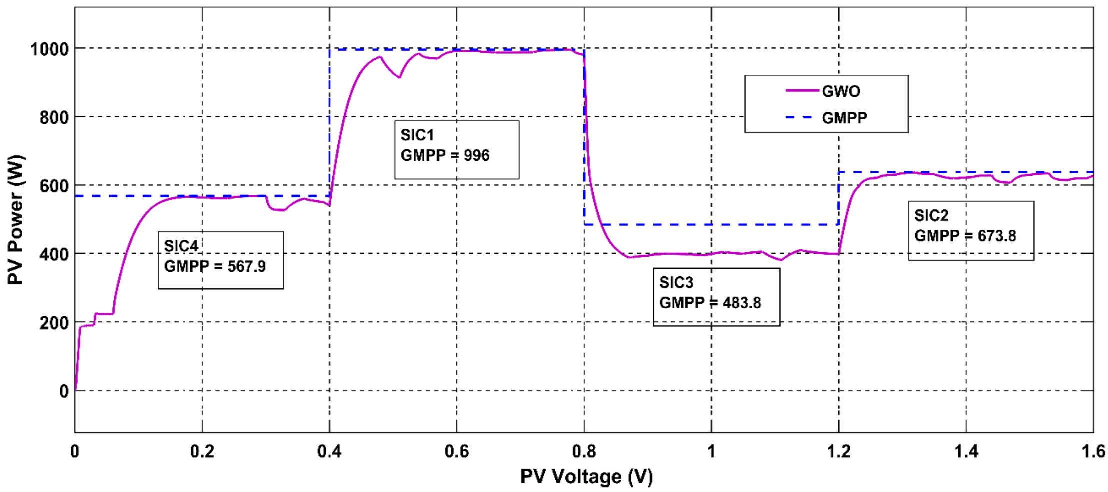

Figure 11. Power curve under different irradiation conditions with GWO

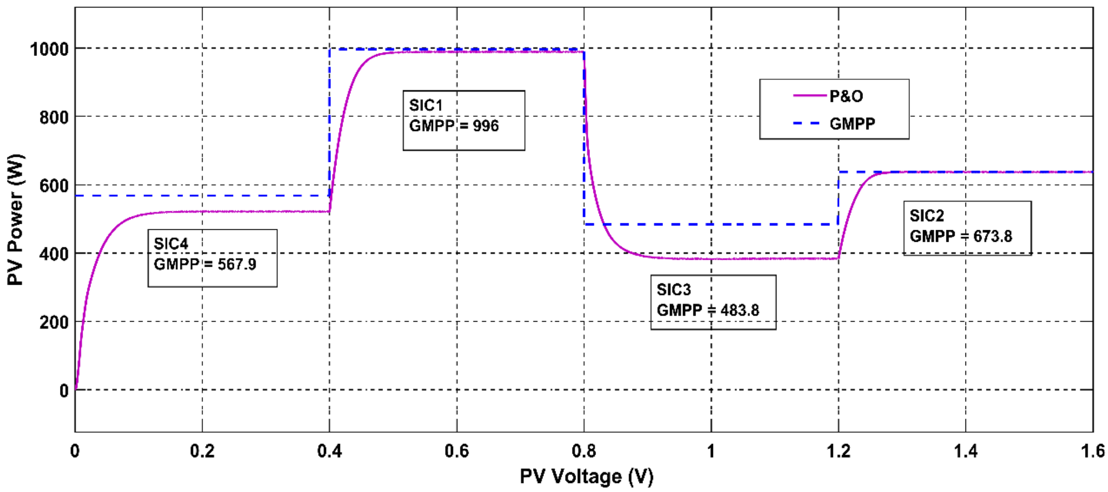

Figure 12. Power curve under different irradiation conditions with P&O

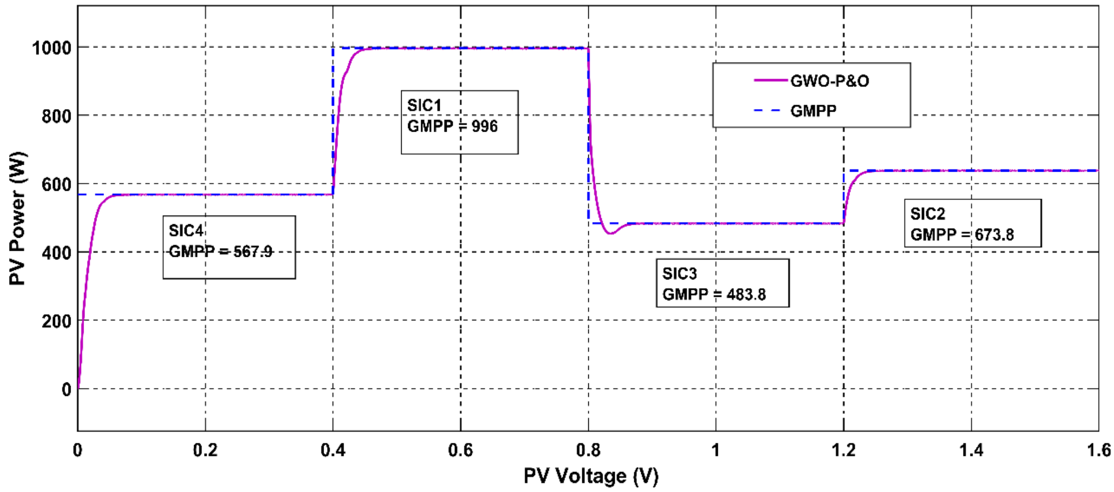

Figure 13. Power curve under different irradiation conditions with GWO-P&O

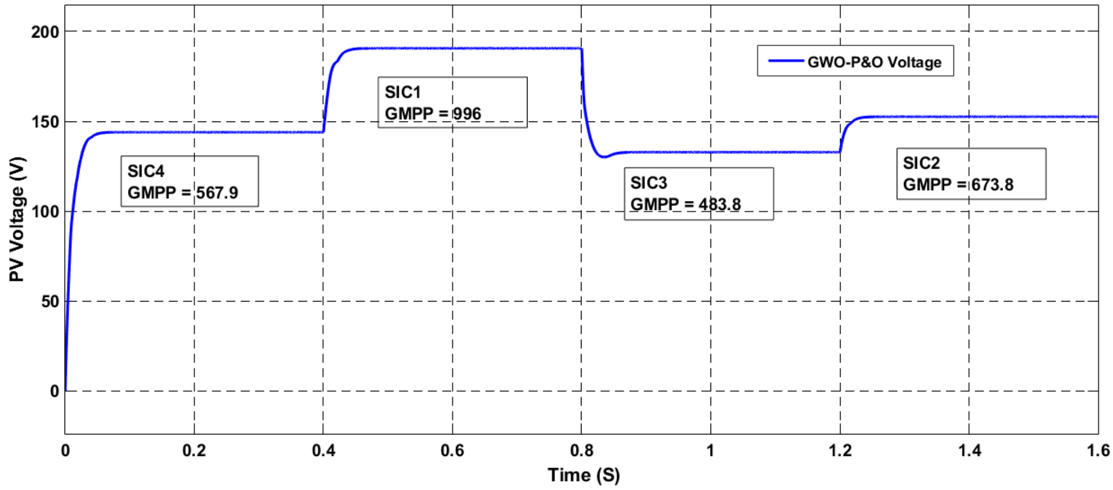

Figure 14. Voltage curve under different irradiation conditions with GWO-P&O

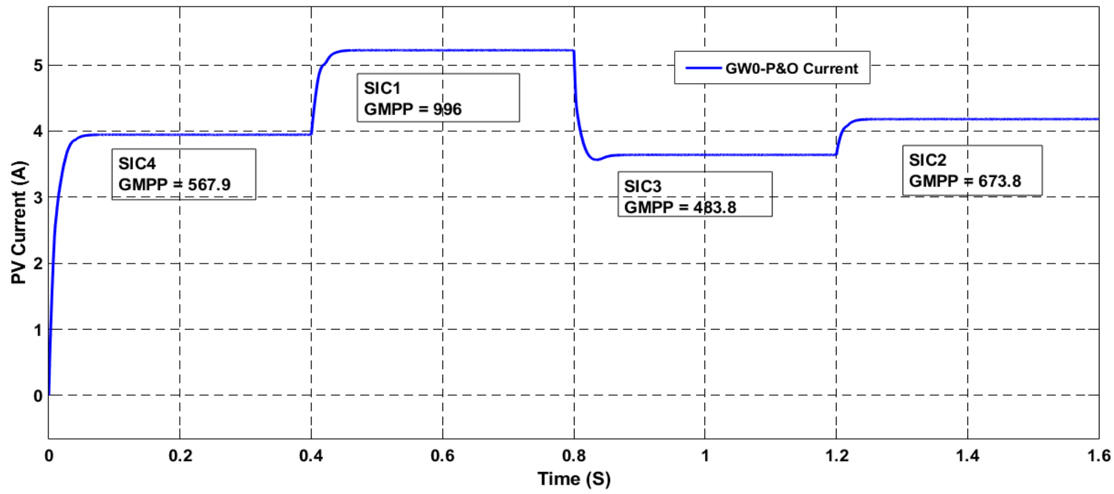

Figure 15. Current curve under different irradiation conditions with GWO-P&O

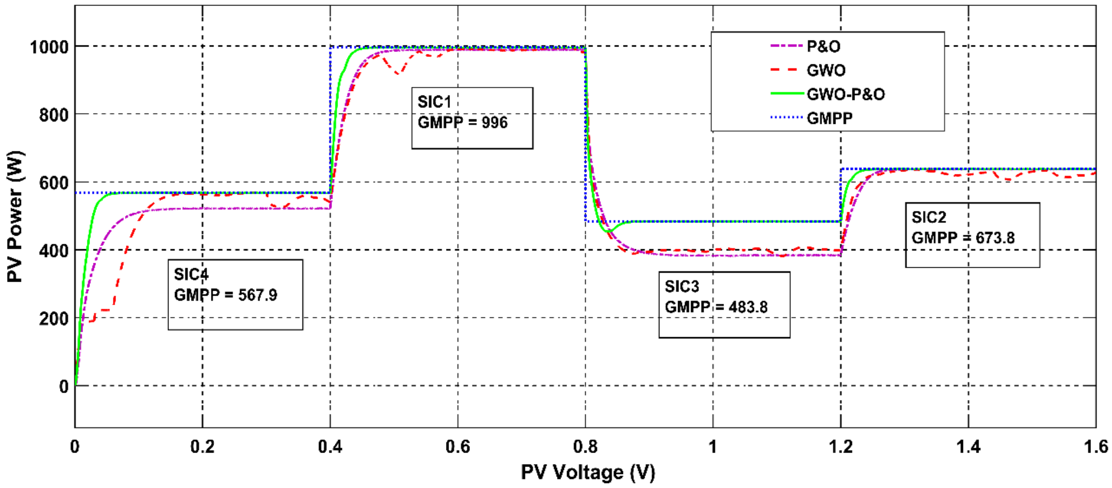

Figure 16. Power curve under different irradiation conditions

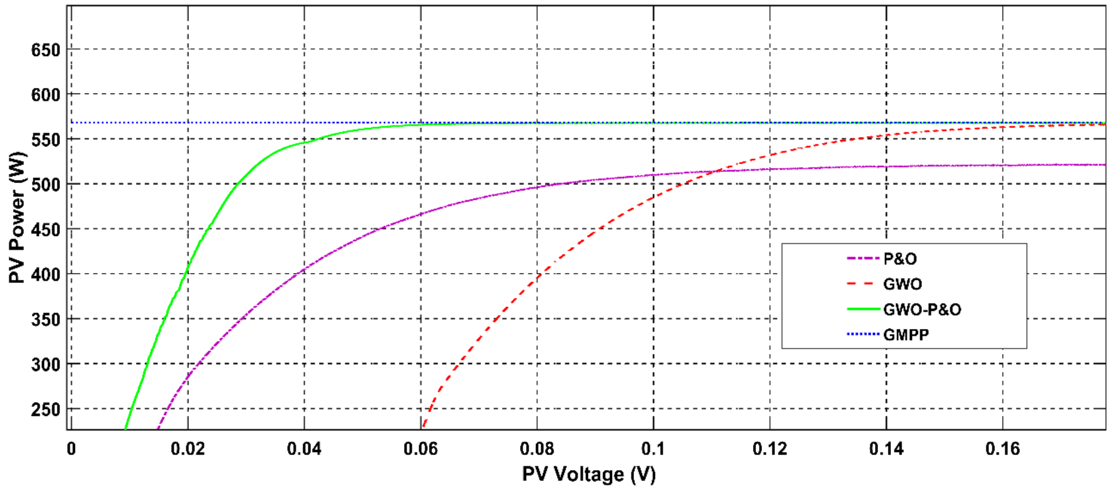

Figure 17. Response time of P&O, GWO, GWO-P&O at the beginning of the simulation during SIC4

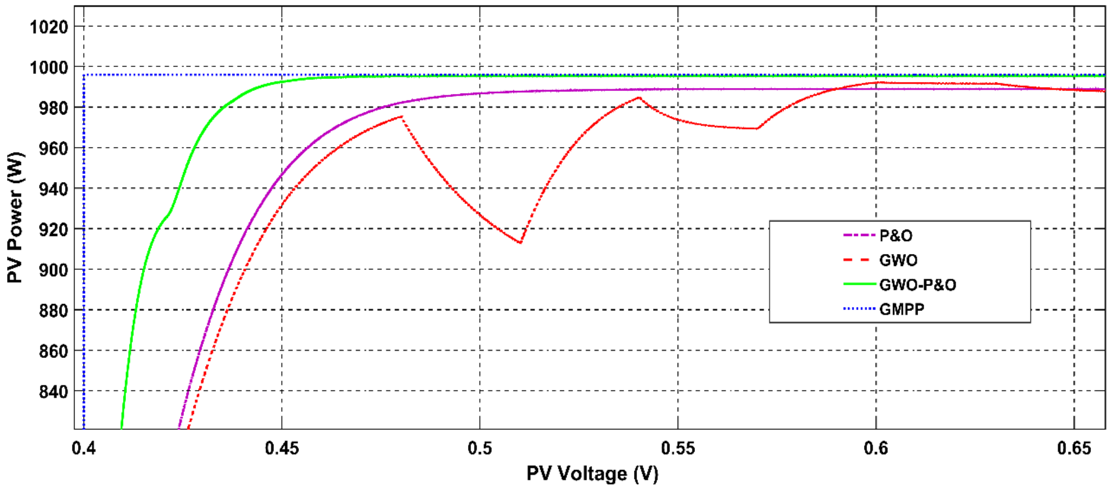

Figure 18. Response time of P&O, GWO, GWO-P&O during the transition from SIC4 to SIC1

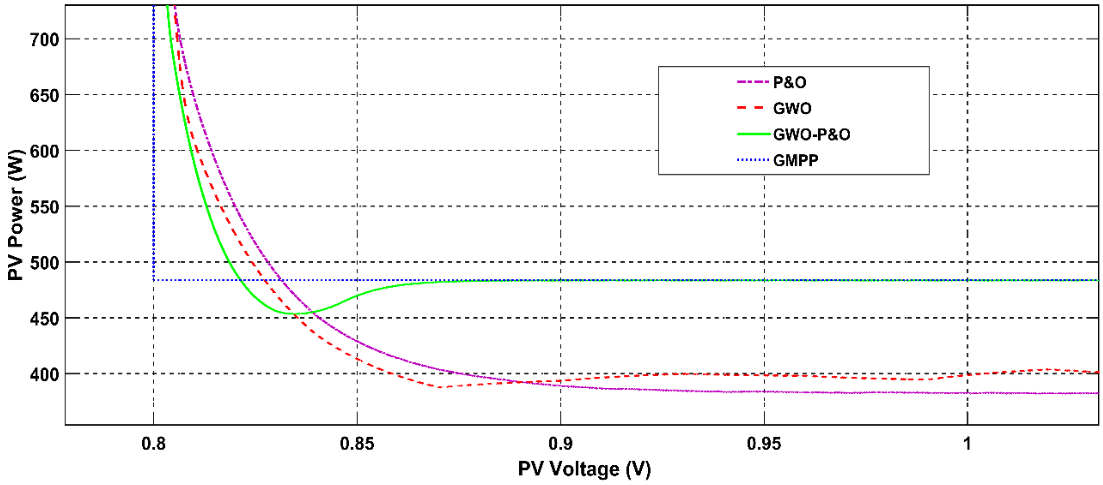

Figure 19. Response time of P&O, GWO, GWO-P&O during the transition from SIC1 to SIC3

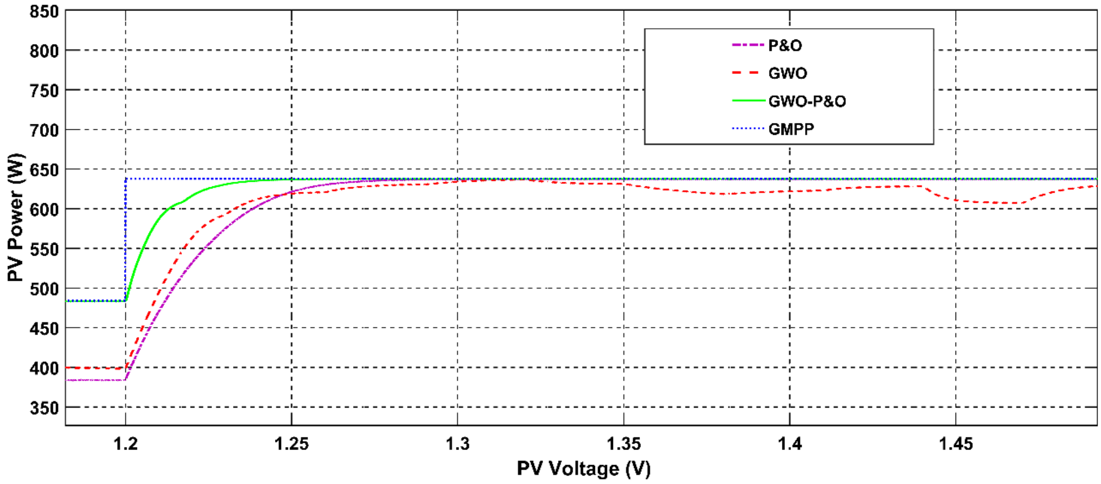

Figure 20. Response time of P&O, GWO, GWO-P&O during the transition from SIC3 to SIC2

Table 3. Comparison of MPPT algorithm performances under different SIC

	MPPT technique	Tracking time (S)	Power tracked (W)	GMPP (W)	Tracking efficiency (%)
SIC4	P&O	0.14	520.6	567.9	91.56
	GWO	0.165	567.4		99.91
	GWO-P&O	**0.07**	**567.6**		**99.95**
SIC1	P&O	0.15	990	996	99.4
	GWO	0.24	990		99.4
	GWO-P&O	**0.04**	**995.5**		**99.95**
SIC3	P&O	0.15	381.4	483.8	78.83
	GWO	0.21	402.6		83.22
	GWO-P&O	**0.07**	**483.6**		**99.95**
SIC2	P&O	0.1	637.3	637.8	99.92
	GWO	0.12	636		99.72
	GWO-P&O	**0.04**	**637.7**		**99.98**

5. CONCLUSION

In this study, an innovative power maximization technique for a photovoltaic (PV) panel, based on the hybridization of the GWO and P&O algorithms, was developed and simulated under different partial and uniform shading conditions, divided into four cases, to best replicate real operating conditions. This technique was evaluated in a comparative study focusing on response time, convergence towards global power, and oscillations around the global power point in steady-state conditions. All simulations were carried out in the MATLAB/Simulink environment.

The results highlight the performance of the proposed technique and its superiority in terms of convergence towards the GMPP, with values reaching 567.6 W for SIC4, 995.5 W for SIC1, 483.6 W for SIC3, and 637.7 W for SIC2, and an efficiency of 99.95% or higher. This method also stands out for its speed, with a reduced response time between 0.04 and 0.07 seconds, compared to P&O, which struggles to track the optimal point in two cases of partial shading, showing a tracking efficiency of 99.4% and a response time of 0.15 seconds under uniform irradiation conditions. On the other hand, the GWO algorithm exhibits significant oscillations in steady-state, with a high response time of up to 0.24 seconds and a minimum tracking efficiency of 83.22% in SIC3, illustrating its main limitations.

The main contribution of this study lies in the hybridization of the metaheuristic GWO technique and the classical P&O method, effectively addressing the limitations of both approaches when used individually under complex partial shading conditions characterized by multiple local maximum power peaks. This hybridization enhances tracking efficiency and improves tracking speed in the research field related to power extraction from photovoltaic systems. This approach offers significant potential for practical applications in photovoltaic installations. Furthermore, a long-term reliability study represents an innovative area of research.

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AUTHOR CONTRIBUTIONS STATEMENT

This paper uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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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

The data that support the findings of this study are available from the corresponding author, upon reasonable request.

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