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Optimizing Grey Wolf Optimization (GWO) For MPPT: Strategic Initial Value Selection And Search Space Narrowing

Moustafa Sahnoune Chaouche[1], Faouzi Didi[1], Malika Amari[1], Zakaria Triki[1], Rachid Sahnoune Chaouche[2], Abdelhamid Chellali[1]

[1]*Laboratory of Renewable Energy and Materials (LREM), Department of Electrical Engineering, Faculty of Technology University Yahia Fares of Medea, 26.000, Algeria*
[2]*Research Laboratory of Electrical Engineering and Automatic LREA University of Medea, Medea, Algeria*
E-mail : moustafa-chaouche@hotmail.fr

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The aim of this paper is to develop a Maximum Power Point Tracker (MPPT). Growing population, industrial expansion, and other factors have led to a continuous rise in power demand. In photovoltaic (PV) systems, an effective MPPT is essential for enhancing the efficiency of solar cells. Various methods have been proposed for MPPT generation from PV modules under different weather conditions. This work introduces the Grey Wolf Optimizer (GWO) algorithm, incorporating a strategic initial value selection and search space narrowing (SIVS-SSN) to create an innovative approach for maximum power point tracking. The simulation results demonstrate that the proposed approach enables the maximum power tracker to accurately and effectively track the maximum power. The performance of the GWO based SIVS-SSN was specifically evaluated in this context.

Keywords: Solar Energy, Grey Wolf Optimizer, Maximum power point tracking MPPT, Photovoltaic system, reducing search space.

1. Introduction

Photovoltaic modules are influenced by external environmental factors, including irradiance, module temperature, and outdoor humidity, which affect their performance. Direct MPPT techniques measure PV voltage and current in real-time, whereas indirect MPPT techniques analyze PV system performance offline. The direct technique has been implemented using a fuzzy logic controller to effectively track the maximum power point (MPP) of a PV system [1]. The maximum power point (MPP) of a photovoltaic (PV) array is a crucial element of a PV system. The rising demand for electricity, coupled with recent environmental changes like global warming, has created a need for a new energy source that is more affordable, sustainable, and produces lower carbon emissions. In this context, solar energy has emerged as a promising solution [2], [3]. Significant research has been conducted to enhance the efficiency of PV modules. Various methods for tracking the maximum power point of PV modules have been developed to address efficiency challenges, leading to the creation of commercially available products based on these techniques [3]. An MPPT is employed to extract the maximum power from the solar PV module and deliver it to the load. However, Optimization algorithms (such as the bat algorithm [4], particle swarm optimization [5] and [6], and P&O [7], …etc.) have gained significant prominence in renewable energy, becoming the preferred solution for estimating the maximum power output of solar panels under varying factors that affect their performance. Therefore, researchers have sought to enhance the behavior of these algorithms to achieve the optimal solution in the shortest possible time. The authors in [4] proposed a modified bat algorithm with a reduced search space for Maximum Power Point Tracking (MPPT) under dynamic partial shading conditions to address this challenge. L. Pervez et al. [8] also proposed a promising strategy to limit the search space of metaheuristic algorithms in order to achieve the optimal solution. In this work, a reducing strategy has been proposed to restrict the search space by extracting all maximum of MPPT to narrow down the optimal value within a tight range, thereby avoiding reliance on the random methods typically used in algorithms.

2. MPPT and Grey Wolf Optimizer outline

2.1. MPPT background

Maximum Power Point Tracking (MPPT) is a critical technology used in photovoltaic (PV) systems to optimize the power output from solar panels. Due to the nonlinear behavior of PV modules, the power generated varies with environmental conditions such as temperature and solar irradiance. MPPT techniques ensure that solar energy systems operate at their maximum power point (MPP), enhancing overall efficiency and performance. PV modules exhibit a nonlinear current-voltage (I-V) relationship. The MPP is the point at which the product of current and voltage is maximized. This varies throughout the day and under changing weather conditions. Solar irradiance and temperature can fluctuate due to clouds, shading, and time of day, leading to frequent changes in the MPP. An effective MPPT algorithm must respond quickly to these variations to maintain optimal performance. By utilizing MPPT techniques, PV systems can increase their energy yield significantly compared to systems without MPPT. Perturb and Observe (P&O is one of the simplest and most widely used methods. It involves perturbing the operating voltage and observing the resulting change in power to determine the direction of adjustment towards the MPP. Incremental Conductance (IncCond) [9] calculates the derivative of the power with respect to voltage and uses this information to find the MPP. It is more effective than P&O under rapidly changing conditions. Advanced Metaheuristic algorithms like Genetic Algorithms [10], Particle Swarm Optimization [5], [6], and the Grey Wolf Optimizer [11], [12] have been proposed for MPPT to improve performance under any operating conditions. Fuzzy Logic Control technique uses fuzzy logic principles to adjust the operating point based on imprecise inputs, providing robust performance in varying conditions [3]. Despite the advantages of MPPT, several challenges remain, including; partial Shading, when some solar cells are shaded, it can lead to multiple MPPs, complicating the tracking process and complexity where some MPPT algorithms may require more computational resources, which can be a limitation for smaller systems.

2.2. Overview of GWO

The Grey Wolf Optimization (GWO) algorithm is a nature-inspired optimization method that mimics the social hierarchy and hunting strategy of grey wolves in nature. Introduced by Mirjalili et al. (2014) [13], GWO is especially effective for solving optimization problems in complex, multimodal landscapes. It simulates the leadership hierarchy and hunting mechanism, using alpha, beta, delta, and omega wolves to search for the optimal solution.

❖ Social Hierarchy

In GWO, the population of wolves is divided into four ranks:

- **Alpha (α)**: The leader, representing the best solution found so far.
- **Beta (β)**: The second-best solution, assisting the alpha in leadership.
- **Delta (δ)**: The third best solution, subordinate to alpha and beta.
- **Omega (ω)**: All remaining wolves that follow the other three and explore the search space.

❖ Mathematical Modeling of Hunting Behavior

GWO mathematically models the wolves' hunting process by updating the positions of omega wolves based on alpha, beta, and delta wolves' positions. The following equations govern the wolves' movements:

✓ **Distance Calculation**: The wolves calculate their distance from the prey (best solution) using:

$$\vec{D} = \left|\vec{C}.\vec{X}_p - \vec{X}\right|$$

Where ;

- $\vec{X}_p$ is the position of the prey (solution found by alpha, beta, or delta),
- $\vec{X}$ is the position of a given wolf,
- $\vec{C}$ is a coefficient vector: $\vec{C} = 2.\vec{r}_2$, where $\vec{r}_2$ is a random vector in [0, 1].

✓ **Position Update**: Each wolf updates its position according to alpha, beta, and delta wolves' positions:

$\vec{X}_1 = \vec{X}_\alpha - \vec{A}_1.\vec{D}_\alpha$

$$\vec{X}_2 = \vec{X}_\beta - \vec{A}_2.\vec{D}_\beta$$

$$\vec{X}_3 = \vec{X}_\delta - \vec{A}_3 . \vec{D}_\delta$$

$$\vec{X} = \frac{\vec{X}_1 + \vec{X}_2 + \vec{X}_3}{3}$$

where:

- $\vec{A}$ is a control coefficient: $\vec{X} = 2. a. \vec{r}_1 - a$,
- a decreases linearly from 2 to 0 over the course of iterations to balance exploration and exploitation.

✓ **Parameter** a:

$$a = 2 - \frac{2. \text{current\_iterration}}{\text{Max\_iterrations}}$$

This parameter gradually reduces, which reduces the wolves' movement range as the algorithm progresses, focusing the search on local areas near the best solutions.

The pseudo code as in Fig. 1 summarized the steps of the GWO algorithm.

Initialize the population of wolves randomly (positions of alpha, beta, delta, and omega)
Initialize a, A, and C

while (stopping criterion not met)
for each wolf (position Xi)
Calculate the fitness of each wolf
Update alpha, beta, and delta (best three solutions found so far)

for each wolf
Update coefficient vectors A and C
Calculate distances D_alpha, D_beta, and D_delta
Update the position Xi according to alpha, beta, and delta

Update the parameter a (decrease linearly)

return alpha (best solution found)

Fig.1. Pseudo code of the GWO algorithm [13]

3. Approach and methodology

Like many algorithms, Grey Wolf Optimization (GWO) often faces challenges in balancing between rapid tracking and precise detection of the maximum power point. Fast-tracking methods can quickly adapt to environmental changes, such as light intensity, but may cause the algorithm to oscillate around the MPP, reducing overall efficiency. In contrast, slower algorithms tend to be more accurate but have delayed responses. Under partial shading conditions, the presence of multiple local maxima in the power-voltage (P-V) curve can lead the algorithm to incorrectly identify a local maximum instead of the global one. Additionally, rapid shifts in environmental factors, such as sunlight and temperature, make it difficult for algorithms like GWO to consistently and accurately track the MPP. As a result, this work aims to extract all potential maxima to isolate the optimal maximum while narrowing the algorithm's search space, ensuring a more precise and efficient search for the best solution.

❖ Initial value and search space in Metaheuristic Algorithms

Metaheuristic algorithms can be highly sensitive to the choice of initial values or starting points. Poorly chosen initial values can lead the algorithm to suboptimal regions of the search space, increasing the likelihood of convergence to local optima. If the initial value is far from the global optimum, the algorithm may waste time exploring unproductive areas, or it might get stuck in local optima early on. This leads to inefficient searches and longer convergence times. The using of very large or high-dimensional search spaces making it difficult for metaheuristic algorithms to explore efficiently. A vast search space increases the computational burden and the time required to find optimal solutions. The algorithm might explore unproductive regions, resulting in slow convergence or failure to find the global optimum. As a result, the proposed strategy refines initial values based on pre-processing, which can help select better initial points. Furthermore, a dimensionality reduction technique to narrow the search space focused the algorithm on tight search region. The summarized procedure of SIVS-SSN is depicted in Fig.2.

Initial Value Selection.

$$If\ P(k) > P(k+1)$$
$$Find\ the\ initial\ Max\ of\ the\ output\ power$$
$$Find\ the\ initial\ position\ of\ wolves\ (int\_pos\_wolves)$$
$$end$$
$$If\ P(k) < P(k+1)$$
$$Find\ the\ initial\ Min\ of\ the\ output\ power$$
$$Find\ its\ position$$
$$end$$
$$Find\ all\ the\ possible\ maxima\ of\ the\ output\ power$$
$$Extract\ the\ best\ Max\ and\ its\ init\_pos\_best_{wolves}$$

Search Space Narrowing

Put $lb < init\_pos\_best_{wolves} < ub$

With $lb = \frac{1}{\tau}.\, init\_pos\_best_{wolves}$

$ub = \tau.\, init\_pos\_best_{wolves}$

$Where\ the\ value\ of\ \tau\ can\ be\ selected\ as \tau \gtrsim 1$

Fig.2. The strategic initial value selection and search space narrowing (SIVS-SSN)

4. Results and discussion

The Grey Wolf Optimization (GWO) algorithm was employed for the MPPT task across different simulated environmental conditions, including standard irradiance and partial shading scenarios. Key performance metrics, such as accuracy in identifying the maximum power point, tracking speed, and stability near the MPP, were evaluated. The GWO-based MPPT reliably converged to the maximum power point with high precision in most cases, particularly under stable irradiance conditions. In dynamic environments, the algorithm adapted swiftly to changes in irradiance and temperature, minimizing power loss more effectively than conventional approaches.

4.1. Performance of GWO for MPPT Under Different Irradiance Conditions

In this study, the Grey Wolf Optimizer (GWO) was applied for tracking the Maximum Power Point (MPP) of a photovoltaic (PV) system under varying irradiance conditions. The focus was on improving GWO by:

- **Strategically selecting the initial values** for the optimization process.
- **Narrowing the search space** to enhance convergence speed and accuracy.

To evaluate the performance of the modified GWO, synthetic data for different irradiance levels (1000 W/m², 800 W/m², and 600 W/m²) were generated, and the corresponding power-voltage (P-V) curves were analyzed. The effectiveness of the proposed modifications was compared to a standard GWO implementation.

4.2. Effect of Initial Value Selection and Search Space Narrowing on Convergence

The initial selection of the wolves (agents) in GWO plays a crucial role in the algorithm's ability to converge to the true MPP efficiently. By choosing initial values closer to the expected MPP based on prior knowledge of the system, the optimization process can avoid unnecessary exploration in irrelevant regions of the search space. Additionally, narrowing the search space dynamically during the optimization process ensures that the wolves focus their search around the region where the MPP is likely to be located.

The accuracy of the MPP tracking was also improved with the new strategy. Table 1 shows the maximum power tracked for each irradiance level. The modified GWO was able to achieve near-optimal power outputs across all conditions:

Table.1. The maximum power tracked for each irradiance level

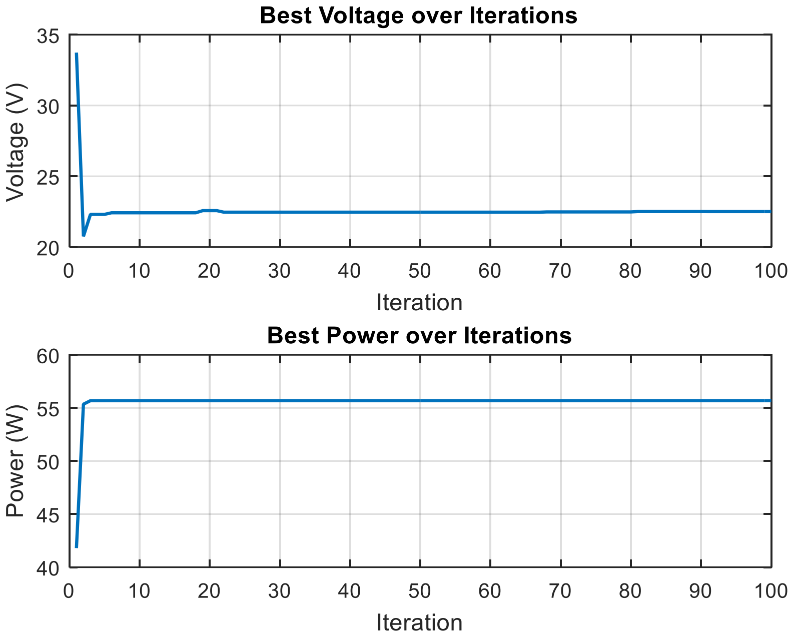
	Irradiance level (W/m^2)		
Algorithms	1000	800	600
	Power (W)	Power (W)	Power (W)
GWO	177.5	142.2	106.5
MGWO	179.9	143.85	107.8

- At 1000 W/m^2, the tracked power was 179.9 W (the true maximum was 180 W).
- At 800 W/m^2, the tracked power was 143.85 W (true maximum was 144 W).
- At 600 W/m^2, the tracked power was 107.8 W (true maximum was 108 W).

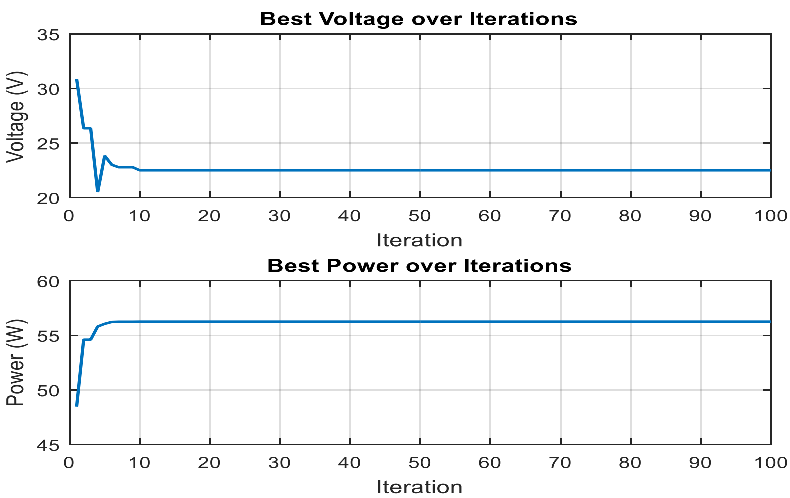
This demonstrates that the narrowing of the search space helped eliminate unnecessary oscillations around the MPP, allowing for more precise tracking. In contrast, the standard GWO showed minor oscillations around the MPP, leading to small power losses due to the slower convergence.

4.3. GWO Performance Under Partial Shading Conditions

The modified GWO was also tested under partial shading conditions, where the P-V curve exhibits multiple local maxima. Figure 3 illustrates the P-V curve under partial shading, showing multiple local maxima and the true global MPP. The standard GWO sometimes converged to a local maximum due to its broad search space and random initialization. However, the modified GWO, with its focused search space and strategic initial values, was consistently able to locate the global MPP. Fig. 3 shows the number of iterations required to track the MPP for both the standard and modified GWO.



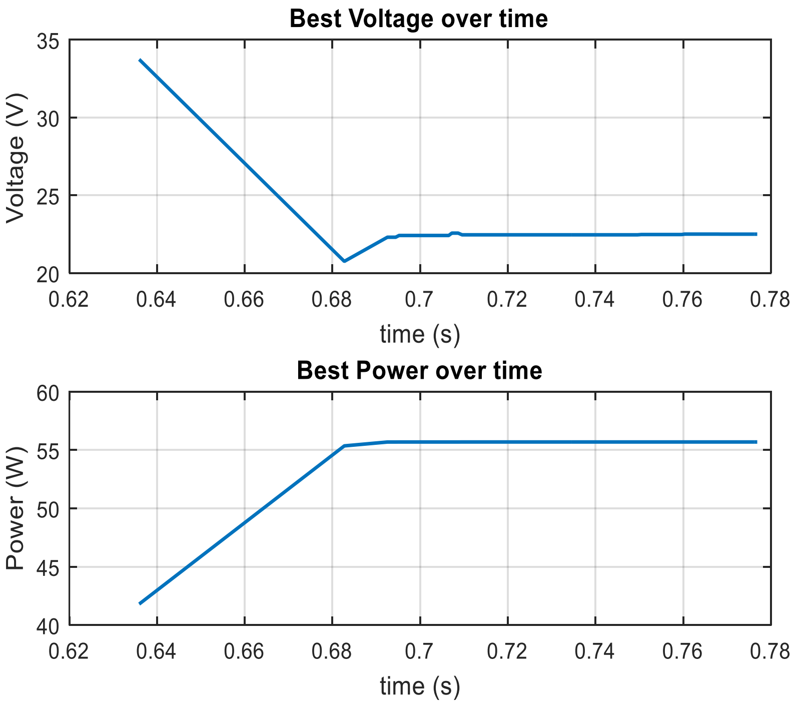
(a)



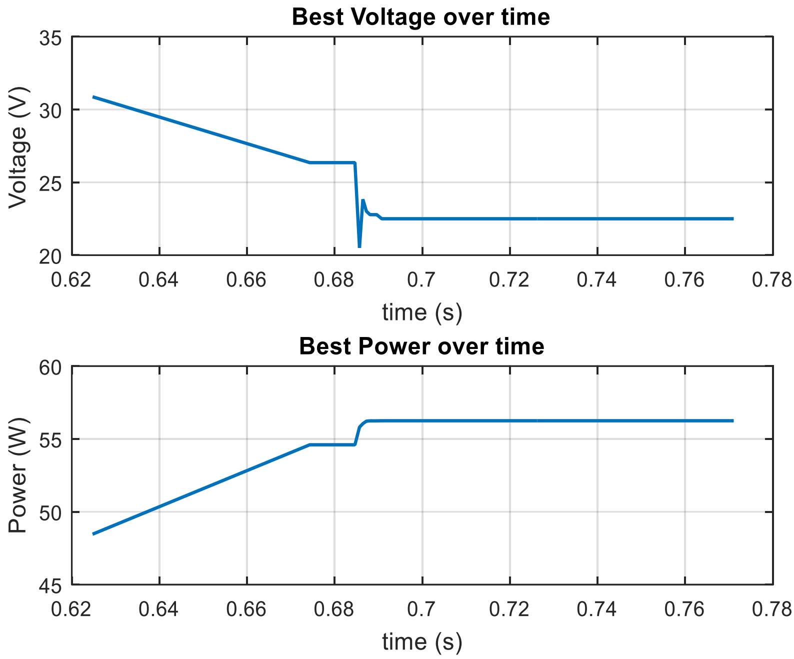
(b)

Figure.3. Iterations required to converge to the MPP: (a) GWO, (b) MGWO

Under partial shading, the modified GWO (MGWO) successfully tracked the global MPP at 56.25 W, while the standard GWO occasionally converged to local maxima, resulting in power outputs between 55 W and 56 W. This demonstrates the robustness of the proposed modifications in handling complex scenarios like partial shading, where local maxima can easily confuse traditional optimization algorithms. The results showed a significant improvement in the convergence speed when the initial values were strategically chosen, and the search space was dynamically narrowed. At an irradiance level of 1000 W/m², the modified GWO converged to the MPP in 10 iterations, compared to 20 iterations for the standard GWO. This improvement can be attributed to the fact that narrowing the search space prevents the optimizer from exploring areas of the power-voltage (P-V) curve where no valid MPP exists, thus speeding up the process. Fig. 4 shows the time required to track the MPP for both the standard and modified GWO. The maximum power tracked using GWO and modified GWO has been compared in term of convergence speed and accuracy as shown in table 2.



(a)



(b)

Figure.4. Time required to converge to the MPP: (a) GWO, (b) MGWO

Table.2. The maximum power tracked using GWO and MGWO

Algorithms	Power (W)	Time (s)	Iterations
GWO	55,6875	0,7100	20
MGWO	56,2500	0,6850	10

The results clearly show that the combination of strategic initial value selection and search space narrowing significantly enhances the performance of GWO for MPPT in photovoltaic systems. Key advantages of the proposed approach include:

- **Improved Convergence Speed**: The reduction in the number of iterations required to find the MPP means faster adaptation to changing environmental conditions, such as fluctuating irradiance or shading.
- **Higher Tracking Accuracy**: By narrowing the search space and focusing the exploration around the expected MPP region, the algorithm was able to track the optimal power point more precisely, reducing power losses due to oscillations.

- **Robustness Under Partial Shading**: The modified GWO was able to avoid local maxima under partial shading, a common challenge in solar energy harvesting, thus improving overall system efficiency.

The results suggest that this modified GWO approach is highly suitable for real-world applications, where fast and accurate MPPT is essential for maximizing the efficiency of solar energy systems.

5. Conclusion

In conclusion, the use of a modified GWO algorithm with strategic initial value selection and search space narrowing significantly improves the performance of MPPT in photovoltaic systems. The results from synthetic data demonstrate that the proposed method achieves faster convergence, more accurate power tracking, and greater robustness in complex conditions like partial shading. Future work could explore the integration of temperature effects and other real-world factors to further enhance the algorithm's performance in dynamic environments.

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