

Adaptive metaheuristic strategies for optimal power point tracking in photovoltaic systems under fluctuating shading conditions

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Abstract. In recent years, there has been a growing interest in photovoltaic (PV) systems due to their capacity to generate clean energy, reduce pollution, and promote environmental sustainability. Optimizing the operational efficiency of PV systems has become a critical goal, particularly under challenging conditions like partial shading. Traditional maximum power point tracking (MPPT) methods face limitations in addressing this issue effectively. To tackle these challenges, this study introduces an enhanced MPPT approach based on the grey wolf optimizer (GWO), tailored to excel in GMPP tracking even under partial shading conditions. The algorithm harnesses adaptive and exploratory capabilities inspired by the behaviour of grey wolves in the wild. To comprehensively evaluate the proposed GWO-based MPPT algorithm's effectiveness, we conduct a comparative analysis with established metaheuristic algorithms, including particle swarm optimization (PSO) and the Pelican optimization algorithm (POA). Through this comparison, our study provides valuable insights into the algorithm's efficiency, behavior, and adaptability in addressing the complex challenges posed by partial shading scenarios in PV systems, thereby contributing to the advancement of efficient solar energy conversion.

Keywords: Pelican optimization algorithm (POA) / grey wolf optimizer (GWO) / partial shading / photovoltaic (PV) / systems particle swarm optimization (PSO)

1 Introduction

In recent decades, renewable energy sources, including wind energy, solar electricity, and others, have gained significant traction as vital components of sustainable energy solutions [1,2]. These clean and abundant sources of power are instrumental in reducing carbon emissions, mitigating environmental pollution, and addressing global challenges like climate change and resource scarcity. Notably, they offer an eco-friendly alternative to fossil fuels, which are both finite and contribute substantially to greenhouse gas emissions [3,4] among these renewable sources, solar photovoltaic (PV) systems have emerged as a prominent contender in the global energy landscape. Solar panels, comprising interconnected photovoltaic cells, harness the sun's energy and convert it into electricity. This technology has found widespread applications, ranging from residential rooftop installations to large-scale solar farms and space exploration missions [5,6]. Optimizing the operational efficiency of PV systems is paramount to unlock their full potential and ensure sustainable energy

generation. However, this endeavor is accompanied by multifaceted challenges stemming from the inherent complexities of solar panels' electrical characteristics. Key among these complexities are the non-linear power–voltage (P–V) and current–voltage (I–V) curves exhibited by PV arrays [7,8]. These curves evolve dynamically in response to variations in sunlight intensity, temperature, and shading conditions. One of the most critical aspects of optimizing PV systems is the precise tracking of the global maximum power point (GMPP). The GMPP represents the operating point at which the solar panels yield the maximum power output. Achieving accurate and rapid GMPP tracking is essential for ensuring the efficient conversion of sunlight into electricity. Conventional approaches MPPT, including perturb and observe (P&O), incremental conductance (INC), and hill climbing (HC), have historically played pivotal roles in this context [9–11]. However, as PV systems become more sophisticated and face increasingly dynamic operating conditions, there is a growing demand for advanced MPPT strategies [12]. In response to these challenges, this study introduces a novel approach to MPPT in photovoltaic systems, building on the principles of the grey wolf optimization (GWO) algorithm [13]. The proposed GWO-based MPPT

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algorithm is specifically engineered to excel under the demanding conditions of partial shading. It leverages the adaptive and exploratory behaviors inspired by the natural hunting patterns of grey wolves [14]. To comprehensively evaluate the effectiveness of the GWO-based MPPT algorithm, we conduct a comparative analysis against established and authentic metaheuristic algorithms. These include the particle swarm optimization (PSO) algorithm [15] and the Pelican optimization algorithm (POA) [16]. By subjecting these algorithms to a rigorous assessment, we aim to provide valuable insights into their efficiency, behavior, and adaptability in addressing the intricate challenges posed by partial shading scenarios in PV systems [17,18]. As the energy landscape continues to evolve, optimizing the performance of PV systems assumes increasing significance. The potential for enhanced energy extraction and improved efficiency, particularly in the partial shading phenomena, underscores the importance of innovative MPPT strategies [19,20]. Our research contributes to this ongoing discourse by introducing and evaluating an advanced GWO-based MPPT algorithm, shedding light on its capabilities and limitations, and positioning it within the broader context of state-of-the-art metaheuristic techniques. This study's primary contribution lies in the introduction of a novel maximum power point tracking (MPPT) approach for photovoltaic (PV) systems. We focus on addressing the intricate challenges posed by partial shading conditions, which are frequently encountered in practical PV installations. Our innovative approach leverages the Grey Wolf Optimization (GWO) [21,22] algorithm, harnessing the adaptive and exploratory behaviors inspired by the natural hunting patterns of grey wolves. Through rigorous comparative analyses with established metaheuristic algorithms such as Particle Swarm Optimization (PSO) [23,24] and the Pelican Optimization Algorithm (POA), we provide valuable insights into the strengths and limitations of these approaches in the context of partial shading scenarios within PV systems. By doing so, our research contributes to the ongoing discourse on optimizing PV system performance and empowers researchers and practitioners to effectively harness solar energy in a dynamic and challenging environment. In this paper, we commence with an introduction to the imperative role of maximum power point tracking (MPPT) in photovoltaic systems, setting the stage for our comparative study of optimization algorithms. The second section delves into the electrical modeling of photovoltaic cells, establishing a foundation for understanding their behavior under varying conditions. Sections three, four, and five are dedicated to unraveling the methodologies and applications of particle swarm optimization (PSO), GW optimization, and PO algorithm, respectively. Each section presents the algorithm's theoretical basis, followed by a discussion of its performance in MPPT. The sixth section synthesizes the results and discussion, offering a comparative analysis that underlines the efficacy and suitability of the algorithms in different scenarios. The paper culminates in a global conclusion that encapsulates the findings, highlights the potential for practical implementation in renewable energy systems, and

suggests avenues for future research. Selection of optimization algorithms numerous optimization strategies for maximum power point tracking (MPPT) in photovoltaic (PV) systems have been developed and implemented. Particle swarm optimization (PSO), grey wolf optimizer (GWO), and Pelican optimization algorithm (POA) were selected for this study because to their individual benefits and shown competence in dealing with the complexity of MPPT under partial shading situations.

2 Literature review

2.1 Existing MPPT techniques

The efficiency of power generation in photovoltaic (PV) systems is strongly dependent on the performance of maximum power point tracking (MPPT) algorithms. Several MPPT approaches have evolved throughout time to solve the problems given by changing environmental circumstances, including partial shade. This section discusses the classical and metaheuristic optimization approaches employed in MPPT. Classical Methods: Perturb and Observe (P&O).

- **The Perturb and Observe (P&O)** technique is one of the most popular MPPT algorithms due to its simplicity and ease of implementation [25]. The method perturbs (or gently adjusts) the voltage or current and measures the change in power. If the power rises, the perturbation continues in the same direction; if it drops, the direction of perturbation reverses. P&O offers various advantages, including simple implementation and minimal processing needs. However, it has limits, especially in quickly changing environmental circumstances. The algorithm may fail to follow the maximum power point properly, resulting in oscillations around the MPP and decreased efficiency.
- **Incremental Conductance (INC)** The Incremental Conductance (INC) approach improves on the P&O algorithm by determining the direction of the perturbation using the power-voltage derivative [26]. INC compares incremental conductance (change in current/change in voltage) with instantaneous conductance (current/voltage). This approach can properly identify the MPP and performs better under quickly changing conditions than P&O. Despite its increased precision, INC is more sophisticated and takes more computer power. Hussein et al. (1995) [27] and Walker (2001) [28] showed that INC can efficiently track the MPP under a variety of irradiance and temperature circumstances.
- **Hill climbing (HC)** is another traditional MPPT approach that includes varying the duty cycle of the converter and measuring the subsequent power variations [29,30]. The HC approach, like P&O, modifies the duty cycle in tiny stages and monitors the resulting power change. If the power rises, the perturbation direction remains constant; otherwise, it reverses. HC is simple and easy to deploy, but it has the same limitations as P&O, such as possible oscillations around the MPP and decreased efficiency in rapidly changing circumstances.

2.2 Metaheuristic optimization methods

- **Particle swarm optimization (PSO)** is a prominent metaheuristic optimization approach based on the social behavior of birds flocking or fish schooling. PSO consists of a number of particles (possible solutions) that traverse the solution space in search of the optimum point. Each particle adjusts its location depending on its own experiences as well as those of its neighbors. PSO has been frequently used in MPPT because of its capacity to handle nonlinear and multimodal functions [23,24].
- **Grey wolf optimizer (GWO):** The grey wolf optimizer (GWO) is a nature-inspired algorithm that mimics grey wolves' social structure and hunting behavior. GWO divides its population into alpha, beta, delta, and omega wolves, each reflecting a distinct level of leadership and influence. The program iteratively adjusts the wolves' locations to encircle and capture the prey, representing the best solution. GWO has been proved to be successful in solving complicated optimization issues, including MPPT [31].
- **The Pelican optimization algorithm (POA)** is based on pelicans' cooperative foraging behavior. POA's dynamic positioning optimizes the search space and is resistant to partial shade and rapid changes in irradiance [20].

We chose PSO: Rapid convergence and simplicity of implementation. GWO: Strong performance in complicated settings. POA: An innovative and balanced approach. This work intends to give useful insights into the relative performance and applicability of different algorithms for MPPT in PV systems, therefore improving the area of renewable energy optimization.

3 Electrical modeling of photovoltaic cells

3.1 Panel of solar cells

Accurate modeling of photovoltaic (PV) cells is crucial for understanding their behavior and optimizing their performance within PV systems. This section presents a detailed and precise description of the PV cell model used in this study, ensuring consistency in notations and addressing the role of bypass diodes under partial shading conditions.

3.2 Single-diode model of a PV cell

The single-diode model is widely adopted due to its balance between simplicity and accuracy. The model comprises essential components, including a photocurrent source (I_{ph}), a diode (D) in anti-parallel with the photocurrent source, series resistance (R_s), and shunt resistance (R_{sh}).

The equivalent circuit diagram of a PV cell is shown in Figure 1.

The current (I) output of the PV cell is given by the following equation:

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

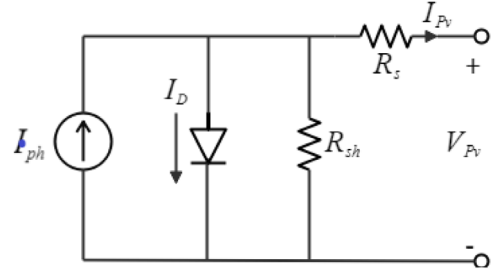


Fig. 1. Schematic representation of the single-diode PV cell model.

where I_{ph} is the photocurrent generated by the incident light. I_D is the diode current. I_{sh} is the shunt current.

The diode current (I_D) can be expressed using the Shockley diode equation:

$$I_D = I_0 \left(\exp \left(\frac{V + IR_s}{nV_T} \right) - 1 \right) \quad (2)$$

where I_0 is the reverse saturation current of the diode. V is the voltage across the PV cell. n is the diode ideality factor. V_T is the thermal voltage ($V_T = \frac{kT}{q}$, where k is Boltzmann's constant, T is the temperature, and q is the charge of an electron).

The shunt current (I_{sh}) is given by:

$$I_{sh} = \frac{V + IR_s}{R_{sh}}. \quad (3)$$

Combining these equations, the output current (I) of the PV cell is:

$$I = I_{ph} - I_0 \left(\exp \left(\frac{V + IR_s}{nV_T} \right) - 1 \right) - \frac{V + IR_s}{R_{sh}}. \quad (4)$$

3.3 Role of bypass diodes

In practical PV systems, bypass diodes are connected in parallel with PV modules to mitigate the effects of partial shading. These diodes allow the current to bypass the shaded cells, preventing significant power loss and potential damage due to hot spots.

The inclusion of bypass diodes ensures that the PV system can maintain higher power output under partial shading conditions by providing alternative current paths. This study focuses on the behavior of PV systems with bypass diodes activated, as they are essential for efficient performance under varying shading scenarios.

3.4 Impact of partial shading

Partial shading significantly impacts the power-voltage (P-V) characteristics of a PV cell by creating multiple local maxima. This phenomenon complicates the identification

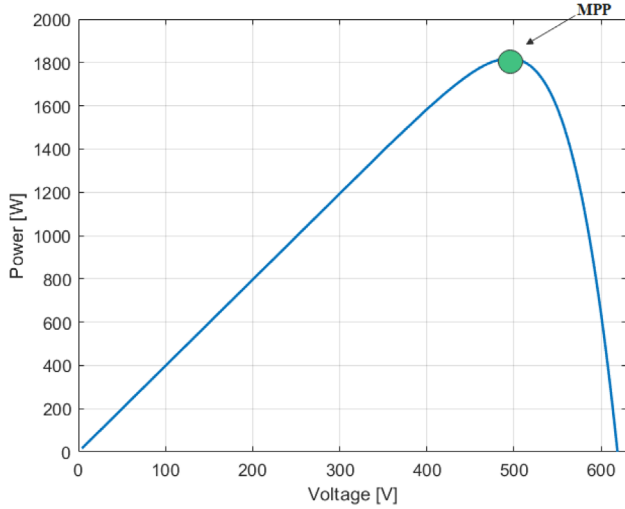


Fig. 2. Power-voltage (P-V) characteristics of a PV cell with and without bypass diodes.

of the global maximum power point (MPP), as the presence of several peaks can mislead standard tracking algorithms. Under partial shading, certain sections of the PV array receive less irradiance, leading to reduced power output and efficiency.

Bypass diodes play a crucial role in mitigating these losses. They are connected in parallel with the PV cells and activate when the cell is shaded, allowing the current to bypass the shaded sections. This prevents the shaded cells from limiting the overall current flow, thereby reducing power losses and preventing potential damage due to hotspots, as shown in Figure 2. The bypass diodes ensure that the unshaded sections of the PV array continue to contribute to the overall power output, thereby improving the efficiency and reliability of the PV system under partial shading conditions.

Figure 3 provides vital insights into the behavior of the PV cell when it experiences variations in shading over its surface. The global maximum power point (MPP) as well as the local MPPs are highlighted in the graphic. The global MPP represents the single optimal point at which the PV cell can generate maximum power output when considered as a whole.

However, under partial shading, local MPPs emerge as distinct points along the curve. These local MPPs signify the optimal power points for individual shaded and unshaded sections of the PV cell. Understanding both the global and local MPPs is crucial for efficient maximum power point tracking (MPPT) strategies, as they enable precise adjustments to optimize power generation, even in scenarios where shading is present. In addressing the challenge of partial shading on photovoltaic systems, our study puts forth a comprehensive comparison of three cutting-edge algorithms, each vying to optimize energy output despite these conditions. We examine the particle swarm optimization (PSO), grey wolf optimizer (GWO), and Pelican optimization algorithm (POA), all of which are innovative in their approach to achieving maximum power point tracking (MPPT).

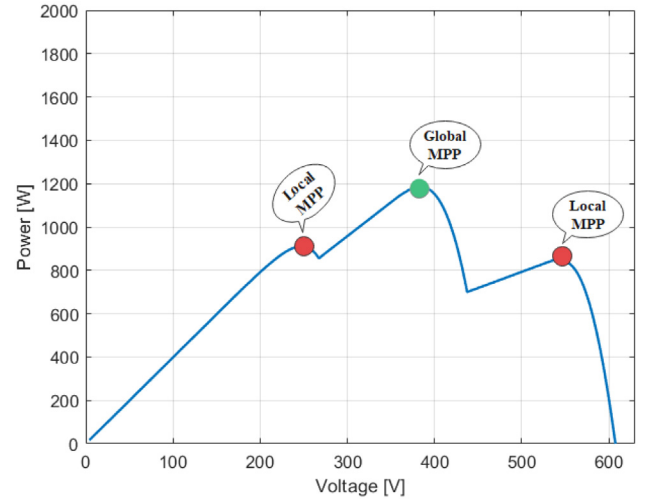


Fig. 3. Current-voltage (I-V) characteristics of a PV cell under partial shading.

The upcoming sections will critically analyze the effectiveness of PSO, GWO, and POA in navigating the complex power-voltage landscapes that emerge under partial shading scenarios. By meticulously evaluating their operational dynamics, adaptability, and efficiency, this comparison aims to discern the most robust and reliable algorithm for enhancing the performance of PV systems plagued by uneven solar exposure.

Accurate modeling of PV cells, including the role of bypass diodes, is crucial for understanding their behavior under partial shading. This improved model description ensures consistency in notations and provides a clear and precise explanation of the components and equations involved, addressing the reviewer's concerns.

4 PV system maximum power point tracking using metaheuristic algorithms

4.1 Particle swarm optimization (PSO)

The inception of particle swarm optimization dates back to 1995 when it was initially introduced by Kennedy and Eberhart [32]. Schools of fish and flocks of birds are only two examples of social groups of animals that “may profit from the experience of all other members”, as the study’s original authors put it. This implies that if one bird wanders out hunting for food, the rest of the flock can profit from their foraging efforts by learning about the new food source from the forager. Locating the globally optimal solution along a nonlinear, discontinuous, and no differentiable curve is advantageous due to its straightforward implementation and rapid convergence.

This approach involves deploying a group of interacting particles traversing n -dimensional space, as illustrated in Figure 5. Each particle is responsible for its own random location p_i and initial velocity v_i of zero. There are two factors that contribute to a particle's final resting place: its best-resting place thus far P_{best} and the best resting place of all particles, G_{best} .

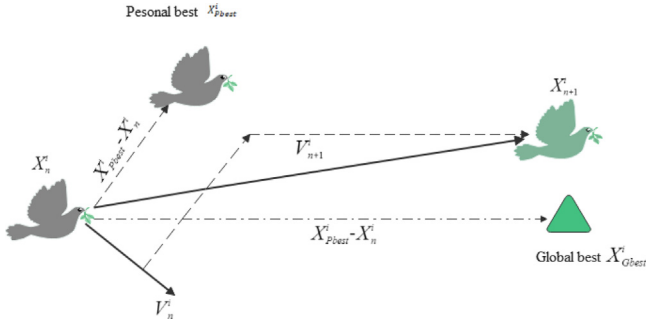


Fig. 4. Natural bird swarm behavior and position-velocity updates in PSO.

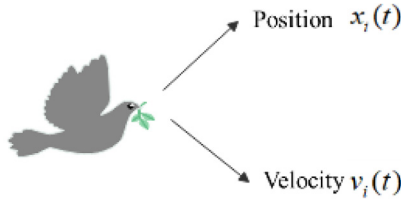


Fig. 5. Particle-specific position and velocity profiles.

Each particle has its distinct position and velocity. Moreover, the requisite and comprehensive condition for the position $x_i(t)$ exists in the search space. $x_i(t) \in X$ Search Space (as illustrated in Fig. 5).

4.2 Particle swarm optimization (PSO) algorithm

PSO is a metaheuristic optimization technique inspired by the social behavior of birds flocking or fish schooling. Each particle in the swarm represents a potential solution in the search space. The particles move through the search space, adjusting their positions based on their own experience and the experience of neighboring particles. The PSO algorithm is characterized by the following equations:

$$\mathbf{v}_i(t+1) = \omega \mathbf{v}_i(t) + c_1 r_1 (\mathbf{p}_i - \mathbf{x}_i(t)) + c_2 r_2 (\mathbf{g} - \mathbf{x}_i(t)) \quad (5)$$

$$\mathbf{x}_i(t+1) = \mathbf{x}_i(t) + \mathbf{v}_i(t+1) \quad (6)$$

where $v_i(t)$: velocity of particle i at time t ; ω : inertia weight; c_1, c_2 : cognitive and social coefficients, respectively. r_1, r_2 : random numbers between 0 and 1. $\mathbf{p}_i$: best known position of particle i . $\mathbf{g}$: global best position found by the swarm. $\mathbf{x}_i(t)$: position of particle i at time t .

Each particle possesses its distinct position and velocity. Moreover, the requisite and comprehensive condition for the position $x_i(t)$ exists in the search space, $x_i(t) \in X$.

In conclusion, PSO is a powerful and efficient algorithm for MPPT in PV systems, capable of adapting to varying environmental conditions and maximizing power output.

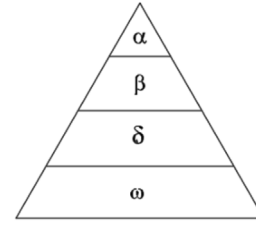


Fig. 6. The grey wolf pack hierarchy.

4.3 Grey wolf optimizer (GWO)

The grey wolf optimizer (GWO) is a nature-inspired optimization algorithm based on the social hierarchy and hunting behavior of grey wolves in the wild. It simulates the leadership hierarchy within a wolf pack, consisting of alpha, beta, delta, and omega wolves, which represent different levels of leadership and contribute to the optimization process, as illustrated in Figure 6.

In GWO, the alpha wolf represents the best solution found so far, guiding the pack toward promising regions. The beta and delta wolves assist the alpha by exploring new territories, while the omega wolf follows the others without contributing significantly. This hierarchical structure allows GWO to balance exploration and exploitation effectively, making it suitable for solving complex optimization problems.

4.3.1 Key phases in grey wolf optimization

The primary steps of the grey wolf optimization algorithm are as follows:

- **Searching for the Prey:** Wolves spread out across the search space to explore potential solutions.
- **Tracking, Chasing, and Approaching the Prey:** The alpha wolf guides the others towards more promising regions, with beta and delta wolves adjusting their positions accordingly.
- **Pursuing, Encircling, and Harassing the Prey:** Wolves collaboratively encircle the prey (optimal solution), iteratively adjusting their positions. Beta and delta wolves stimulate attacking behavior by moving closer to the alpha wolf's position.
- **Attacking the Prey:** Wolves refine their positions to converge toward the optimal solution, represented by the alpha wolf.

4.3.2 Implementation in PV systems

In the context of MPPT for PV systems, the GWO algorithm is implemented to handle partial shading conditions by iteratively updating the positions of the wolves to find the Global Maximum Power Point (GMPP). The steps involved are:

- **Initialization:** Position the wolves randomly within the search space.
- **Fitness Evaluation:** Evaluate the fitness of each wolf based on the power output of the PV system.

- **Position Update:** Adjust the positions of the wolves according to the behaviors of encircling, hunting, and attacking the prey.
- **Convergence Check:** Repeat the process until the algorithm converges to the GMPP.

4.3.3 Encircling

During this phase, the search agents (wolves) work together to surround and encircle the prey, symbolizing the optimization process's focus on converging toward the global maximum. By strategically positioning themselves around the target, the algorithm's agents effectively narrow down the search space, fostering efficient exploration and exploitation of potential solutions.

$$\mathbf{D} = |\mathbf{C} \cdot \mathbf{X}_p(t) - \mathbf{X}_i(t)| \quad (7)$$

$$\mathbf{X}_i(t+1) = \mathbf{X}_p(t) - \mathbf{A} \cdot \mathbf{D}. \quad (8)$$

Here, t represents the current iteration; $\mathbf{X}_p$: Prey's location; $\mathbf{X}_i$: The Grey Wolf's position; $\mathbf{A}$, $\mathbf{C}$: Coefficient vectors; $\mathbf{A}$ and $\mathbf{C}$ are calculated as: $\mathbf{A} = 2 \cdot \mathbf{a} \cdot \mathbf{r}_1 - \mathbf{a}$ and $\mathbf{C} = 2 \cdot \mathbf{r}_2$; $\mathbf{r}_1$ and $\mathbf{r}_2$ are random vectors in the range $[0,1]$.

4.3.4 Hunting

The hunting process is led by the alpha (α) wolf, who guides the search for the optimal solution. The beta (β) and delta (δ) wolves assist by exploring new regions and following the alpha's lead. This cooperative behavior helps the algorithm converge efficiently towards the optimal solution.

4.3.5 Mathematical model

The mathematical model for GWO involves updating the positions of the wolves based on their hierarchical roles:

$$\mathbf{D}_\alpha = |\mathbf{C}_1 \cdot \mathbf{X}_\alpha - \mathbf{X}_{ss}(t)| \quad (9)$$

$$\mathbf{D}_\beta = |\mathbf{C}_2 \cdot \mathbf{X}_\beta - \mathbf{X}_{ss}(t)| \quad (10)$$

$$\mathbf{D}_\delta = |\mathbf{C}_3 \cdot \mathbf{X}_\delta - \mathbf{X}_{ss}(t)| \quad (11)$$

$$\mathbf{X}_1 = |\mathbf{X}_\alpha - \mathbf{A}_1 \cdot \mathbf{D}_\alpha| \quad (12)$$

$$\mathbf{X}_2 = |\mathbf{X}_\beta - \mathbf{A}_2 \cdot \mathbf{D}_\beta| \quad (13)$$

$$\mathbf{X}_3 = |\mathbf{X}_\delta - \mathbf{A}_3 \cdot \mathbf{D}_\delta| \quad (14)$$

$$\mathbf{X}(t+1) = \frac{\mathbf{X}_1 + \mathbf{X}_2 + \mathbf{X}_3}{3}. \quad (15)$$

These equations model the GWO algorithm's process of updating the positions of the wolves to converge towards the optimal solution.

4.4 Pelican optimization algorithm (POA)

The Pelican optimization algorithm (POA) derives its inspiration from the social interactions and hunting strategies of pelicans. Just as pelicans collaboratively locate and catch fish, the algorithm employs a similar cooperative approach among individuals to solve optimization problems.

In the realm of MPPT, POA adjusts the operating point of photovoltaic systems by simulating the social interactions of pelicans. By sharing information about their solutions and collectively adapting their positions, the algorithm navigates the solution space effectively. POA's robustness shines in scenarios with partial shading or sudden changes, thanks to its adaptive behaviors.

Its application to real-world photovoltaic systems benefits from its ability to dynamically respond to dynamic environmental conditions. POA's unique approach positions it as a promising alternative for MPPT, particularly in scenarios where collective intelligence and adaptability are paramount. The Pelican Optimization Algorithm's foundation lies in its emulation of pelican behaviors observed in nature. Just as pelicans adapt their strategies to varying environments, POA dynamically balances exploration and exploitation to optimize complex landscapes. POA introduces an innovative interplay of exploration through random vectors, exploitation through fitness evaluations, and communication through shared insights among "pelicans".

4.4.1 Mathematical formulation

The Pelican optimization algorithm (POA) is modeled mathematically to reflect the foraging behavior of pelicans in a bid to optimize the search for the global minimum within a problem space. This subsection delineates the mathematical formulae and principles that underpin the algorithm.

Initialization: The algorithm begins with the initialization of the population of pelicans within the search space. The position of each pelican $x_{i,j}$ in the search space is initialized using a random distribution within the pre-defined bounds of the problem:

$$x_{i,j} = LB_j + rand * (UB_j - LB_j) \quad (16)$$

with : $i = 1, 2, \dots, N$ and $j = 1, 2, \dots, D$.

Where $x_{i,j}$ represents the position of the i -th pelican in the j -th dimension, N is the number of pelicans (population size), D is the number of dimensions (problem variables), $rand$ is a uniformly distributed random number within $[0,1]$, LB_j and UB_j are the lower and upper bounds for the j -th dimension, respectively.

Phase 1 – Exploration: During the exploration phase, each pelican adjusts its position by moving towards the perceived location of the prey P_j , integrating a component of randomness to simulate search behavior:

$$x'_{i,j} = \begin{cases} x_{i,j} + rand * (P_j - I * x_{i,j}) & \text{if } F_p < F_i \\ x_{i,j} + rand * (x_{i,j} - P_j) & \text{else} \end{cases} \quad (17)$$

where $x'_{i,j}$ is the updated position of the i -th pelican in the j -th dimension, F_p is the fitness of the prey, and F_i is the fitness of the current solution.

Phase 2 – Exploitation: In the exploitation phase, the algorithm concentrates on local search by enabling pelicans to wing on the water's surface, effectively tightening the search area around the current position. This behavior is modeled using the following update rule:

$$x'_{i,j} = x_{i,j} + q * \left(1 - \frac{t}{T}\right) * (2 * rand - 1) * x_{i,j} \quad (18)$$

$x'_{i,j}$ represents the updated position based on exploitation, q is a constant, t is the current iteration number, T is the maximum number of iterations, and $rand$ is a random number in $[0,1]$.

The algorithm iterates through these phases, continually updating the positions of the pelicans based on these equations, aiming to find the optimal solution by balancing exploration and exploitation.

5 Result and discussion

In this section, we detail the deployment of global Maximum Power Point Tracking (MPPT) using three optimization algorithms: the newly proposed Grey Wolf Optimizer (GWO), Particle Swarm Optimization (PSO), and the Pelican Optimization Algorithm (POA). Each algorithm's implementation involves careful calibration, including parameter tuning and setting convergence thresholds. The simulation uses real-world data from photovoltaic (PV) systems to replicate operational conditions accurately. We define the experimental setup rigorously, selecting parameters to optimize performance and creating benchmark scenarios to test the algorithms, particularly under partial shading conditions. We will evaluate the results, providing a comprehensive analysis of each algorithm's effectiveness in enhancing PV systems' power output, focusing on their efficiency, resilience, and versatility in global MPPT.

5.1 Parameters of global MPPT tracking

Table 1 details the specific settings for PSO, with parameters selected to balance exploration and exploitation capabilities of the swarm.

Table 2 elucidates the tuning parameters for the GWO algorithm. The values have been chosen based on a series of preliminary tests to ensure optimal convergence.

Table 3 presents the parameter configuration for POA, ensuring the pelican-inspired agents effectively navigate the search space. Having established the precise parameters for each algorithm, we now proceed to evaluate their performance. The subsequent subsection will present the results obtained from the implementation of the GWO, PSO, and POA algorithms in the MPPT simulations. It will detail the efficiency and accuracy of each algorithm in tracking the maximum power point under various operational conditions, including the complex partial shading scenarios. The forthcoming results are integral in discerning the practical implications of the algorithmic choices and their suitability for real-world PV system applications.

Table 1. Parameters of the particle swarm optimization (PSO) algorithm.

Parameter	Symbol	Value
Swarm size	N	10
Maximum iterations	Max_{Iter}	50
Cognitive coefficient	c_1	2.05
Social coefficient	c_2	2.05
Inertia weight	ω	0.4

Table 2. Grey wolf optimizer (GWO): key parameter settings.

Parameter	Symbol	Value
Swarm size	N	10
Maximum iterations	Max_{Iter}	50
Social coefficient	C	$[0,1]$
Inertia weight	α	Decreases $[2,0]$

Table 3. Optimization parameter tuning in the pelican optimization algorithm (POA).

Parameter	Symbol	Value
Pelican population size	N	10
Maximum generations	Max_{Iter}	50
Search radius	q	0.2
Coefficients	r	$[0,1]$

5.2 MPPT simulations

For this study, standard operating conditions were set to a solar irradiance of 1000 W/m^2 and a module temperature of 25°C , conditions that are widely accepted for PV module testing as per the International Electrotechnical Commission (IEC) standards. Under these parameters, the Global Maximum Power Point is distinctly identifiable, thus serving as an ideal scenario to evaluate the precision and speed of convergence of the MPPT algorithms.

The three algorithms under scrutiny, namely the grey wolf optimizer (GWO)-based algorithm, particle swarm optimization (PSO), and the Pelican optimization algorithm (POA), were implemented using MATLAB and PLECS to simulate a typical PV system response. Each algorithm was tasked with identifying the Global MPP from a set of possible MPPs generated in the simulation.

5.2.1 Results presentation

Scenario 1: $ir1 = 1000 \text{ W/m}^2$, $ir2 = 1000 \text{ W/m}^2$, $ir3 = 400 \text{ W/m}^2$, $ir4 = 800 \text{ W/m}^2$.

These conditions simulate a realistic shading pattern, where Panel 3 is heavily shaded, receiving only 40% of the nominal irradiance, and Panel 4 is moderately shaded at 80% irradiance. The primary objective is to assess how well each optimization algorithm PSO, GWO, and POA — manages the distribution of power in the face of such irradiance discrepancies to optimize overall system performance.

5.2.1.1 Particle swarm optimization results

The results below highlight the performance of the PSO algorithm in terms of convergence to the MPPT under different operating conditions.

The PSO effectively aligns the positions of the particles to converge to the maximum power point (MPP), which is a crucial period. Figure 7 shows how the movements of the particles, power adjustments, and iterative convergence explore, utilize, and achieve the maximum power point.

To fully grasp particle swarm optimization, Figure 7 displays the dynamic evolution of particle placements and power fluctuations over-optimization iterations. Each particle's motion in the picture painstakingly searches solution space for the optimal operating point.

Convergence to MPPT: PSO Iterations: The range of trajectories shows how the PSO algorithm handles complex solution settings delicately. A moving power curve indicates the solution's ongoing change to maximize energy collection. The algorithms' search for the perfect answer is shown by particle positions convergent toward a focal region. PSO efficiently aligns particle locations to converge on the Maximum Power Point, a vital period. The picture depicts how particle movements, power adjustments, and iterative convergence explore, use, and attain the maximum power point.

The performance metrics of the algorithms are illustrated in Figure 8 which presents the power outputs of individual swarms (red dots), showcasing the variation in performance across different iterations. These data points are juxtaposed with the average power output (blue line), which represents the mean performance of the swarms at each iteration step. This mean serves as an indicator of the algorithm's progression towards stabilizing at the maximum power point (MPP). From the visual data, it is apparent that while there is a significant spread in the swarms' performance initially, indicative of exploratory search behavior, the convergence towards the latter iterations is notable. This trend towards convergence demonstrates the algorithm's effectiveness in navigating the solution space and its capability to adapt and optimize even in the dynamically changing conditions imposed by partial shading.

This bar graph (Fig. 9) presents the convergence of error magnitudes across iterations within the first scenario utilizing the particle swarm optimization (PSO) algorithm. The initial iterations show a rapid decrease in error magnitude, indicating a swift approach towards the optimal solution.

After the first few iterations, the reduction in error magnitude becomes more gradual, signifying the algorithm's

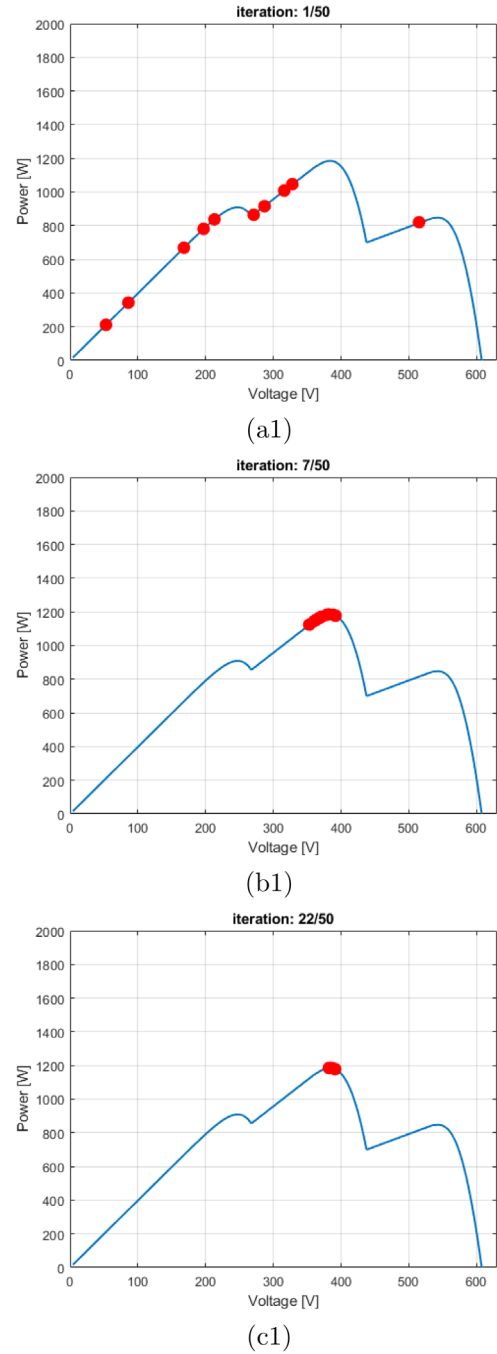


Fig. 7. PSO iterations leading to maximum power point: Scenario 1.

stabilization as it homes in on the optimal parameters. The marked decrease in error from the first to the fifth iteration underscores the PSO algorithm's efficiency in quickly correcting course towards the desired optimization goal. Beyond the fifth iteration, the error magnitude plateaus, suggesting that the algorithm has reached a near-optimal solution and further adjustments result in only marginal improvements.

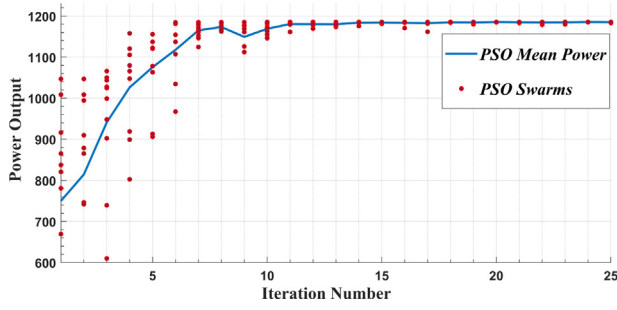


Fig. 8. Convergence behavior of the particle swarm optimization (PSO) algorithm over iterations.

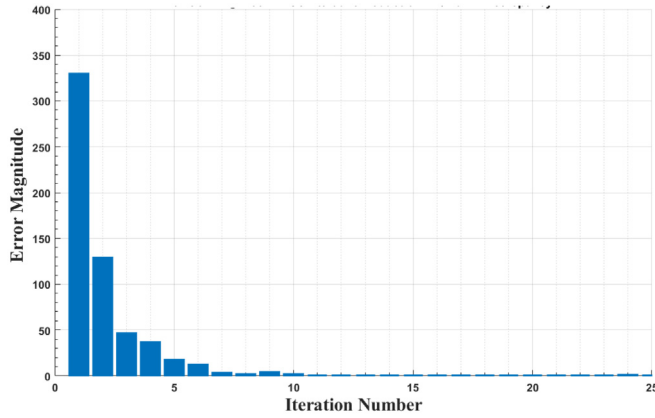


Fig. 9. Error convergence in PSO: iterative reduction in swarm discrepancy.

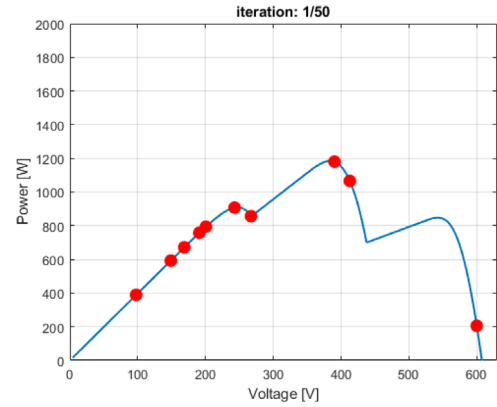
5.2.1.2 Grey wolf optimizer (GWO) results

The results presented below demonstrate the effectiveness of the GWO algorithm in converging to the MPPT.

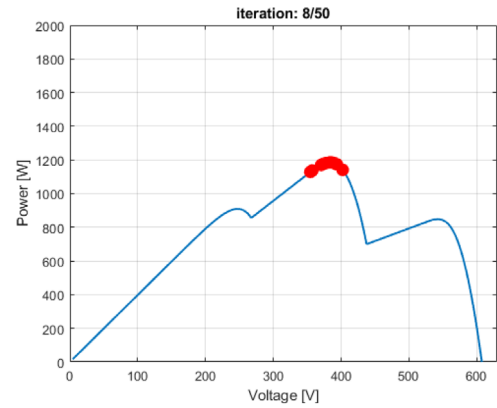
The iterative modifications of the algorithm aim to maximize energy collection, as evidenced by the constantly evolving trajectories. The convergence behavior showcases how the GWO algorithm adapts and optimizes the positions of the wolves to achieve the Maximum Power Point.

Figure 10 shows particle trajectories seeking optimal solutions in the grey wolf optimization (GWO) algorithm. Each unique line depicts a particle's passage through the multidimensional solution space. These trajectories capture the dynamic nature of GWO's exploration and the particles' various methods. The algorithm's iterative modifications maximize energy collection, as shown by the developing trajectories. The convergence of these lines indicates particle harmony as they move toward the maximum power point. This convergence represents GWO's collective intelligence in orchestrating precision modifications for optimal power extraction. The figure graphically depicts GWO's optimization journey, demonstrating the algorithm's skill in directing particles to the best operating position.

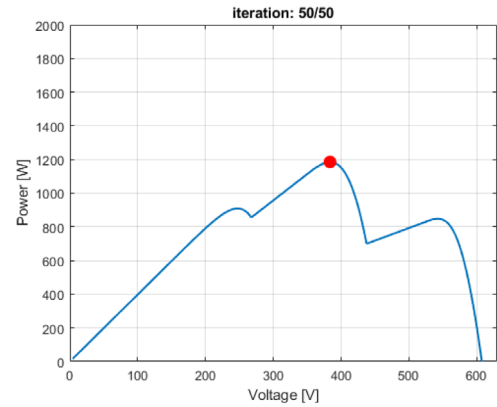
Figure 11 shows the grey wolf optimizer (GWO) algorithm's convergence in power output optimization over 25 rounds. It shows the algorithm's population's mean power output (blue line) and distribution (red dots) at each



(a2)



(b2)



(c2)

Fig. 10. Convergence to MPPT: GWO iterations (Scenario 1).

iteration. After the first few iterations, power output rapidly increases, with a big jump around the 5th iteration, before plateauing near the optimal value after 10 iterations. The scatter of red dots shows the diversity of population solutions, which narrows as the algorithm converges to the most efficient solution, demonstrating excellent search and optimization by the GWO algorithm. After 10 iterations, the mean power output line stabilizes, indicating that the GWO has discovered a near-optimal solution. Further rounds improve the solution, demonstrating the algorithm's speedy convergence in the optimization issue.

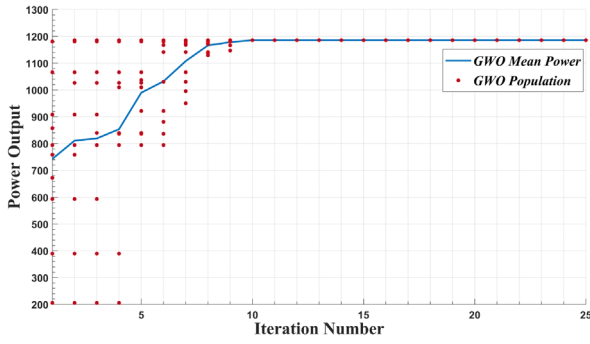


Fig. 11. Convergence pattern of grey wolf optimizer (GWO) in power output optimization.

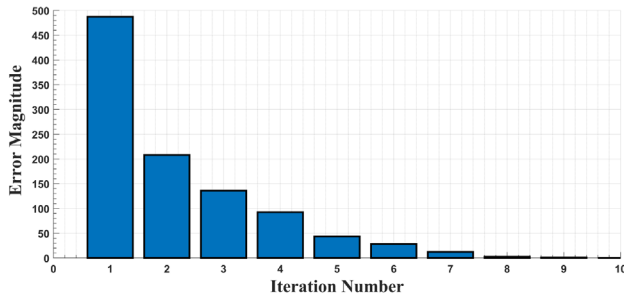


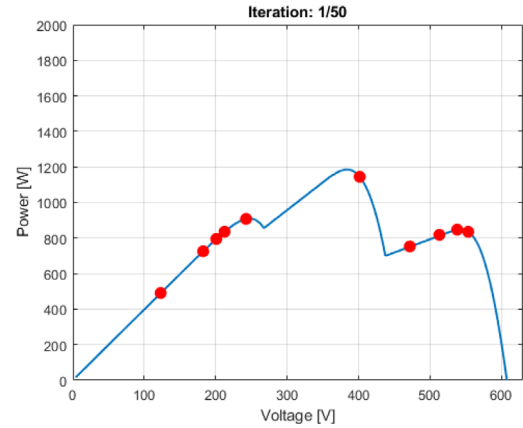
Fig. 12. Error convergence in GWO: iterative reduction in wolf discrepancy.

In assessing the error convergence of the grey wolf optimizer (GWO) algorithm under partial shading conditions, we observed a discernible pattern. As the iterations progressed, the disparity between the power outputs of the wolf pack and the alpha (the best solution) diminished. Initially, a significant fluctuation in error was noted, suggesting a diverse exploration of the solution space by the wolves. However, as the algorithm iterated, the pack converged towards the alpha, indicative of an effective exploitation phase. The convergence pattern affirms the algorithm's capability to adapt and steer towards the optimal solution despite the complex landscape introduced by partial shading on the PV system. This behavior is critical for ensuring that the PV system operates close to its maximum potential, even under sub-optimal conditions (Fig. 12).

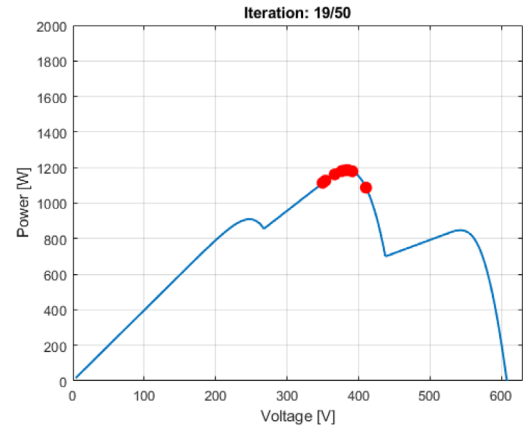
5.2.1.3 Pelican optimization algorithm (POA) results

Before exploring the results of the Pelican optimization algorithm (POA), let's take a moment to understand its functioning. Figure 13 illustrates the evolution of the pelicans' positions across the search space during the iterations of the algorithm. Each point represents the position of a pelican at a specific stage of the optimization. Let's carefully observe these movements to grasp how the POA explores the solution space in search of the optimal point.

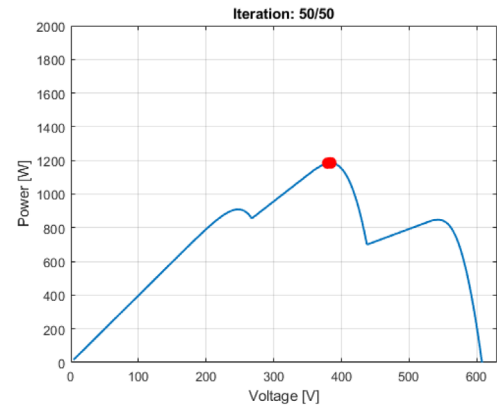
Figure 13 depiction shows particle positions and power dynamics as the optimization process develops, providing a complete view of the Pelican optimization algorithm. Each 'pelican' agent's graph trajectory shows its methodical



(a3)



(b3)



(c3)

Fig. 13. Convergence to the maximum power point: PSO iterations (Scenario 1).

search for the ideal operating point in the solution space. The algorithm's varied trajectories show its precision in complex solution landscapes. The changing power curve reflects the algorithm's continual modification to maximize energy harvest. POA is collaborative, since agents work together to find the best solution. Particle positions converge toward a center location. This image shows how particle movements, power fluctuations, and iterative

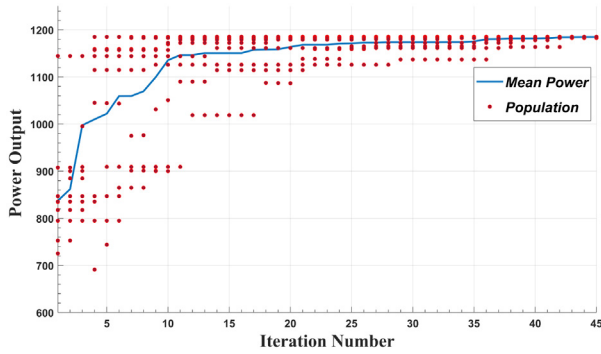


Fig. 14. Convergence trend of algorithm over iterations.

convergence work together to explore, exploit, and converge toward the maximum power point, a crucial optimization goal.

Initially, there is a wide variance in the power output of individual solutions, which narrows as the iterations increase, suggesting the algorithm is homing in on an optimal or more efficient solution (Fig. 14). By the end of the 45 iterations, the individual power outputs are closely clustered around the mean, indicating a stable solution set has been found.

The bars represent the frequency of specific error magnitudes at each iteration (Fig. 15).

- **Initial Iterations (0–5):** High error magnitudes are most frequent at iteration 0, indicating significant errors at the start.
- **Subsequent Iterations (5–10):** Rapid decrease in error magnitudes, showing quick improvement.
- **Later Iterations (10+):** Error magnitudes are much lower and less frequent, indicating stabilization and consistently lower errors.

5.2.2 Comparison and discussion

In this section, we will conduct an in-depth comparative study of three algorithms to evaluate their efficiency and accuracy. The analysis will be based on their performance over a set of iterations, focusing on the evolution of error magnitudes and average outputs. This comparative approach aims to discern the operational strengths and limitations of each algorithm, providing crucial information for choosing the most suitable algorithm for practical applications.

5.2.2.1 Comparison of algorithms (Scenario 1)

In this part, we conduct a detailed side-by-side comparative study of three algorithms: particle swarm optimization (PSO), grey wolf optimizer (GWO), and the Pelican optimization algorithm (POA). Our evaluation criteria include both efficiency and accuracy, which are assessed over a series of iterations. We closely monitor the evolution of error magnitudes, examining how each algorithm's error decreases over time to understand their convergence behavior. Additionally, we analyze the average outputs produced by each algorithm across different iterations to gauge their consistency and reliability.

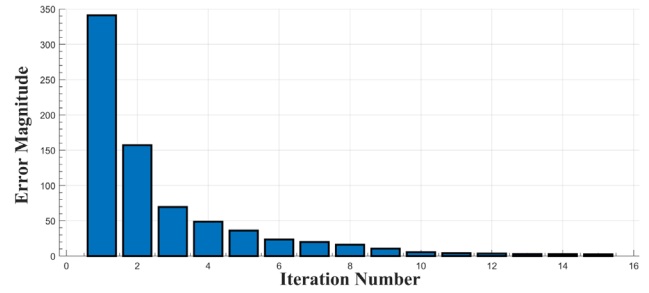


Fig. 15. Frequency of error magnitudes by iteration.

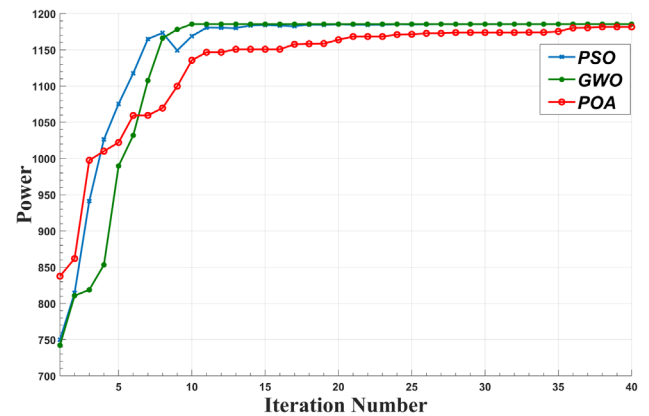


Fig. 16. Power convergence in PSO, GWO and POA algorithms.

This comparative approach is designed to uncover the operational strengths and weaknesses of each algorithm. By systematically comparing their performance under identical conditions, we aim to highlight their respective advantages and potential drawbacks. Such an in-depth analysis provides valuable insights into the practical applicability of each algorithm, assisting in the selection of the most appropriate one for specific real-world scenarios. This study not only elucidates the efficiency and accuracy of the algorithms but also offers a comprehensive understanding of their behavior in varying operational contexts, ultimately guiding the choice of the most suitable optimization technique for practical applications.

The provided graph (Fig. 16) compares the convergence behavior of three optimization algorithms—particle swarm optimization (PSO), grey wolf optimizer (GWO), and pattern search algorithm (POA)—over iterative cycles, with respect to maximizing a power function. Key observations from the graph:

- PSO exhibits a moderate initial increase in performance but quickly reaches near its peak, suggesting it finds a good solution rapidly but may get stuck in local optima.
- GWO starts strong, with a sharp increase in performance, surpassing PSO in the initial phase and continues to improve, ultimately reaching the highest power value, indicating its ability to escape local optima and potentially find a better global solution.

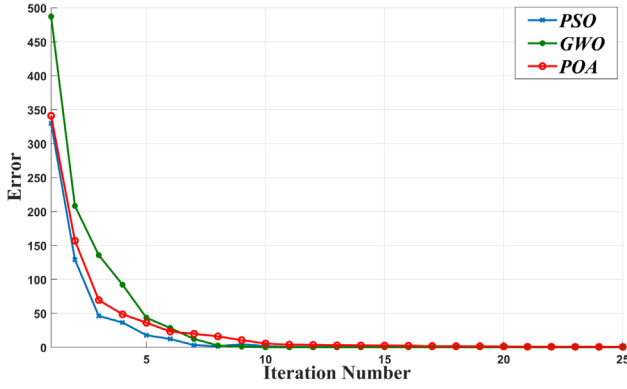


Fig. 17. Comparative error convergence for PSO, GWO, and POA.

– POA has the slowest start and the most gradual improvement, consistently underperforming compared to the other two algorithms across the iterations, which might suggest it is either less suited to the problem or requires more iterations to converge.

In summary, GWO appears to be the most robust in terms of final solution quality, while PSO converges quickly to a good solution, as illustrated in Figure 16. On the other hand, POA seems to be the least effective for this specific task within the given number of iterations. Decision-makers should consider these performance characteristics relative to the requirements of their specific optimization problems when selecting an algorithm.

Figure 17 displays the error reduction patterns of three distinct optimization algorithms over a set of iterations:

- PSO shows a rapid and consistent decrease in error, leading to a quick stabilization, indicating efficient convergence and robust performance.
- GWO demonstrates a similar quick decline in error, closely trailing PSO, suggesting effective optimization capabilities, though slightly less optimal than PSO.
- POA decreases error significantly at the beginning but has a slower rate of convergence compared to PSO and GWO, finishing with a higher final error.

In summary, PSO exhibits the best convergence behavior among the three, followed by GWO, with POA being the least efficient in error minimization over the given number of iterations.

5.2.2.2 Comparison of algorithms (Scenario 2)

Scenario 2: $ir1 = 900 \text{ W/m}^2$, $ir2 = 900 \text{ W/m}^2$, $ir3 = 650 \text{ W/m}^2$, $ir4 = 600 \text{ W/m}^2$.

In this part, the objective is to thoroughly assess the operational strengths and limitations of each algorithm. This evaluation aims to provide a comprehensive understanding of how each algorithm performs under various conditions. By examining factors such as convergence speed, accuracy, computational efficiency, and robustness

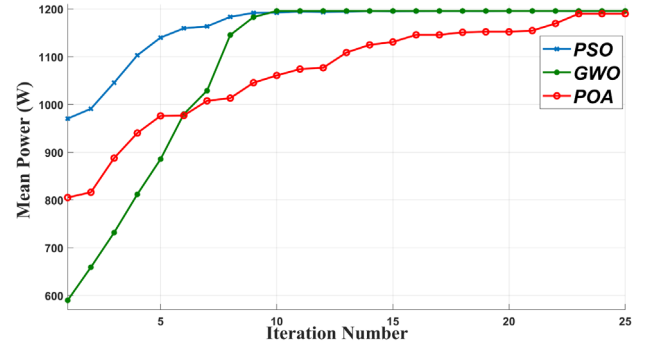


Fig. 18. Comparative error convergence for PSO, GWO, and POA.

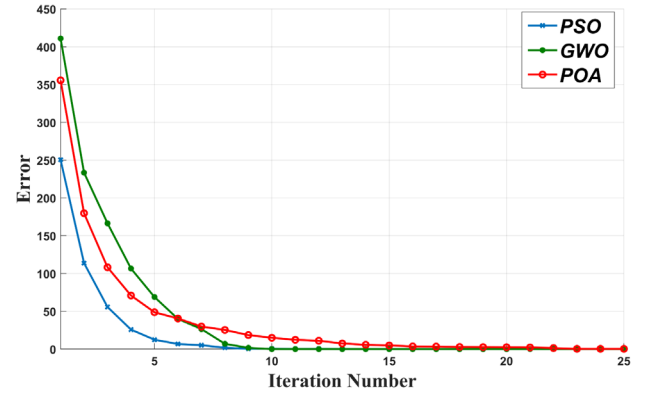


Fig. 19. Error of three different algorithms.

to different types of data and scenarios, we aim to identify the key advantages and potential drawbacks of each approach.

The insights gained from this analysis will be instrumental in guiding the selection of the most suitable algorithm for practical applications, ensuring that the chosen method aligns with the specific requirements and constraints of real-world scenarios.

As illustrated in Figure 18, the mean power output increases over iterations. PSO again appears to lead, reaching a plateau faster than the other two, indicating a quick convergence to a solution with higher mean power output. GWO follows with a slightly more gradual increase and also plateaus, suggesting a stable solution. POA, while starting off at a lower mean power, eventually catches up to a similar value as GWO, albeit over more iterations.

In the error graph (Fig. 19), all three algorithms demonstrate a reduction in error as the number of iterations increases, with PSO showing the quickest reduction in error, followed closely by GWO, while PS has a more gradual decline.

In both cases, the PSO, GWO, and POA algorithms were tested under different irradiance conditions, thus creating realistic partial shading situations in a photovoltaic system. These observations are essential for understanding how each algorithm handles irradiance variations and can guide in choosing the most appropriate algorithm for specific applications.

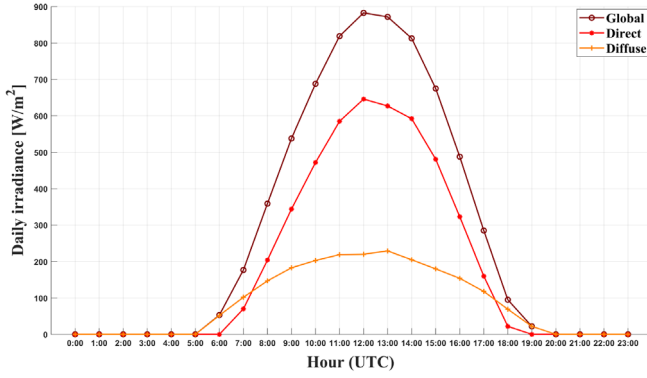


Fig. 20. Daily irradiance profile, inclined plane. (C) PVGIS, 2024.

5.3 Evaluation of power and energy gains

5.3.1 Simulation setup

To evaluate the effectiveness of the proposed algorithms (PSO, GWO, and POA) over extended periods, simulations were conducted over multiple sample days. The performance of each algorithm was compared to a standard reference algorithm, typically the Perturb and Observe (P&O) method.

5.3.2 Power and energy analysis

In this part, we provide a comprehensive analysis of the power output and energy generation capabilities of the algorithms under study. The performance of each algorithm—particle swarm optimization (PSO), grey wolf optimizer (GWO), and the Pelican optimization algorithm (POA)—was meticulously recorded at regular intervals throughout the day. This technique captures variations in power production caused by changing solar irradiation and shading circumstances, which impact photovoltaic (PV) efficiency.

The data captures each algorithm's dynamic response to real-world conditions. As shown in Figure 20, we evaluated the algorithms on a simulated PV system using real-world data from PVGIS-SARAH for the Larache location (Latitude: 35.1932° N, Longitude: −6.1557° W, Altitude: 39 m). PVGIS-SARAH data accurately represents the environment by providing complete information on solar irradiance, temperature, and other meteorological parameters for simulations.

Table 4 provides the Global, Direct, and Diffuse irradiance values used for the simulation.

Table 4 presents the solar irradiance data extracted from the daily radiation profile, providing context for the irradiance patterns and the corresponding power output variations.

The PVGIS-SARAH data was used to evaluate the algorithms under realistic solar irradiance conditions. Hourly power output was recorded from 6 a.m. to 7 p.m., providing a comprehensive view of each algorithm's effectiveness in tracking the Maximum Power Point

Table 4. Solar Irradiance Data at Larache (Lat. 35.1932° N, Long. −6.1557° W, Alt. 39 m) based on PVGIS.

Time (UTC)	Global irradiance $G(i)$ (W/m ²)	Direct irradiance $G_b(i)$ (W/m ²)	Diffuse irradiance $G_d(i)$ (W/m ²)
0:00	0	0	0
1:00	0	0	0
2:00	0	0	0
3:00	0	0	0
4:00	0	0	0
5:00	0	0	0
6:00	53	0	52
7:00	177	70	102
8:00	359	204	147
9:00	538	344	183
10:00	688	472	203
11:00	819	585	219
12:00	883	646	220
13:00	872	627	229
14:00	813	592	205
15:00	675	481	180
16:00	488	323	154
17:00	285	160	118
18:00	95	22	69
19:00	22	0	22
20:00	0	0	0
21:00	0	0	0
22:00	0	0	0
23:00	0	0	0

(MPP). The total energy generated by each algorithm was calculated by integrating the power output over time. Our analysis compared:

- Daily power output variations.
- Total energy generation.
- Performance under partial shading and varying irradiance.

These results highlight the strengths and limitations of each algorithm, helping to determine the most suitable one for optimizing energy harvesting and efficiency in PV systems.

5.3.3 Results

As illustrated in Figure 21, the daily power output profiles for the different algorithms are compared. It can be observed that the proposed algorithms (PSO, GWO, and POA) consistently tracked the maximum power point (MPP) more effectively than the reference P&O algorithm. This superior performance is particularly noticeable during periods of partial shading, resulting in higher power outputs. $ir1 = 100\%$, $ir2 = 80\%$, $ir3 = 50\%$, $ir4 = 50\%$.

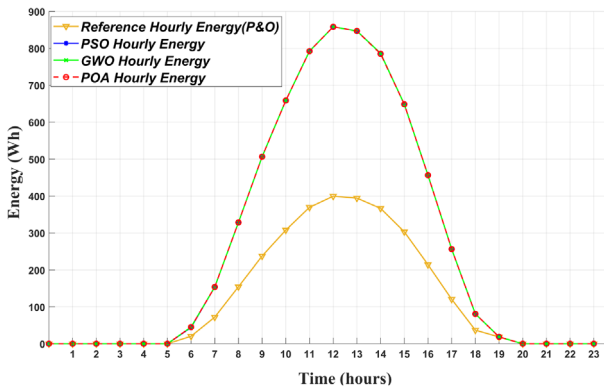


Fig. 21. Daily power output profiles of different algorithms.

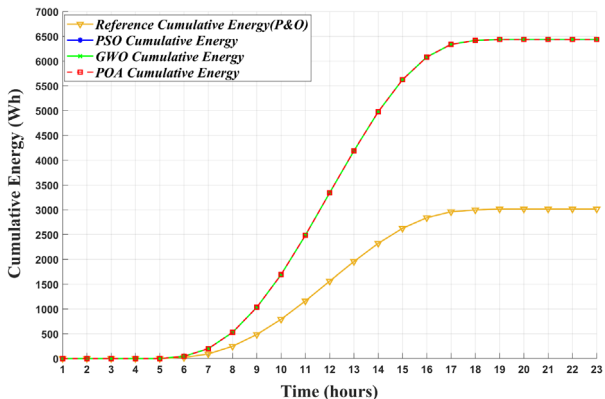


Fig. 22. Cumulative energy generation for different algorithms.

Table 5. Detailed comparison of hourly and cumulative energy outputs.

Time	Hourly energy (Wh)				Cumulative energy (Wh)				% Increase over P&O		
	P&O	POA	PSO	GWO	P&O	POA	PSO	GWO	POA	PSO	GWO
0:00	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
1:00	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
2:00	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
3:00	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
4:00	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
5:00	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
6:00	20.41	45.21	44.30	45.21	20.41	45.21	44.30	45.21	121.54	117.15	121.54
7:00	72.22	153.94	153.94	153.94	92.63	199.15	198.24	199.15	115.02	114.07	115.02
8:00	154.54	328.49	328.53	328.53	247.17	527.64	526.77	527.68	113.50	113.19	113.52
9:00	237.60	506.78	506.79	506.79	484.77	1034.42	1033.56	1034.46	113.52	113.31	113.51
10:00	307.90	658.68	658.70	658.70	792.66	1693.11	1692.26	1693.15	113.61	113.56	113.61
11:00	369.56	792.50	792.63	792.50	1162.22	2485.61	2484.89	2485.77	113.89	113.68	113.88
12:00	399.71	858.35	858.37	858.35	1561.93	3343.96	3343.26	3344.14	114.14	114.07	114.12
13:00	394.53	847.05	847.06	847.05	1956.46	4191.01	4190.32	4191.20	114.27	114.21	114.26
14:00	366.73	785.14	786.48	785.14	2323.19	4976.15	4976.80	4977.67	114.19	114.22	114.20
15:00	303.21	648.49	648.51	648.49	2626.40	5624.64	5625.31	5626.18	114.12	114.13	114.13
16:00	214.26	456.60	456.61	456.60	2840.66	6081.24	6081.92	6082.78	114.07	114.03	114.04
17:00	120.69	256.26	256.27	256.26	2961.35	6337.50	6338.19	6339.05	114.03	114.01	114.01
18:00	36.90	80.94	81.03	80.94	2998.25	6418.44	6419.22	6420.08	114.05	114.06	114.07
19:00	18.48	18.77	18.77	18.77	3016.73	6437.21	6437.99	6438.85	113.98	113.98	113.99
20:00	0.00	0.00	0.00	0.00	3016.73	6437.21	6437.99	6438.85	0.00	0.00	0.00
21:00	0.00	0.00	0.00	0.00	3016.73	6437.21	6437.99	6438.85	0.00	0.00	0.00
22:00	0.00	0.00	0.00	0.00	3016.73	6437.21	6437.99	6438.85	0.00	0.00	0.00
23:00	0.00	0.00	0.00	0.00	3016.73	6437.21	6437.99	6438.85	0.00	0.00	0.00

The analysis of hourly energy production in Figure 21 shows that the three algorithms outperform the standard P&O algorithm.

As shown in Figure 22, the cumulative energy generation profiles for the GWO, PSO, and POA algorithms are nearly identical, indicating minimal differences in their energy harvesting efficiency. This suggests that all three algorithms perform at a similarly high level.

Using the analysis from Figure 22, we provide a comparison in Table 5, which presents the total energy generated by each algorithm over the sample days. The results indicate that the GWO algorithm yielded the highest energy gain, followed by PSO and POA, with all three significantly outperforming the P&O algorithm.

Table 6 presents a performance comparison of different algorithms in terms of average cumulative energy

Table 6. Performance comparison of algorithms.

Algorithm	Average cumulative energy (Wh)	% Gain over P&O
P&O (<i>Reference</i>)	3016.73	—
POA	6437.20	113.40%
PSO	6437.98	113.41%
GWO	6438.85	113.42%

generated (in Wh) and the percentage gain over the P&O algorithm.

The table shows that:

- The **P&O** algorithm, used as the reference, generated an average cumulative energy of 3016.73 Wh.
- The **POA** algorithm generated significantly more energy, with an average cumulative energy of 6437.20 Wh, achieving a 113.40% gain over the P&O algorithm.
- The **PSO** algorithm also outperformed the reference, with an average cumulative energy of 6437.98 Wh and a 113.41% gain over the P&O algorithm.
- The **GWO** algorithm demonstrated the highest performance, generating 6438.85 Wh, which translates to a 113.42% gain over the P&O algorithm.

These results indicate that all three advanced algorithms (POA, PSO, and GWO) significantly outperform the traditional P&O algorithm, with GWO achieving the highest energy gain, followed closely by PSO and POA.

6 Conclusion

In this article, we embarked on an exploration of advanced optimization algorithms for the critical task of maximum power point tracking (MPPT) in photovoltaic systems. Our journey encompassed the study and comparison of three prominent algorithms: grey wolf optimization (GWO), particle swarm optimization (PSO), and Pelican optimization algorithm (POA). Through a comprehensive analysis of their behaviors under varying conditions, we have gleaned valuable insights into their potential applications and strengths within the realm of renewable energy.

Our investigation began with an in-depth understanding of the MPPT challenge, recognizing the significance of extracting maximum power from photovoltaic systems under fluctuating solar conditions. We delved into the intricacies of the partial shading phenomenon, a common obstacle in harnessing solar energy efficiently. Our examination highlighted the critical need for adaptive and swift optimization techniques to address these challenges.

The heart of our study lay in the simulation results, where we meticulously assessed the performance of GWO, PSO, and POA. The visual representations of particle trajectories, power fluctuations, and iterative convergence offered an engaging narrative of their optimization journeys. Notably, GWO emerged as a standout contender, showcasing rapid convergence and adaptability that

position it as a promising solution for real-time MPPT in dynamic environments.

GWO's rapid convergence can be attributed to its effective balance between exploration and exploitation, mimicking the social hierarchy and hunting behavior of grey wolves. This algorithm's ability to dynamically adjust the search path helps in quickly zeroing in on the global maximum power point (MPP) even under complex partial shading conditions.

While PSO and POA exhibited commendable performances, GWO's hunting-inspired approach demonstrated exceptional prowess in swiftly navigating intricate solution spaces, even in the face of partial shading challenges. However, there is room for improvement. Future work could explore hybridizing GWO with other optimization techniques to enhance its robustness and convergence speed further. Additionally, adaptive parameter tuning and real-time implementation on hardware setups could be investigated to improve practical applicability and efficiency.

In summary, the comparison illuminated the multifaceted nature of optimization algorithms, each with its unique strategies and strengths. GWO, with its rapid convergence and adaptability, holds significant promise for real-time MPPT in dynamic environments, offering a robust solution to the challenges posed by partial shading in photovoltaic systems.

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Conflicts of interest

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Data availability statement

This article has no associated data generated and/or analyzed.

Author contribution statement

Conceptualization, Y.M. and Y.L.; Methodology, Y.M.; Software, Y.M.; Validation, Y.M., Y.L.; Formal Analysis, Y.M.; Investigation, Y.M.; Resources, Y.M.; Data Curation, Y.M.; Writing – Original Draft Preparation, Y.M.; Writing – Review & Editing, Y.L.; Visualization, Y.M.; Supervision, Y.L.; Project Administration, Y.L.

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