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Research Article

MPPT command enhancement based on an ameliorated grey wolf optimization algorithm for a standalone PV system

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Abstract
Photovoltaic (PV) energy is a widely adopted renewable energy source renowned for its abundance, non-polluting attributes, and minimal maintenance requirements. Despite these benefits, it remains one of the least efficient methods for converting sunlight to electricity. Moreover, PV cell efficiency substantially declines when they operate away from their maximum power point (MPP), which shifts based on varying environmental factors. Numerous strategies have been employed to track the MPP effectively. This research aims to enhance PV systems, especially those embedded in electric vehicles and satellites, by developing and refining a maximum power point tracking (MPPT) algorithm using the grey wolf optimization (GWO) method. This approach is designed to minimize oscillations around the global maximum power point tracker (GMPP) and reduce tracking time. The proposed technique has been corroborated through MATLAB/Simulink simulations. Results demonstrate that the advanced MPPT method significantly improves GMPP tracking by notably decreasing tracking time and diminishing power oscillations, thereby increasing the energy harnessed from mobile PV systems. This study markedly contributes to the enhancement of photovoltaic system efficiency and its more effective integration into portable devices.

Keywords
Photovoltaic (PV), Solar energy, Global maximum power point tracker (GMPPT), Maximum power point tracker (MPPT), Grey wolf optimization (GWO), Partial shading.

1.Introduction
Photovoltaic (PV) systems represent a promising renewable energy technology with the potential to decrease greenhouse gas emissions and mitigate climate change impacts. These systems produce electrical energy by converting solar irradiance. However, despite significant technological advancements, the conversion efficiency of these electrical generators remains relatively low, even under optimal environmental conditions [1–3]. Extensive research has been conducted to minimize losses across all components of PV systems. Despite these efforts, limitations in harnessing available power persist, primarily due to environmental conditions, inverter efficiency, and the algorithms that control the direct current to direct current (DC-DC) converters tasked with tracking the maximum power point (MPP) of the system. [4]. The non-linear and dynamic nature of the power-voltage characteristic in PV systems requires sophisticated maximum power point tracking (MPPT) algorithms.

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These algorithms vary based on factors like cost, efficiency, response time, required information, and the ability to track the global maximum power point (GMPP) during partial shading or rapidly changing environmental conditions, as well as the complexity of implementation. Traditional methods, such as Perturb and Observe (P&O), face limitations in convergence speed, oscillations around the MPP, and accuracy, especially when environmental conditions fluctuate [5, 6].

The current research paper is motivated by the inefficiencies and challenges identified in the existing literature. While various MPPT algorithms have been proposed, they differ significantly in terms of their efficiency, convergence time, complexity, and adaptability to changing environmental conditions. Most notably, they struggle with oscillations and prolonged time to converge to the GMPP, especially in scenarios like partial shading [7]. While the grey wolf optimization (GWO) algorithm demonstrates a promising exploratory nature and quick convergence capabilities, it is susceptible to persistent oscillations around the GMPP, affecting its practical application [8]. The goal of this research is to provide an improved GWO algorithm-based MPPT command that minimizes oscillations around the GMPP and shortens the tracking time needed to reach the GMPP compared to utilizing the traditional GWO method alone [9], since the generated duty cycle oscillates around the desired point even after reaching the maximum power because the aspect of this algorithm resides in the effect of deviation of the MPP to explore large possibilities when searching for other local optimums better than the current position [10]. The key contributions of this study lie in the introduction of the ameliorated GWO-based MPPT algorithm, specifically tailored to tackle partial shading effects, increase power extraction, and significantly reduce oscillations and convergence time to reach the GMPP.

This research paper is structured as follows: Section 1 provides an introduction, including the background and challenges associated with PV systems, the motivation for this research, and the objectives. Section 2 offers a literature review of PV systems and MPPT algorithms. Section 3 discusses the proposed GWO-based MPPT algorithm and its improvements over traditional GWO. Section 4 presents the simulation results, while Section 5 explores into discussions. Finally, Section 6 concludes the paper and discusses prospects of this research.

2.Literature review

PV systems play a fundamental role in harnessing solar energy for electricity generation, providing a sustainable and environmentally friendly power source. Comprised primarily of PV panels assembled to form a PV field, these systems generate electricity directly from sunlight. However, as the system is operational only during daylight hours, batteries are incorporated to store excess energy, ensuring a consistent power supply even in the absence of sunlight. To prevent overcharging and deep discharging of the batteries, a charge regulator is employed. In applications where alternating current is required, an inverter is integrated to convert the direct current generated by the PV system into alternative current (AC) [11, 12].Connecting the load directly to the PV array forces the PV array to operate at a point determined by the load's power demand. However, this operating point often deviates from the MPP, the point where the PV array delivers its maximum power [13]. This discrepancy arises from the PV array's nonlinear power-voltage characteristic, which is influenced by two primary factors: irradiance and temperature. To ensure the PV system operates at its optimal point, a DC-DC converter, specifically a boost converter, is employed between the load and the PV field. This boost converter imposes the MPP voltage on the load, effectively aligning the PV array's operating point with the MPP [14]. While the MPP shifts dynamically in response to changing environmental conditions, necessitating prompt tracking, MPPT controllers address this challenge by generating a duty cycle based on real-time power measurements, enabling the control of the boost converter to maximize power output and reach the MPP. The PV system implemented in this study is depicted in *Figure 1*.

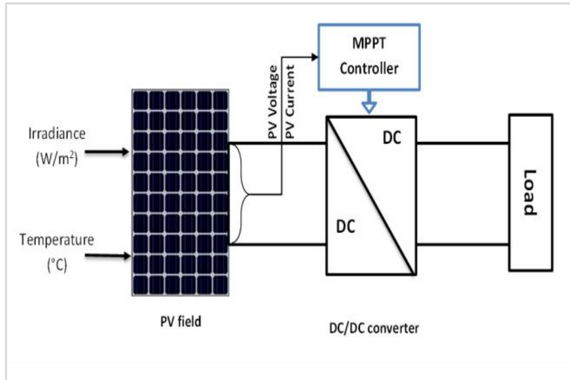


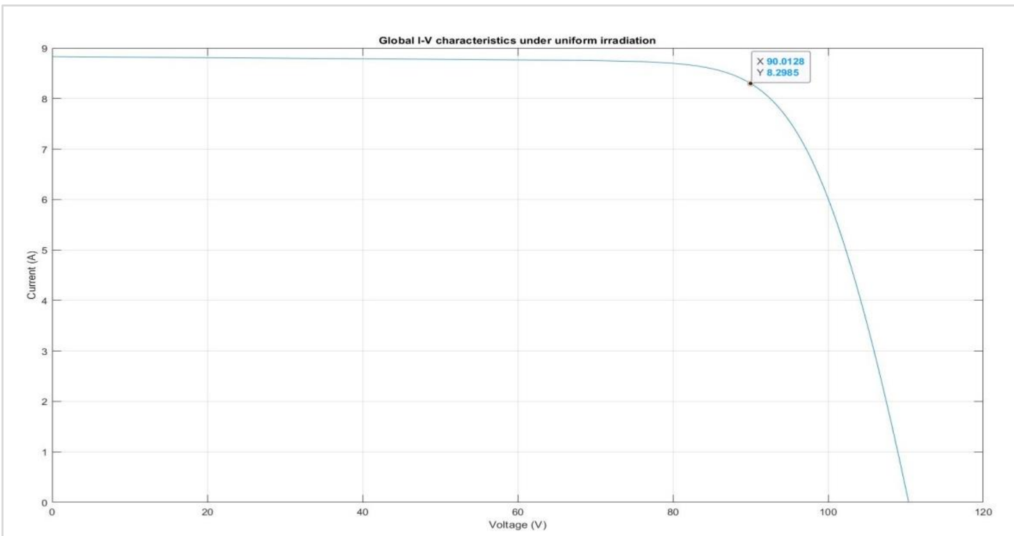
Figure 1 Schematic representation of the employed PV system

In this paper, a 250-watt polycrystalline module was utilized from Tata Power Solar Systems manufacturer, whose detailed specifications are provided in *Table 1*. To emulate partial shaded conditions (PSC), three PV panels from the same model detailed in *Table 1* were arranged in a three-series PV panel configuration. This arrangement ensures that each PV module receives a different irradiance level, allowing us to observe the performance of the MPPT technique under PSC. The irradiance levels applied to the PV modules in the three series PV panel configuration are 1000 W/m², 700 W/m², and 500 W/m², while the temperature is maintained at a constant 25°C.

Figure 2 and *Figure 3* illustrate the characteristic curves of the three series PV panel configurations under standard test conditions (STC) and PSC, respectively. These figures clearly demonstrate the impact of partial shading, as evidenced by the presence of three distinct MPPs.

Table 1 TP250MBZ PV module parameters under STC

Value	**System parameter**
249 W	Maximum power
60 cells	Cell per module
36.8 V	Open-circuit voltage (Voc)
8.83 A	Short circuit current (Isc)
30 V	The voltage at MPP (Vmpp)
8.3 A	Current at MPP (Impp)
Tata Power Solar Systems	Manufacturer
TP250MBZ	Model number



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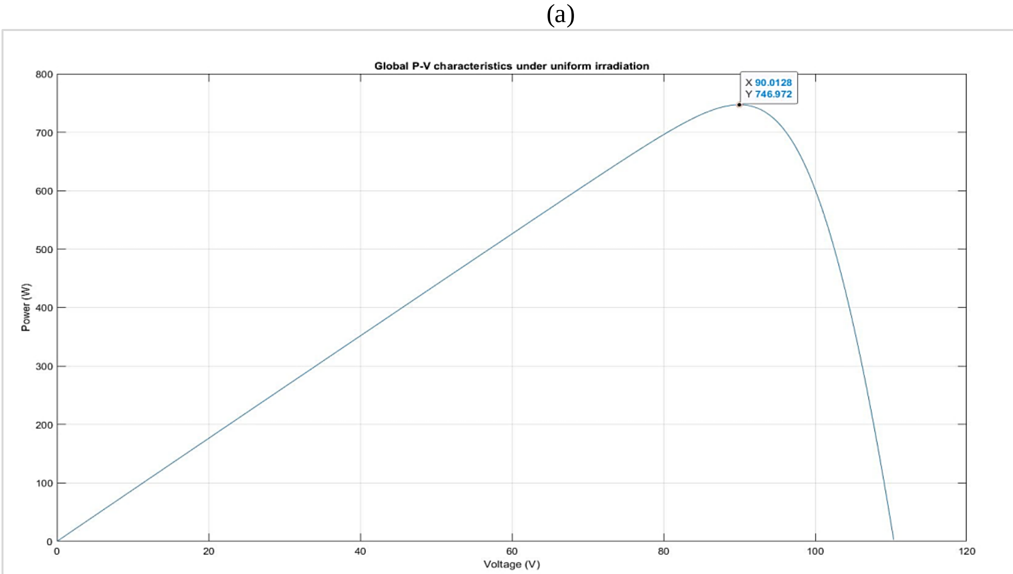
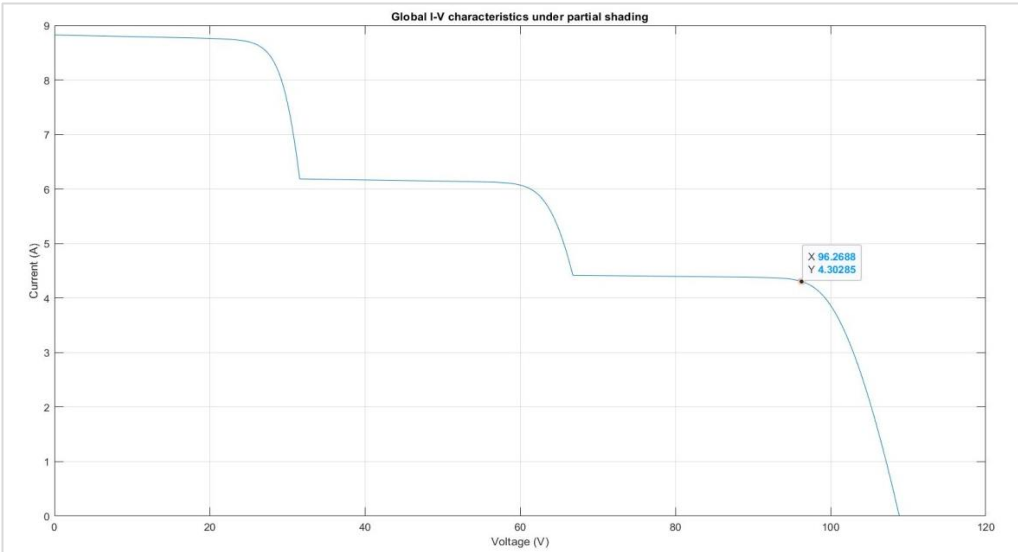


(b)

Figure 2 The current-voltage (I-V) (a) and power-voltage (P-V) (b) curves of the PV array under standard test conditions



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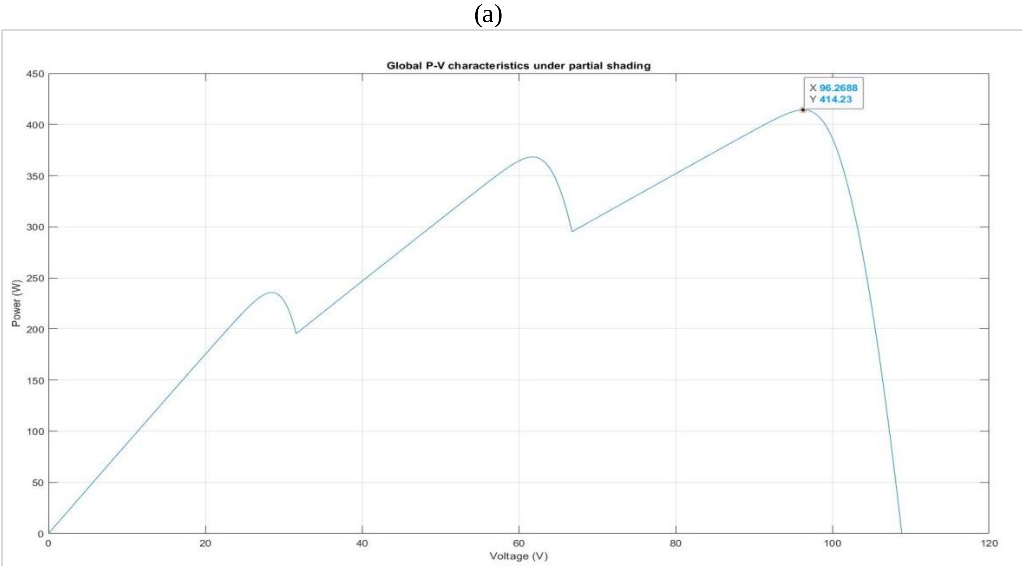


(b)

Figure 3 The current-voltage (I-V) (a) and power-voltage (P-V) (b) curves of the PV array under partial shading (1000W/m^2 - 700W/m^2 - 500W/m^2)

To improve the performance of PV systems, the goal was to develop and optimize a MPPT controller algorithm designed to mitigate the effects of fluctuating weather conditions on the characteristics of the PV array. The effectiveness of an MPPT controller is generally assessed by its ability to quickly reach the MPP, reduce oscillations around the MPP, and maintain tracking accuracy despite changing environmental conditions. PV systems are frequently exposed to a variety of climatic circumstances, including partial shading, which decreases the instantaneous performance of PV modules by exposing them to irregular irradiance levels caused by things like cloud cover, building shadows, or bird droppings [7]. Therefore, making the PV array operate at the MPP is crucial in maximizing power output and optimizing system efficiency. Conventional MPPT techniques, such as P&O, incremental conductance (IncCond), and hill-climbing, have gained widespread adoption due to their straightforward implementation and low computational requirements [15–17]. P&O iteratively adjusts the operating voltage and observes the resulting power changes, while IncCond relies on the slope of the power-voltage curve to determine the direction of perturbation. While these methods demonstrate effectiveness in many scenarios, they exhibit inherent limitations, including persistent oscillations around the MPP, slow convergence to the MPP, and reduced tracking accuracy under rapidly changing environmental conditions, especially when partial shading occurs. These methods are trapped easily in the local MPPs [18, 19]. The shortcomings of conventional MPPT techniques have motivated research into more sophisticated MPPT algorithms. Fuzzy logic control (FLC) has garnered attention for its inherent adaptability to changing environmental conditions, demonstrating superior tracking accuracy compared to traditional methods but FLC achieves slower convergence to the GMPP and might get stuck in a local maximum instead [20, 21]. Likewise, artificial neural network (ANN) hold promises due to their self-learning and adaptive capabilities, enabling precise tracking under fluctuating solar radiation and temperature conditions but still being inefficient in terms of convergence speed, oscillation, and complexity in implementation. The performance of ANNs heavily relies on the quality and quantity of the training data, then insufficient or inaccurate data can lead to slow convergence, inaccurate tracking, and potential instability and also can lead to over-sensitivity to noise and lead to unwanted oscillations around the GMPP [22, 23].

Recent advancements in MPPT algorithms have incorporated metaheuristic optimization techniques, expanding the scope of MPPT control. Particle swarm optimization (PSO), artificial bee colony (ABC), ant colony optimization (ACO), and genetic algorithms (GA) have all shown promise in global optimization, effectively addressing the dynamic and nonlinear properties of photovoltaic systems However many metaheuristic methods rely on randomness in their search process, leading to non-deterministic convergence behavior, and also their performances are sensitive to their control parameters and configuration [23–29]. Inspired by the hunting strategies of grey wolves, GWO has emerged as a promising technique, demonstrating efficient and robust optimization capabilities well-suited for MPPT applications [8, 30–32]. Also, the convergence of MPPT algorithms and machine learning has yielded innovative approaches that enhance the adaptability and learning capabilities of MPPT systems. Support vector machines (SVMs) and reinforcement learning (RL) have emerged as promising techniques in this domain. These techniques utilize historical data and real-time observations to dynamically adjust the operating point, enabling efficient operation under diverse operating conditions [33–36]. Despite significant advancements in MPPT algorithms, challenges remain. The implementation of these algorithms may present difficulties due to their intrinsic complexity, and the selection of the appropriate algorithm is dependent upon various aspects, including hardware restrictions, environmental circumstances, and system design. Furthermore, future research should prioritize the enhancement of current algorithms, the development of hybrid methodologies, and the resolution of computational demands associated with advanced techniques. Before attacking the next phase of this work, let's discuss the motivation behind selecting the GWO algorithm for enhancing the MPPT controller. The GWO algorithm offers several advantages that make it well-suited for this application:

- **Simplicity of implementation:** The GWO algorithm is characterized by its straightforward implementation, making it readily adaptable to various MPPT controller architectures.
- **Ease of parameter adjustment:** Modifying the GWO algorithm's parameters is relatively simple, allowing for fine-tuning the algorithm's performance to match specific system requirements.
- **Efficient optimization with minimal information:** The GWO algorithm exhibits the remarkable ability to optimize a problem using a minimal amount of information, making it well-suited for real-time MPPT applications.
- **Extensive literature support:** The GWO algorithm has gathered significant attention in the research community, with a substantial number of articles published on its application and advancements. This extensive literature base provides a wealth of knowledge and guidance for utilizing the GWO algorithm effectively.

The output voltage of a PV array is typically lower than the voltage required for most applications. This necessitates the use of DC-DC converters to raise the voltage of the PV array to the desired level. Among the various DC-DC converter topologies, boost converters have emerged as a preferred choice due to their simplicity, high efficiency, and wide range of input voltage capabilities. Boost converters play an essential role in PV systems by enabling efficient power conversion from the low voltage output of PV arrays to the higher voltage levels required for grid connection or direct use by various electrical appliances, as shown in Equation 1 [14, 37, 38].

$$V_{out} = \frac{V_{in}}{1-D} \tag{1}$$

Where V_{in} is the input voltage, V_{out} is the output voltage and D is the duty cycle generated by the MPPT controller.

The boost converter operates by storing energy during the on-state of a switching element, a metal-oxide-semiconductor field-effect transistor (MOSFET) as an example, and then transferring this stored energy to the output load during the off-state, resulting in a voltage boost. The boost converter, *Figure 4*, employed in this paper was designed based on the specifications outlined in *Table 2:*

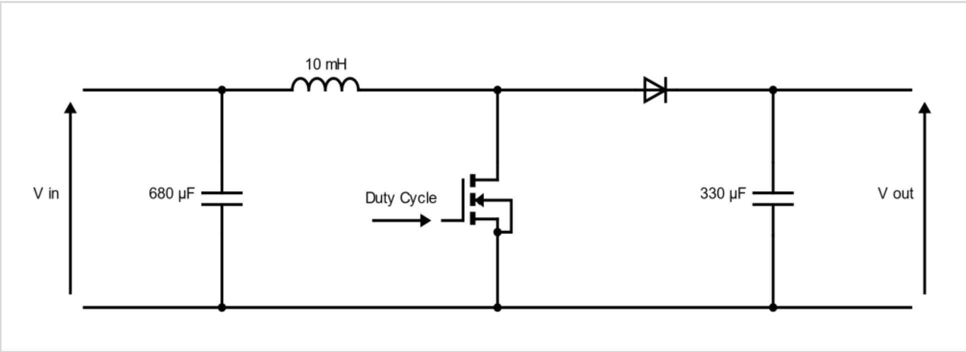


Figure 4 Boost converter with MOSFET N-Channel controlled by duty cycle generated from MPPT controller

Table 2 Table of specifications for the employed boost converter

Value	Parameter
Boost converter	Type
680 µF	Cin
330 µF	Cout
10 mH	L
50 KHz	fsw
1Kw	Maximum Power

3.Methods: ameliorated GWO algorithm-based MPPT

The GWO technique is a swarm-based metaheuristic that takes cues from grey wolves' hunting patterns and hierarchical organization. These animals are renowned for their effective hunting tactics in packs [31]. In general, it is an iterative stochastic algorithm designed to solve difficult optimization problems in which an efficient classic method is not known perfectly. It manipulates one or more solutions in search of the optimum. The GWO's interest comes from its ability to avoid local optima by using a population of points as a search method. The successive iterations make it pass from a bad solution to an optimal one; the algorithm stops after having reached a stopping criterion, generally to reach the specified number of iterations or the required precision. One of the advantages of this algorithm is its aptitude to optimize a problem with a minimum of information or parameters, giving a fast approximation of the global optimum [10, 31, 39].

3.1Mathematical modelling

Grey wolves are recognized as predatory animals that tend to reside within a well-organized group of typically 5 to 12 wolves, commonly referred to as a pack. The entire pack adheres to a highly rigorous dominance hierarchy; the Alpha comes at the top of the pyramid, and they are responsible for making decisions, followed by the Beta, who reinforces the command; under the Beta comes the Delta; and the rest of the wolves at the bottom of the pyramid are called Omega. Apart from their hierarchical social structure, grey wolves follow a specific hunting technique consisting of three primary phases when hunting in groups: the first step is tracking the prey, the second step involves surrounding the prey until it ceases its movement, and the last step is attacking toward the prey [10, 31, 39].

To construct the mathematical representation of the social hierarchy of grey wolves, we will assign Alpha as the optimum and designate Beta and Delta as the second and third best results. Accordingly, all other solutions will be compiled by Omega. The optimization progression in the GWO algorithm is guided by Alpha, Beta, and Delta, with Omega following their lead. In the current paper, we consider Alpha as the duty cycle, which gives the GMPP, Beta, and Delta the duty cycles that help to a better position around the possible GMPP point, while Omega updates its duty cycle according to Alpha, Beta, and Delta, so that will be placed randomly in a point closer to the GMPP [13].

Practically, grey wolves possess the capability to identify the precise location of their prey and subsequently encircle it. During the hunt, the alphas, betas, and deltas lead, with the omega following their lead. However, in abstract searches, we don't know the prey's position or the optimum in advance, so to emulate the hunting instincts of grey wolves, we adopt the premise that the alphas, betas, and deltas possess a greater understanding of where the potential prey might be situated. As a result, we retain the top three solutions achieved and compel the remaining search agents to adjust their positions in line with the best agents' positions using the specified Equations 2 to 8 above:

$$\overrightarrow{d_{alpha}} = \left|\overrightarrow{C_1}.\overrightarrow{X_{alpha}(n)} - \overrightarrow{X(\mathrm{n})}\right| \quad (2)$$

$$\overrightarrow{d_{beta}} = \left|\overrightarrow{C_2}.\overrightarrow{X_{beta}(n)} - \overrightarrow{X(n)}\right| \quad (3)$$

$$\overrightarrow{d_{delta}} = \left|\overrightarrow{C_3}.\overrightarrow{X_{delta}(n)} - \overrightarrow{X(n)}\right| \quad (4)$$

$$\overrightarrow{X_1} = \left|\overrightarrow{X_{alpha}(n)} - \overrightarrow{A_1}.\overrightarrow{d_{alpha}}\right| \quad (5)$$

$$\overrightarrow{X_2} = \left|\overrightarrow{X_{beta}(n)} - \overrightarrow{A_2}.\overrightarrow{d_{beta}}\right| \quad (6)$$

$$\overrightarrow{X_3} = \left|\overrightarrow{X_{delta}(n)} - \overrightarrow{A_3}.\overrightarrow{d_{delta}}\right| \quad (7)$$

$$\vec{X}(n+1) = \frac{5.\overrightarrow{X_1}+3.\overrightarrow{X_2}+2.\overrightarrow{X_3}}{10} \quad (8)$$

where n denoting the present iteration, $\vec{A}$ and $\vec{C}$ are vectors of random coefficients calculated respectively by the Equations 9 and 10, $\overrightarrow{X_{alpha}}(n)$, $\overrightarrow{X_{\beta}}(n)$ and $\overrightarrow{X_{\delta}}(n)$ are respectively the duty cycle vector of alphas, betas, and deltas for the present iteration, $\vec{X}(n)$ is the duty cycle vector of grey wolf for the succeeding iteration, $\overrightarrow{d_{alpha}}$, $\overrightarrow{d_{beta}}$ and $\overrightarrow{d_{delta}}$ are the distance between the current optimal position and the current position.

The vectors $\overrightarrow{A_k}$ and $\vec{C}_k$ are considered as follows:

$$\overrightarrow{A_k} = 2.\vec{a}.\overrightarrow{r_1} - \vec{a} \quad (9)$$

$$\vec{C}_k = 2.\overrightarrow{r_2} \quad (10)$$

Where k= {1;2;3}, and over the iterations, while $\overrightarrow{r_1}$ and $\overrightarrow{r_2}$ are randomized vectors within the given interval (0.1) and the vector $\vec{a}$ undergoes exponential decay, starting from 2 and decreasing to 0 as shown in Equation 11:

$$\|\vec{a}\| = 2.e^{\frac{-2.3.n}{M}} \quad (11)$$

Where n denoting the present iteration, M the maximum iteration count. As it can be observed from these equations, the grey wolf is capable of updating its location depending on the location of the prey and its previous location, via changing parameters $\vec{A}$ and $\vec{C}$; By taking into consideration the randomized vectors $\overrightarrow{r_1}$ and $\overrightarrow{r_2}$, the grey wolf can access any location within the neighborhood of its target prey.

Figure 5 demonstrates how a search agent adjusts its position by referencing alpha, the superior search agent. It is noticeable that the end position would be within a random location in the circle designated by the alpha, beta, and delta locations in the search area.

The next step is attacking the prey, in which there are two phases: the exploitation phase and the exploration phase. In the first one, grey wolves conclude their hunt by assaulting the prey when it ceases to move. The mathematical modeling of this approach is based on the gradual decrease of the magnitude of vector $\vec{a}$, which starts at 2 and decreases to 0 during the iterations. As the vector $\vec{A}$ *lies* within the interval (-2a, 2a), a grey wolf's position can shift to any point between its current location and the prey, given that the random values of $\vec{A}$ are within the interval (-1, 1). Hence, when $\overrightarrow{|A|} \leq 1$ grey wolves are obliged to attack the prey.

During the exploration phase, grey wolves disperse to explore for prey and then unite to hunt it down. To mathematically represent this dispersion, we use A arbitrary values greater than 1 or less than -1, which compel grey wolves to move away from their prey. This facilitates the GWO algorithm in searching for an optimal global solution [12].

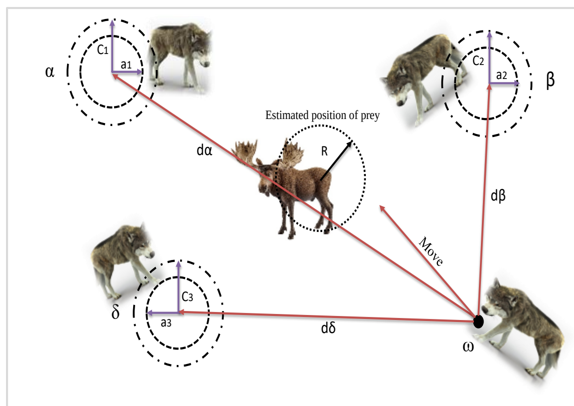


Figure 5 The position of omega is adjusted based on the places of alpha, beta, and delta wolves

3.2GWO algorithm application on MPPT

The primary objective of employing the GWO algorithm is to maximize the output power of the PV array. To achieve this goal, the duty cycle 'D' is considered the key variable that will be manipulated to modify the output power. The objective function is defined as the maximization of P(D) while 'D' adheres to the specified duty cycle constraints $D_{min} \leq D \leq D_{max}$, where D_{min} and D_{max} represent the duty cycle limits. The flowchart illustrating the ameliorated GWO algorithm is presented in *Figure 6*. The flowchart outlines the algorithm's primary steps, which include:

- **Initialization:** Initializing the number of agents with MSA=16, as well as the random value of the duty cycles (AlphaDC, BetaDC, DeltaDC) between D_{min} = 0,02 and D_{max} = 0.98, and the maximum iteration to Maximum_Iteration = 20.
- **Evaluate the MPP's position:** Measure and compare the power for each agent (Random_DutyCycle_table), and assign D_{alpha} (AlphaDC), D_{beta} (BetaDC) and D_{delta} (DeltaDC) to the best duty cycles with the highest power from Ppv_maximum_table;
- **Update of duty cycle positions:** The duty cycle values are updated according to Equations 5. 6 and 7, with d_{alpha}, d_{beta} and d_{delta} designating the distances of duty cycles D_{alpha} (AlphaDC), D_{beta} (BetaDC) and D_{delta} (DeltaDC) from the MPP. Then power is recalculated for the new duty cycle table.
- **Stop criterion:** The algorithm stops when the maximum iteration has been reached or an optimal duty cycle has reached the GMPP and the variation of power is still smaller than the defined ratio in Equation 12.
- **Algorithm reset:** The algorithm starts again if the power obtained decreases or increases by a predefined ratio, as exposed in Equation 12, or if the number of iterations has reached its maximum.

$$\frac{|P(d_{alpha})-P_{pv}|}{P(d_{apha})} \geq 4\% \qquad (12)$$

4.Results

This section introduces the MATLAB/Simulink model developed to assess the effectiveness of the proposed ameliorated GWO-based MPPT algorithm given in *Figure 7*. This model contains three series PV modules, voltage and current sensors, a boost converter, and a variable resistive load. The MOSFET is controlled by the pulse width modulation (PWM) signal generated by the proposed algorithm.

The experimental setup for this research involves a comprehensive integration of hardware and software components. The hardware configuration includes a Dell workstation computer with an 11th Gen Intel(R) Core (TM) i5-11500H Processor (64 bits) running Windows 11 (64 bits). Additionally, a specific model of the PV array, tailored to the research objectives and outlined in *Table 1*, is employed. The hardware setup further incorporates a boost converter, as detailed in *Table 2*, and a variable resistive load. This hardware configuration is complemented by sophisticated software tools, with MATLAB/Simulink serving as the primary computational environment. The selection of MATLAB/Simulink is motivated by its robust simulation capabilities, providing a conducive platform for modeling and analyzing the dynamic behavior of the PV system under diverse operating conditions. The integration of this hardware-software framework enables a meticulous examination of the proposed MPPT algorithm's performance, facilitating a detailed evaluation of its efficacy and adaptability within the specified parameters.

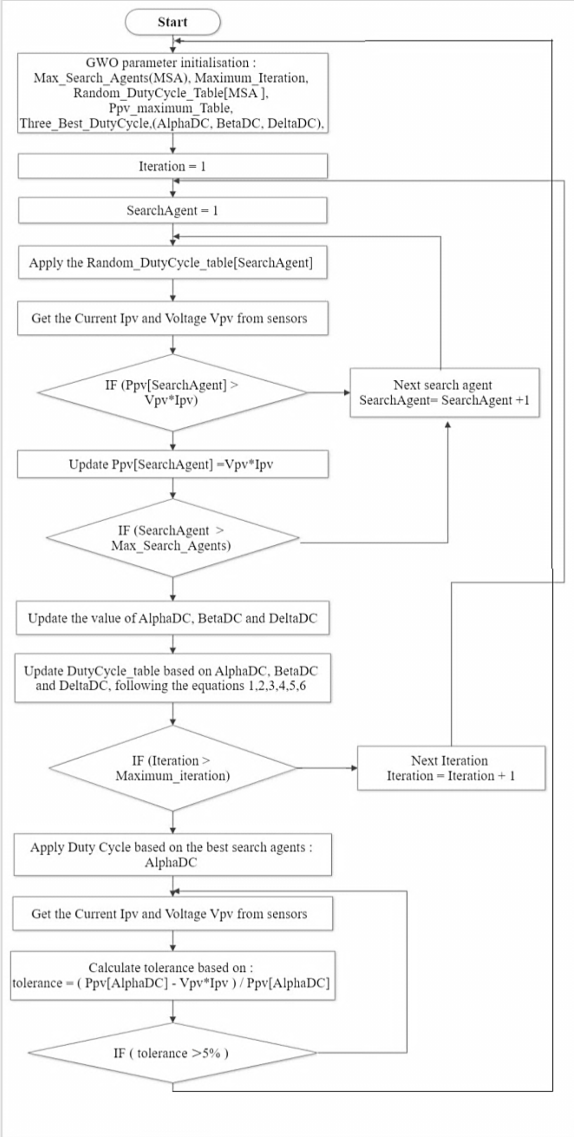


Figure 6 Flowchart of the Ameliorated GWO algorithm applied to MPPT

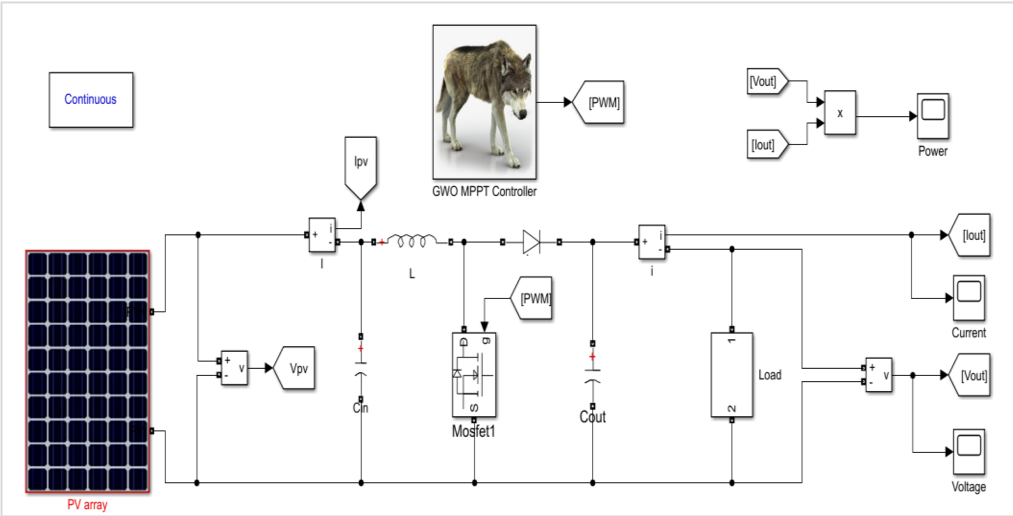
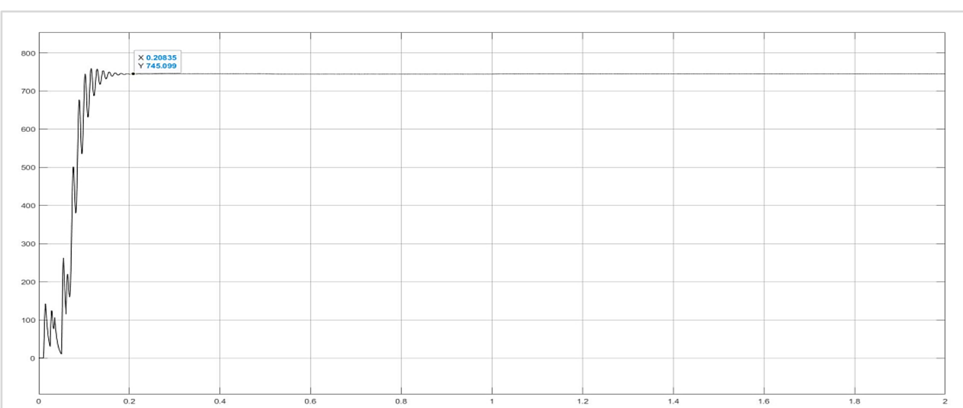


Figure 7 Simulink model of the PV system with Ameliorated GWO-based MPPT

The simulation was performed with a three-series PV panel subject to three configurations patterns. The first pattern is a uniform irradiation of 1000 W/m^2 on the three PV panels as shown in *Figure 8*, the second pattern is a variety of irradiations on each PV module, respectively 1000 W/m^2, 700 W/m^2 and 500 W/m2 as shown in *Figure 9*, and the third pattern is a variety of irradiations on each PV module, respectively 1000 W/m^2, 700 W/m^2 and 1000 W/m^2 as shown in *Figure 10(a)*, with a constant temperature at 25°C. Under STC, the MPP reaches 746.97 W, while under PSC, the GMPP reaches 414.23 W (*Figure 3 (b)*) in the first case, and 572, 95 W in the second case (*Figure 10 (b)*).

The achievements illustrated in *Figures 8(a), 9(a), 10(a)*, and *11(a)* represent a notable advancement in the domain of MPPT algorithms. These achievements not only align with the current trend of optimizing tracking curves, but also demonstrably surpass them by achieving faster convergence times, improved accuracy, and significantly reduced oscillations. The proposed ameliorated GWO-based MPPT algorithm has demonstrated remarkable performance, achieving the MPP and the GMPP within a short time frame of approximately 0.21 seconds, coupled with an impressive accuracy rate of 99.75% in STC and, respectively, 0.48 seconds, coupled with an accuracy rate of 99.59% in PSC for the second pattern and a tracking time of approximately 0.31 seconds, coupled with an impressive accuracy rate of 99.55% in PSC for the third pattern. *Figure 8 (b), Figure 9 (b)* and *Figure 10 (c)* show the duty cycle evolution behind these tracking curves. To assess the response of our GWO-based MPPT algorithm under rapid irradiance fluctuations, a transition from STC to PSC was simulated, and the resulting power-voltage curves (a) and duty cycle evolution (b) are presented in *Figure 11*.



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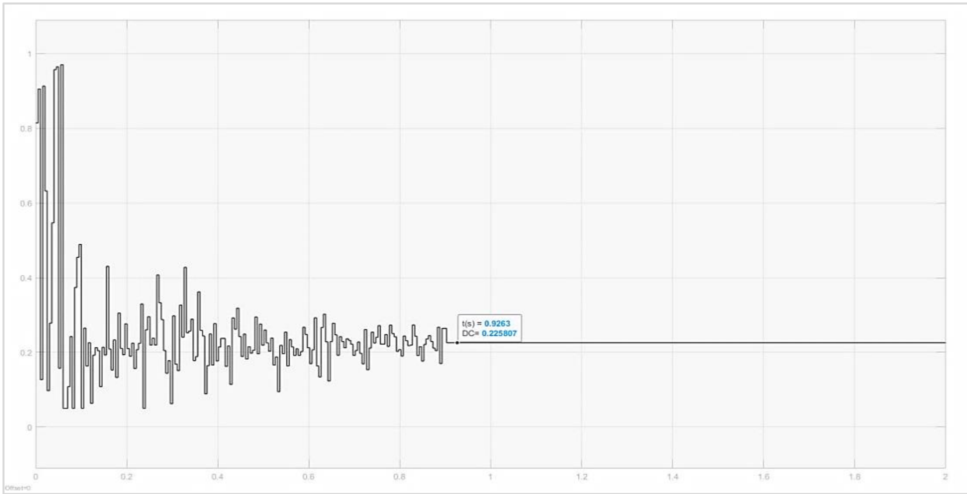
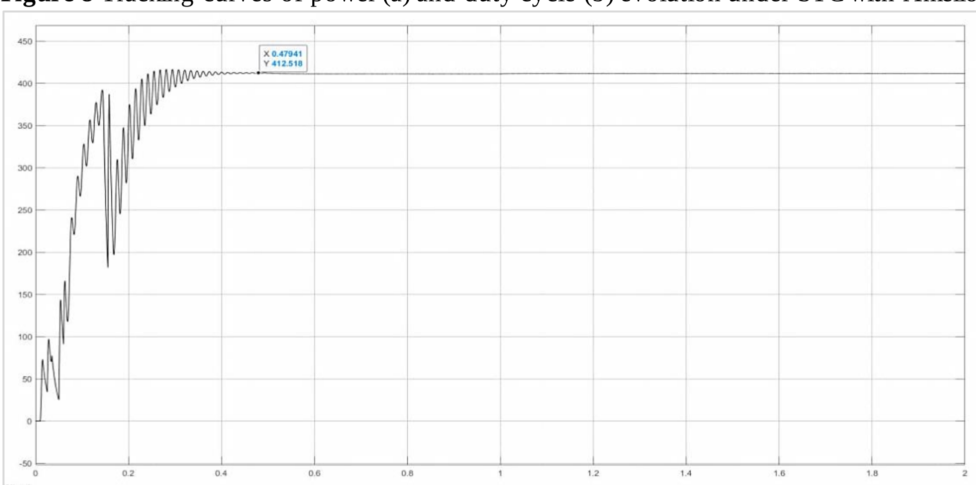


(b)

Figure 8 Tracking curves of power (a) and duty cycle (b) evolution under STC with Ameliorated GWO-based MPPT



(a)

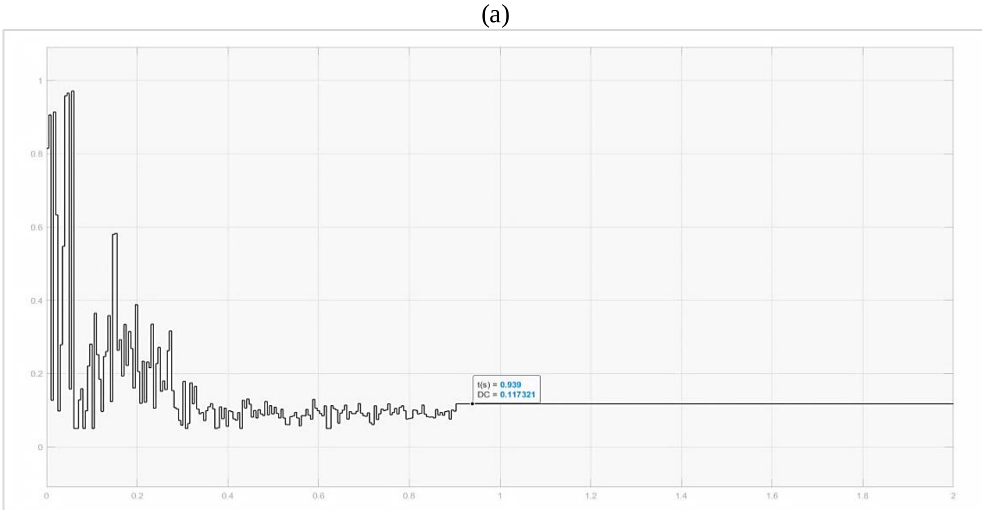


Figure 9 Tracking curves of power (a) and duty cycle (b) evolution under PSC (1000W/m^2 - 700W/m^2 - 500W/m^2) using Ameliorated GWO-based MPPT

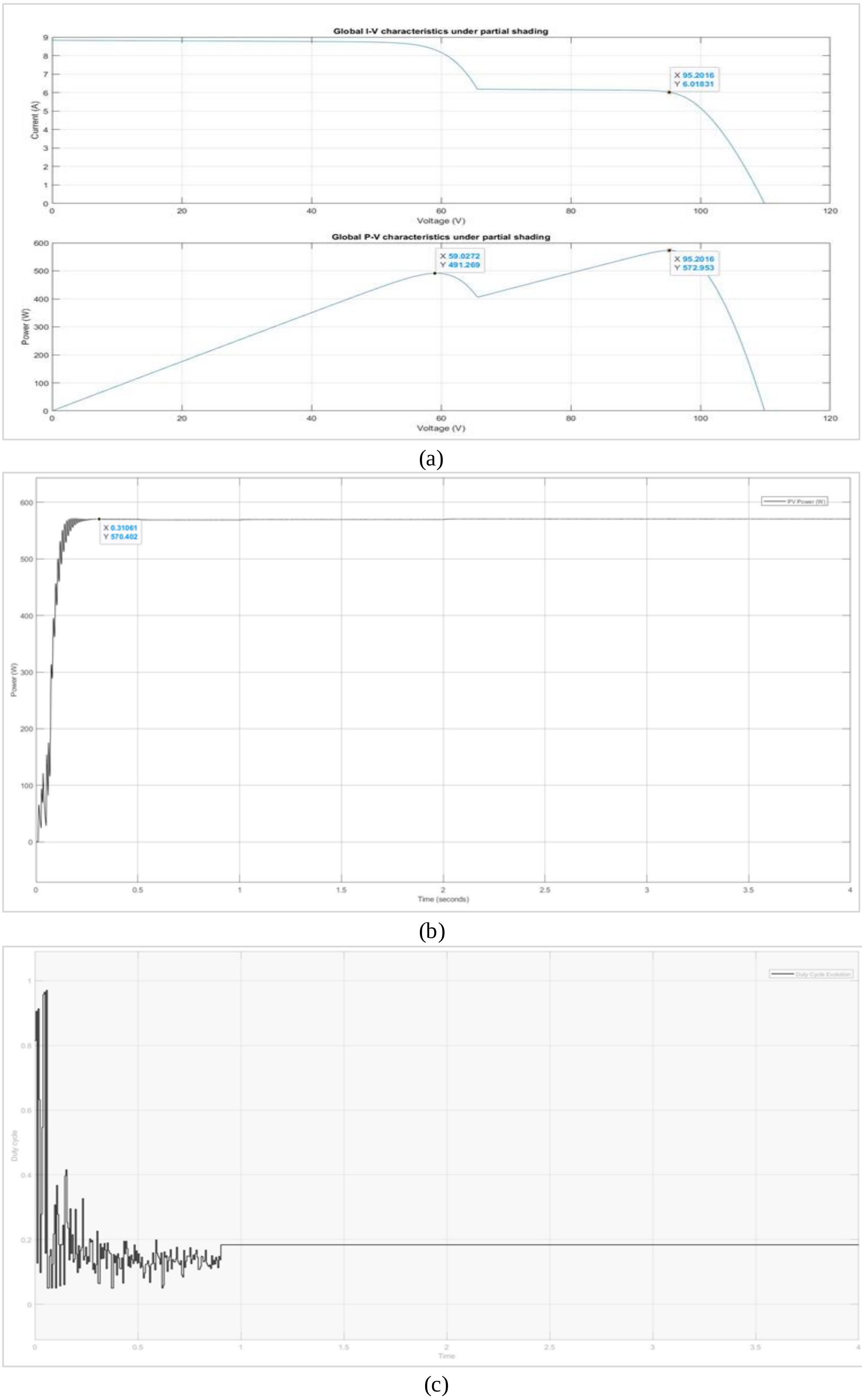
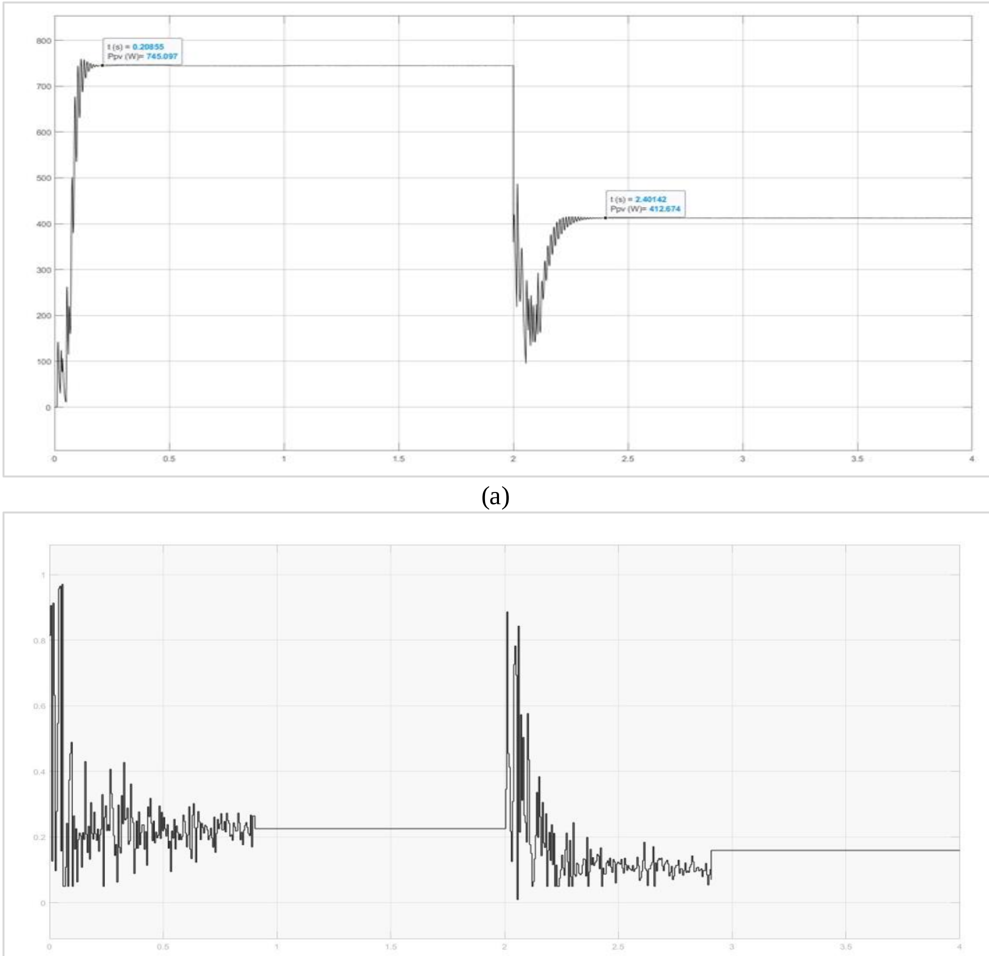


Figure 10 The (I-V) and (P-V) curves (a) and tracking curves of power (b) and duty cycle (c) of the PV array under PSC (1000W/m^2 - 700W/m^2 - 1000W/m^2) using Ameliorated GWO-based MPPT



(a)

(b)

Figure 11 Tracking curves of power (a) and duty cycle (b) evolution under the transition from the first to the second pattern irradiation using Ameliorated GWO-based MPPT

5.Discussion

The achievement marked by the ameliorated GWO algorithm is a noteworthy improvement over existing MPPT techniques, which often require more time to converge to the GMPP and might not consistently attain such high levels of accuracy and minimal oscillation. The ability of this algorithm to rapidly converge to the GMPP holds great promise for enhancing the efficiency of PV systems, particularly in scenarios where rapid fluctuations in solar irradiance occur, such as during cloudy conditions or other dynamic environmental factors.

The ameliorated GWO-based MPPT algorithm exhibits significant advancements in the field of MPPT algorithms, as evidenced by its ability to achieve GMPP within a very short time and with high accuracy rates under both STC and PSC. This performance aligns with the findings of recent research that highlights the potential of metaheuristic optimization techniques like GWO in enhancing the performance of MPPT algorithms.

To contextualize these results, a comparative analysis with recent relevant studies in the literature is essential. Recent advancements in MPPT algorithms, particularly those employing metaheuristic optimization techniques, have shown a trend toward enhancing both convergence speed and accuracy. The proposed ameliorated GWO-based MPPT algorithm, as evidenced by the simulation results, aligns with and even surpasses the benchmarks set by contemporary approaches.

Several recent papers have reported on the application of GWO for MPPT in PV systems. In a 2019 study, Da et al. [40] proposed a GWO-based MPPT algorithm that achieved an efficiency of 99.99% and a convergence time of 0.7 seconds under STC, while in PSC, it achieved an efficiency of 99, 86% and a convergence time of 0.72 seconds. Similarly, by Chtita et al. [41] presented a GWO-based MPPT algorithm that attained an efficiency of 99.96% and a tracking time of 2.75 seconds under STC, while in PSC, it achieved an efficiency of 99,58% and a convergence time of 2.87 seconds. In another 2022 research paper, Motahhir et al. [19] also proposed a GWO-based MPPT algorithm that reached an efficiency of 99.97% but a tracking time of 2.63 seconds under STC, while in PSC the achievement in efficiency was 99,74% and 2,76 seconds in convergence time, as shown in *Table 3*. The ameliorated GWO-based MPPT algorithm outperforms these algorithms in terms of both convergence time and accuracy. Its ability to achieve GMPP within 0.21 seconds in STC, and 0.48 seconds in PSC, coupled, respectively, with accuracy rates of 99.75% and 99.59%, represents a significant improvement over previous GWO-based MPPT algorithms. The superior performance of the ameliorated GWO-based MPPT algorithm can be attributed to several improvements, including:

- **Optimal parameter tuning for the GWO algorithm**: The GWO algorithm's performance is influenced by various parameters, including the number of search agents, weight coefficients, and the number of iterations. Tuning these parameters to their optimal values led to the best results in our application.
- **Improved exploration and exploitation:** The algorithm's enhanced exploration capabilities allow it to thoroughly search the search space, while its improved exploitation capabilities enable it to refine its search towards the GMPP. This improvement stems from the diminished randomness of the duty cycles over iterations, achieved by employing the decreasing exponential function in Equation 10 instead of the linear decreasing function, which gives the results shown in *Figure 8 (b), Figure 9 (b), Figure 10 (c),* and *Figure 11 (b)* that lead to quicker identification of the GMPP under dynamic weather conditions. This translates to reduced energy losses and higher efficiency.
- **Adaptive parameter tuning:** The algorithm's ability to dynamically adjust its parameters based on the current operating conditions contributes to its robustness and adaptability to reduce oscillations and improve convergence speed.
- **Effective noise filtering:** The algorithm's incorporation of noise filtering techniques like median filtering and moving average filtering to mitigate the impact of noise on its tracking performance.

In summary, ameliorated GWO truly shines in challenging situations, especially during dynamic weather conditions such as fluctuating clouds or partial shading. In contrast to traditional MPPT algorithms that may struggle in these scenarios, Ameliorated GWO excels. Its exceptional tracking abilities guarantee optimal energy capture even in swiftly changing environments. Additionally, its efficiency is notably advantageous in large-scale PV systems. Consider the significant cost savings and environmental benefits achieved by maximizing power output on extensive solar farms! These instances illustrate how the enhanced performance of ameliorated GWO translates into tangible advantages in practical applications. However, despite its advantages, the GWO-based MPPT algorithm has some limitations:

- **Parameter sensitivity:** The performance of the GWO algorithm is sensitive to the selection of its parameters, such as the number of search agents, the weight coefficients, and the number of iterations. Improper parameter selection can lead to slow convergence, oscillation around the MPP, or early convergence to a local maximum.
- **Limited output voltage range:** One of the primary limitations of a boost converter is its limited output voltage range. The output voltage is always greater than the input voltage, but it is limited by the maximum voltage rating of the switching element (MOSFET in our case) and the inductor.
- **Output voltage ripple**: Boost converters produce a pulsating output voltage due to the switching action of the transistor. This ripple can be a source of noise in the system and can affect the performance of sensitive electronic devices.
- **Balance between exploration and exploitation:** The GWO algorithm needs to strike a balance between exploration and exploitation. Exploration enables the algorithm to search a wide area of the search space to find the global maximum, while exploitation allows it to refine its search around the MPP. If the algorithm favors exploration too much, it may take a long time to converge, while if it favors exploitation too much, it may get stuck in local maxima.
- **Voltage spike issue**: During the initial stage of the MPPT process, the GWO algorithm may generate sudden changes in the duty cycle of the boost converter, leading to voltage spikes in the DC output.

- **Parameter tuning for boost converter:** The optimal parameters for the GWO algorithm may need to be adjusted based on the specific characteristics of the boost converter and the PV system. This can be a time-consuming and complex process.

Table 3 Comparison between Ameliorated GWO and GWO-based MPPT algorithm [9] under the defined scenarios

Shading patterns	Tracking algorithm	Tracking time (s)	Optimal power (W)	Reached power (W)	Efficiency (%)
First Pattern (STC)	Ameliorated GWO	0,21	746,7	745	99,77
	GWO[9]	2,63	160	159,95	99,97
Second Pattern (PSC)	Ameliorated GWO	0,48	414	412,5	99,63
	GWO[9]	2,85	90,77	90,44	99,64
Third Pattern (PSC)	Ameliorated GWO	0,31	572,9	570,4	99,55
	GWO[9]	2,76	117,59	117,28	99,74
Transition from STC to PSC	Ameliorated GWO	0,21-0,4	746,7- 414	745,1-412,6	99,79-99,66

The ongoing development and enhancement of metaheuristic optimization techniques, such as GWO, are crucial for further improving the performance of MPPT algorithms in PV systems.

Researchers are diligently exploring innovative methods to enhance the convergence speed, accuracy, and adaptability of these algorithms. Such advancements are instrumental in paving the way for more efficient and reliable solar energy systems in the future. A complete list of abbreviations is shown in *Appendix I*.

6.Conclusion and future work

This study introduces a precise analytical model of a PV system operating under PSC. An ameliorated GWO-based MPPT algorithm is suggested, which adjusts the pursuit behavior by prioritizing the alpha agent in Equation 8 of the conventional GWO algorithm. This facilitates more accurate tracking of the GMPP of the PV system under PSC in a shorter tracking time.

To assess the effectiveness of the suggested ameliorated GWO algorithm, multiple simulations are conducted on three series PV panel configurations exposed to uniform irradiation and three distinct shading patterns. The dynamic performance of the algorithm is evaluated by subjecting the proposed configurations to 4 seconds of changing shading patterns. It is noted that the proposed algorithm achieves more precise GMPP tracking in less time. As a result of the stochastic nature of heuristic algorithms, it was found that the proposed algorithm does not get stuck in local MPP, as well as has a shorter tracking time than the traditional GWO-based MPPT algorithms [9]. Based on the performance analysis, the ameliorated GWO algorithm emerges as a superior choice compared to the comparative achievements in terms of stabilizing power output around the GMPP and enhancing tracking speed.

Future research will focus on the experimental results of applying this approach. It has been noted that the currently proposed algorithm struggles to track minor variations in irradiation under the predefined ratio of Equation 12, and small oscillations persist. To address this issue, the plan is to integrate the presented algorithm with the Kalman filter, which has demonstrated significant efficacy in tracking. This combination aims to enhance the algorithm's precision and stability, leading to more efficient PV system performance.

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Conflicts of interest

The authors have no conflicts of interest to declare.

Author’s contribution statement

I. Belaalia: conceptualization, investigation, data curation, writing – original draft, writing – review and editing. **N. Taifi:** Investigation, data collection, analysis and interpretation of results, review and editing. **A. Malaoui:** Investigation, data collection, analysis and interpretation of results, review and editing. **K. Taifi:** Data collection and review and editing.

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Appendix I

S. No.	Abbreviation	Description
1	ABC	Artificial Bee Colony
2	AC	Alternative Current
3	ACO	Ant Colony Optimization
4	ANN	Artificial Neural Networks
5	FLC	Fuzzy Logic Control
6	DC	Direct Current
7	GA	Genetic Algorithms
8	GMPP	Global Maximum Power Point
9	GMPPT	Global Maximum Power Point Tracker
10	GWO	Grey Wolf Optimization
11	IncCond	Incremental Conductance
12	MOSFET	Metal-Oxide-Semiconductor Field-Effect Transistor
13	MPP	Maximum Power Point
14	MPPT	Maximum Power Point Tracker
15	P&O	Perturb and observe
16	PSC	Partial Shaded Conditions
17	PSO	Particle Swarm Optimization
18	PV	Photovoltaic
19	PWM	Pulse Width Modulation
20	RL	Reinforcement Learning
21	STC	Standard Test Conditions
22	SVMs	Support Vector Machines