Experimental study on modified GOA-MPPT for PV system under mismatch conditions

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ABSTRACT

This paper presents a modified grasshopper optimization algorithm (GOA) tailored for optimizing the power extraction capability of a solar photovoltaic (PV) system. The algorithm`s focus is on addressing one of the issues associated with mismatch loss (MML), particularly the mismatch (MM) in solar irradiance conditions, to attain maximum output power. The core strategy of the GOA involves optimizing the duty cycles of the converter to achieve the maximum power point (MPP) for the PV system. The PV system configuration comprises three PV modules connected in series and a SEPIC converter. To facilitate efficient maximum power point tracking (MPPT), the paper proposes using the GOA as a controlling mechanism. The study employs a comparative approach, contrasting the performance of the proposed system against established algorithms, such as PSO and GWO. The results of these evaluations exhibit the superior performance of the proposed GOA when compared to other optimization techniques. The GOA exhibits exceptional MPPT tracking characteristics, characterized by rapid tracking speed, heightened efficiency, and minimal oscillations within the PV system. Consequently, the GOA effectively addresses one of the MML issues.

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1. INTRODUCTION

Owing to the escalating demand for energy, the inescapable diminishment of fossil fuel reserves (coal, oil, and natural gas), and the swift environmental deterioration attributed to global warming, there has been a notable surge in global endeavors to explore renewable energy sources such as wind, solar energy, hydropower, and geothermal energy in the past decade [1]. The focal point of the worldwide market revolves around seeking resolutions to these challenges. Moreover, using renewable energy sources for power generation holds the dual advantage of curbing greenhouse gas emissions and preserving billions of barrels of crude oil [2]. The term "solar energy" encapsulates the pure energy emanating from the sun. Notably devoid of detrimental environmental repercussions, solar energy is a cutting-edge, environmentally friendly renewable energy option for power generation. The energy radiated by the sun is a thousandfold more abundant than the energy derived from fossil fuels within a single day [3]. An additional advantage lies in the potential of nearly all nations to independently harness solar energy for power generation, unburdened by interdependence. Its perpetuity and boundless nature assure solar energy`s long-term applicability.

One technology that directly converts solar energy into electricity is the photovoltaic (PV) system, utilizing solar cells or an array of them. The utilization of PV systems offers several advantages, including straightforward installation, absence of moving components, reduced maintenance requirements, heightened reliability, diminished susceptibility to power loss, and scalability [4]. These attributes have led to a notable upsurge in solar energy production. Due to these benefits, solar energy is poised to play a pivotal role in the escalating proportion of renewable energy within the electricity sector. Predictions indicate that the share of renewable energy will surge from 25% in 2017 to a projected 85% by 2050, with solar energy being a driving force [5]. Applications such as solar cars, street lighting, and hybrid renewable energy systems exemplify the diverse uses that harness PV technology.

The performance of a PV system is contingent upon weather conditions. Factors such as cloud-induced shading, structural elements, and dust accumulation can all reduce system output. Notably, the electrical characteristics of PV systems exhibit inherent nonlinearity. When examining instantaneous current and voltage outputs, a specific operational point emerges where the maximum power is generated. This optimal point is achieved by precisely adjusting the converter`s duty cycle utilizing a pulse width modulation (PWM) signal [6]. An MPPT controller is the most efficient strategy to enhance a PV system`s power generation capability. Nevertheless, current challenges persist within PV energy conversion systems used in electricity generation from PV installations (e.g., modules, strings, and arrays) [7]. The primary drawback lies in suboptimal electricity production during overcast days. Consequently, solar irradiance and temperature variations lead to continuous fluctuations in the PV array`s power output. The second limitation involves the non-linear nature of the power-voltage (PV) curve, posing challenges in identifying the maximum power point (MPP). Lastly, the high capital cost of PV power generation systems underscores the necessity for effective system design.

Moreover, the impact of mismatch (MM) emerges as a crucial factor necessitating consideration in PV array systems. This phenomenon arises when modules exhibit disparate behaviors under standard test conditions (STCs). A phenomenon referred to as mismatch loss (MML) occurs when the collective output power of a PV array falls short of the combined actual output power of the individual panels functioning autonomously [8]. According to [9], mismatch loss within a solar PV system can stem from various sources. For instance, manufacturer tolerances in cell characteristics can result in physical discrepancies between cells or variations in cell processing materials during regular production. This leads to slightly divergent characteristic parameters among cells. Another cause is environmental stress, which encompasses impacts such as hail. Environmental stresses can lead to partial or complete string openings due to cell fractures or other factors. This not only contributes to MML but also has the potential to induce excessive heating in power dissipation areas. Furthermore, shadowing issues constitute another rationale behind MML. Solar cell arrays in the field are subject to shadows originating from both predictable sources and unforeseeable factors like bird droppings or fallen leaves. In the case of smaller arrays with limited or no parallel connections, even a single leaf could cause the system`s output to plummet to a fraction of its rated power, potentially leading to system failure. Shadowed cells obstruct current flow and tend to become reverse-biased. Consequently, localized hotspots develop in the shadowed cell regions, risking cell damage or cracking and ultimately resulting in module failure. These factors underline the necessity of averting or mitigating MML conditions within PV systems.

Multiple strategies exist for mitigating or minimizing MM conditions. The primary methodologies to address MML involve incorporating a maximum power point tracking (MPPT) controller per PV string or integrating power optimizers within individual PV modules. According to [10], both approaches effectively mitigate or eliminate the issue of MML. However, it`s noteworthy that both techniques also contribute to increased system costs and potential reliability concerns. Given the substantial initial investment associated with solar power plants, it becomes imperative for users to maximize their return on investment (ROI) by enhancing the efficiency of the PV system to the greatest extent possible. Consequently, the fundamental objective of this study centers on devising a suitable algorithm-based MPPT approach to mitigate or circumvent the effects of MML, thereby bolstering ROI. While this research focuses on developing an MPPT algorithm, the study`s illustrative cases of mismatch loss (MML) underscore the specific impacts of shading on the PV system.

The MPPT algorithm is meticulously crafted to optimize the power output of a PV module across diverse environmental scenarios. This achievement is realized by aligning the operational point on the current-voltage (I-V) curve through a proficiently integrated power converter capable of effectively accommodating the inherent non-linear characteristic of the I-V curve. The precise operational point, situated at the zenith of the curve, is influenced by variables like temperature, solar irradiance, and fluctuations in the connected load. Due to the non-linear interplay among voltage, current, and power within a PV system, employing an MPPT algorithm becomes imperative for accurately ascertaining and tracking the most advantageous maximum power point (MPP).

Numerous classical or conventional algorithms have been formulated and utilized for MPPT purposes, all aimed at tracing the optimal maximum power point (MPP). These well-established algorithms encompass perturb and observe (P&O) [11], incremental conductance (INC) [12], and ripple correlation control (RCC) [13]. The P&O algorithm functions by perturbing either voltage or current and subsequently analyzing the resultant variations. Conversely, HC directly perturbs the duty cycle of the power converter. In contrast, INC involves comparing the derivatives of conductance with the instantaneous conductance and then making adjustments towards the MPP as soon as the derivative approaches zero. The conventional MPPT algorithm is particularly suited for monitoring the MPP within static scenarios characterized by oscillations near the MPP peak. Nevertheless, it is acknowledged that conventional MPPT algorithms face challenges in effectively addressing MML conditions [14]. Despite their straightforward setup, these algorithms are prone to becoming trapped at false power peaks, particularly when there are swift fluctuations in solar irradiance [15]. Consequently, they result in significant power loss from the PV system. As a remedy, an advanced MPPT algorithm is imperative to ensure precise MPP tracking and enhance the system's dynamic response.

In recent years, scholars have advocated for integrating metaheuristic algorithms in the realm of MPPT, drawn by their exceptional effectiveness in addressing intricate real-world challenges. This strategy seeks to surmount the limitations linked to technique-centered intelligent control methods such as fuzzy logic (FL) control [16] and artificial neural networks (ANN) [17]. FL control frequently necessitates substantial memory resources, whereas ANN mandates extensive data training. Subsequently, the considerable data demands of these methods contribute to an onerous storage load during the processing phase. Hence, adopting metaheuristic algorithms has garnered attention for their heightened proficiency in problem-solving. Metaheuristic algorithms have gained widespread applications as search techniques for single- and multi-objective optimization challenges. Their suitability for MPPT algorithms is particularly noteworthy due to the photovoltaic (PV) systems combination of unimodal and multimodal characteristics. A range of concepts and parameters influences the optimization process of metaheuristic algorithms. In the realm of MPPT applications for PV systems, prominent metaheuristic algorithms encompass particle swarm optimization (PSO) [18] genetic algorithm (GA) [19], ant colony optimization (ACO) [20], grey wolf optimization (GWO) [21], and various others.

Conventional metaheuristic algorithms may display sluggish tracking and convergence tendencies, demanding a substantial number of iterations akin to configurations noted in [22]. Effective outcomes hinge on proper initialization and periodic parameter tuning. The absence of suitable periodic tuning choices can yield inadequate initialization and parameter adjustments, leading to heightened particle update rates that trigger initial oscillations throughout the optimization process. This erosion of diversity and randomness, essential for pinpointing the optimal duty cycle [23], can result. Furthermore, standard metaheuristic algorithms are acknowledged to exhibit relatively slower tracking speeds compared to their conventional counterparts [7].

The grasshopper optimization algorithm (GOA), a bio-inspired optimizer, has been selected to tackle these issues. GOA has a straightforward structure requiring just two parameter adjustments, rendering it user-friendly. This optimizer amplifies search speed and curbs steady-state oscillations during the initial tracking phase. In solving challenges, bio-inspired optimizers, a subdivision of metaheuristic algorithms, are increasingly applied for intricate engineering design problems within obscure and demanding spaces, particularly within the context of MML conditions encountered in PV system problems.

The remainder of this paper is organized as follows: i) Section 2 provides an explanation of the proposed GOA as MPPT controller; ii) Section 3 presents the simulation results and discussion of an analysis of the GOA technique and compares it with other techniques; and iii) Section 4 concludes the paper.

2. PROPOSED GOA AS MPPT CONTROLLER

Environmental factors such as irradiance and temperature significantly impact the efficiency of a photovoltaic (PV) system`s power generation and power-voltage (PV) behavior. As a result, even minor fluctuations in these atmospheric conditions can lead to corresponding changes in the maximum power point (MPP) of the PV arrays PV curve. This variation presents a complex, non-linear challenge for accurate MPP tracking. The complexity is further heightened by the time-sensitive nature of finding a solution. In the context of these dynamic atmospheric conditions, the PV characteristics of the PV array undergo frequent adjustments. To tackle this issue, this study suggests employing the grasshopper optimization algorithm (GOA) for the maximum power point tracking (MPPT) controller. The primary goal of this technique is to enhance the optimization of MPP tracking across a range of shifting atmospheric conditions.

2.1. Standard grasshopper optimization algorithm (GOA)

The grasshopper optimization algorithm (GOA) is an optimization technique based on nature-inspired phenomena, which mimics the behavior of grasshopper swarms in nature for solving optimization problems such as finding food sources. The life cycle of grasshoppers is shown in Figure 1, and the algorithm solves issues by updating the location of all grasshoppers and quickly tracking the best location. Like other nature-inspired algorithms, GOA has two phases: exploration and exploitation.

Exploration is a highly randomized behavior used to find promising regions, while exploitation involves searching locally for the exact global best point. Figure 1 also illustrates the social interaction between grasshoppers searching for the best target in the network. The repulsion force allows grasshoppers to explore the search space, while the attraction force encourages them to exploit the promising region. The balance between both forces is achieved in a zone called the comfortable zone (R_c), where there is no movement in social interaction between grasshoppers and the formula to calculate the comfort zone as (1).

$$R_C = \frac{l \ln f}{1-l} \quad (1)$$

The parameters f and l represent the intensity and length scale of attraction, respectively, while r represents the distance between two grasshoppers [24].

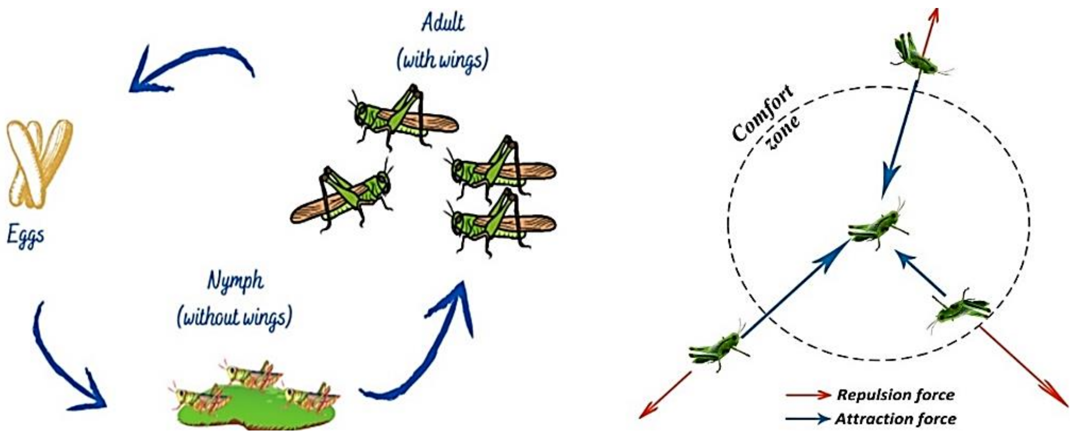

Figure 1. Life cycle of grasshoppers and grasshoppers' social behaviors

Food-seeking behavior plays a crucial role in grasshopper swarming, with grasshoppers naturally engaging in exploration, exploitation, and targeted hunting for food. This behavior has inspired the development of a nature-inspired algorithm, with a mathematical model designed based on these characteristics [25]. The general mathematical model used in this grasshopper optimization algorithm (GOA) is presented as (2).

$$X_i = a_1.S_i + a_2.G_i + a_3.A_i \quad (2)$$

In this equation X_i represents the position of the i^{th} grasshopper, S_i represents their social interactions, G_i represents the strength of gravity affecting the i^{th} grasshopper, and A_i represents the wind advection acting on each grasshopper. To introduce a level of randomness, the equation is adjusted by adding the values of a_1, a_2, and a_3. As explained before, the social interactions among grasshoppers are considered the most crucial element as (3).

$$S_i = \sum_{\substack{j=1 \\ j \neq i}}^{N} s(d_{ij})\, \widehat{d_{ij}} \quad (3)$$

The distance between the i^{th} and j^{th} grasshopper, represented by d_{ij}, is calculated as the absolute value of the difference between their positions, given by the equation $d_{ij} = |x_j - x_i|$. A unit vector from the i^{th} grasshopper to the j^{th} grasshopper is denoted by $\hat{d}_{ij} = \frac{x_j - x_i}{d_{ij}}$. The strength of social forces is determined by the function s as shown in (4). The formula for calculating the s function, which specifies the social forces, is as (4).

$$s(r) = f.e^{\frac{-r}{l}} - e^{-r} \tag{4}$$

The function s captures the impact of social interactions and is adjusted to achieve a trade-off between the initial and final stages of the optimization process. By substituting the values of social interaction parameters into (2), we obtain as (5).

$$X_i = a_i.\sum_{\substack{j=1 \\ j \neq i}}^{N} s.\left(\left|x_j - x_i\right|\right).\frac{x_j - x_i}{d_{ij}} + a_2.G_i + a_3.A_i \tag{5}$$

The equation above uses the social function s ($s(r) = f.e^{\frac{-r}{l}} - e^{-r}$), where N represents the total number of grasshoppers. However, this equation is not suitable for swarm and optimization simulation methods, as it restricts the algorithm`s ability to explore and exploit the search space around a potential solution. To overcome this limitation in optimization problems, a modified version of (5) is proposed as (6) and (7).

$$X_i^d = c.\left(\sum_{\substack{j=1 \\ j \neq i}}^{N} c.\frac{ub_d - lb_d}{2}.s.\left(\left|x_j^d - x_i^d\right|\right).\frac{x_j - x_i}{d_{ij}}\right) + \widehat{T_d} \tag{6}$$

$$c = c_{max} - t\,\frac{c_{max} - c_{min}}{L} \tag{7}$$

$\hat{T}_d$ represents the best value of the target, d_{th} is the current iteration`s dimension, and the decreasing coefficient is denoted as c (where c_{max} and c_{min} represents the maximum and minimum values, respectively). The upper and lower limits of the d_{th} dimension is denoted by u_{bd} and l_{bd}, respectively. The maximum number of iterations is represented by L, and t denotes the current iteration.

2.2. Proposed GOA based MPPT technique

Dealing with fluctuations in temperature and solar irradiance is of paramount importance when it comes to managing MPPT algorithms. Even a slight deviation in irradiance, leading to a minor shift in the optimal point, can trigger a gradual decline in the attainable power within a photovoltaic (PV) system. Consequently, this results in a notable drop in overall efficiency. This issue becomes even more pronounced when the PV system encounters mismatch shading condition, necessitating an MPPT algorithm capable of promptly and effectively adapting to these abrupt environmental changes. A solution to this challenge has been proposed: integrating the grasshopper optimization algorithm (GOA) into the maximum power point tracking (MPPT) process. The primary focus of this approach is to address the problems associated with mismatch loss (MML) scenarios, which involve shading issues in PV systems. A visual representation of the procedure can be observed in Figure 2, illustrating the step-by-step sequence for implementing the GOA as an MPPT technique. A direct duty cycle (D) control strategy has been employed to ensure the algorithm remains straightforward.

The algorithm follows a structured sequence of steps. Firstly, it commences with an initialization phase in which in the initial values of duty cycles, coefficient parameters are denoted as ‘c’, social force parameters are represented as ‘s’, and the maximum iteration count is established. Secondly, the algorithm advances to the stage of fitness evaluation. It reads and evaluates the tracked output power derived from the initial duty cycle transmitted to the DC-DC SEPIC converter. The highest attained output power among the initial duty cycles is recorded as the current best target value. Moving to the third step, the algorithm computes the coefficient ‘c’ using (7) and determines the social force ‘s’ using (4). These computed values play a role in updating the position of the duty cycles, akin to the movement of grasshoppers, in preparation for subsequent iterations. This process of iteratively adjusting positions continues until a predefined termination criterion, represented as a global maximum power point (GMPP), is satisfied. Upon meeting this termination criterion, the duty cycle and power output associated with the best target are returned as the most precise approximation for the global optimum.

Nevertheless, the suggested adaption of the GOA for the grasshopper’s equation incorporates a series of adjustments to the standard GOA as (6), culminating as (8).

$$D_i^t = c\left(\sum_{\substack{j=1 \\ j \neq t}}^{N} c.\frac{D_{max,t} - D_{min,t}}{2}.s.\left(\left|D_j^t - D_i^t\right|\right).\frac{\left(D_j^t(t) - D_i^t(t)\right)}{d_{ij}}\right) + \widehat{T_d} \tag{8}$$

$$d_{ij} = \left|D_j - D_i\right| \tag{9}$$

Here, D_i denotes the position of the i^{th} grasshopper (represented as new duty cycles), replacing X_i. Additionally, D_{max} and D_{min} define the duty cycle boundary limits. These modifications are rooted in the integration of the duty cycle boundary technique. These limits replace the standard lower and upper boundaries $[l_b, u_b]$ utilized in the standard GOA equation for the grasshopper's position. By implementing the duty cycle boundary technique, the search agents are allocated to fixed-range positions constrained by the specified boundary limits $[D_{min}, D_{max}]$, ensuring uniform intervals between them. This restricted distribution enables a more focused exploration within the designated duty cycle range.

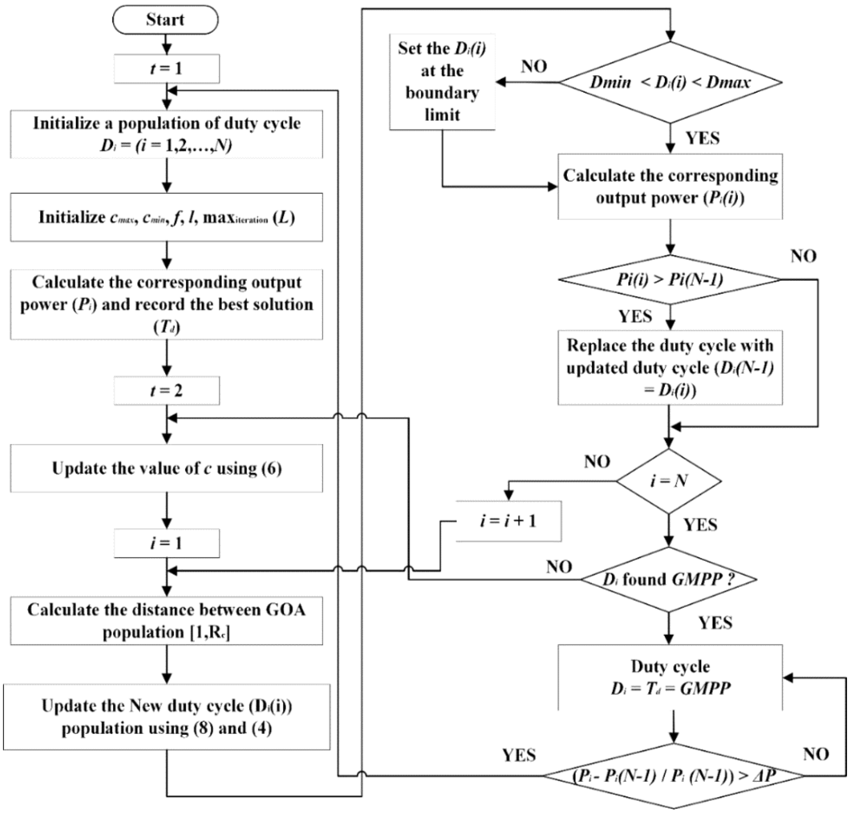

Figure 2. Diagram illustrating the flowchart of GOA MPPT algorithm

Subsequently, in contrast to the standard application of the GOA, the optimization procedure for GOA-based MPPT has been refined and enhanced. In the standard GOA approach, the parameter 't' is directly linked to the number of iterations, and the coefficient 'c' generates a sequence of values until reaching the maximum iteration count (L). Nevertheless, due to the dynamic nature of PV power generation, this method is less adept at addressing challenges within PV systems. An adjustment has been introduced to surmount this limitation and ensure an uninterrupted exploration of promising regions without early termination. In this modified approach, coefficient 'c' value remains constant throughout the process, irrespective of the iteration count. This alteration recognizes that PV systems lack a defined endpoint, thereby warranting the algorithm`s avoidance of premature halting. Consequently, accurately establishing the values of c_{min}, c_{max}, and L becomes crucial. These parameter values are pivotal in preventing the algorithm from becoming trapped in a specific region, enabling it to navigate promising solution spaces effectively.

Within the standard operational circumstances of a photovoltaic (PV) system, the surroundings undergo consistent fluctuations due to evolving weather conditions. As a consequence, the location of the global maximum power point (MPP) also varies. Thus, an MPPT algorithm should be equipped with the capacity to seek out the global MPP in reaction to evolving weather conditions or dynamic changes. The search process must be reset with a comprehensive reinitialization procedure to fulfill this necessity whenever dynamic conditions change. The standard GOA exhibits a constraint wherein it fails to identify a fresh optimal point when all elements converge and lose responsiveness to environmental shifts. To overcome these limitations, a commonly employed approach involves rejuvenating the landscape information by restarting the optimization process upon detecting environmental changes.

To bolster the efficacy of the proposed GOA algorithm in managing dynamic MPPT challenges, the subsequent reinitialization function, illustrated in (10), is applied to reset the positions of the grasshoppers.

$$\left(\frac{P_i - P_i^{(N-1)}}{P_i^{(N-1)}}\right) > \Delta P \quad (10)$$

Where P_i represents the current instantaneous power, $P_i^{(N-1)}$ denotes the previous power, and ΔP stands for the power threshold. By employing (10), the algorithm detects notable shifts in irradiance or the occurrence of mismatched shading. It accomplishes this by comparing $\left(\frac{P_i - P_i^{(N-1)}}{P_i^{(N-1)}}\right)$ with ΔP. Should $\left(\frac{P_i - P_i^{(N-1)}}{P_i^{(N-1)}}\right)$ surpass the present threshold ΔP, which indicates a sudden alteration in the power ratio of the array, the algorithm triggers a reinitiating of the optimization process. The specific value of the threshold ΔP is determined through simulations and experimental trials to capture substantial power changes. Thus, with the integration of this reinitialization step, the proposed algorithm effectively tackles the challenges presented by dynamic MPPT scenarios.

3. RESULTS AND DISCUSSION

To assess the viability and effectiveness of the proposed control technique for tracking the MPP, the system depicted in Figure 3 is instantiated using MATLAB/Simulink. In this study, the photovoltaic (PV) array comprises three PV modules connected in series. The specifications model of the PV array, with parameter values, is provided in Table 1.

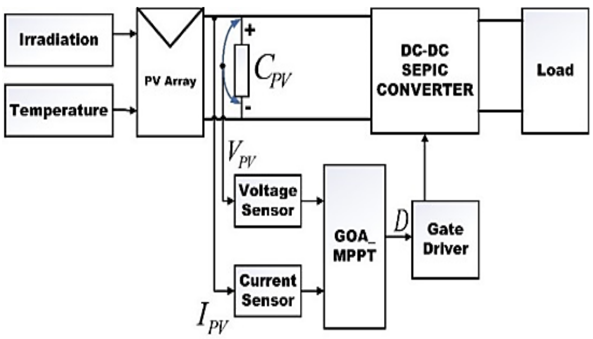

Figure 3. PV system with GOA based MPPT algorithm

Table 1. Specifications of 3 solar panel 1000 W/m² and 25 °C

Specification (KC50T)	Information
Power at the maximum point	162 W
Voltage at the maximum point	52.2 V
Current at the maximum point	3.11 A
Open Circuit Voltage	65.1 V
Short Circuit Current	3.31 A
Temperature Coefficient of V_{OC}	0.1206 %/°C
Temperature Coefficient of I_{SC}	-0.3783 % /°C
Number of cells per module	36

To highlight the advantages of the introduced control technique, various techniques like particle swarm optimization (PSO) and grey wolf optimization (GWO) are also evaluated under variable mismatch shading solar irradiance with constant temperature (25℃). The testing spanned four distinct dynamic solar irradiance conditions (as depicted in Figure 4), with solar irradiance changing every 2.0 seconds and 4.0 seconds. These scenarios included static changes in solar irradiance and mismatched solar irradiance conditions. Metrics like tracking speed, steady-state oscillation, and efficiency were analyzed across all algorithms. For a clearer understanding of the configuration of the proposed algorithm and parameter tuning of each tested method, Table 2 lists the parameter tunings of the MPPT algorithms, while Table 3 details the parameter settings specific to the implemented GOA-based MPPT.

Table 2. Parameters tuning of the MPPT algorithms

Algorithm	Parameter tuning
Grasshopper optimization algorithm	f = 0.9, l = 2.0, c_{min} = 0.8, c_{max} = 1.0
Particle swarm optimization (PSO)	c_1 = 1.2, c_2 = 1.6, w = 0.4
Grey wolf optimization (GWO)	$\vec{A}$ = 0.008, $\vec{C}$ = 2

Table 3. Parameters setting of GOA-MPPT

Parameter setting	Parameter value
Number of particles, N	4
Minimum duty cycle, D_{min}	0.1
Maximum duty cycle, D_{max}	0.7
Sampling time, t_a	0.03 seconds
Maximum iteration, L	50
c_{max}	1.0
c_{min}	0.9
Intensity of attraction, f	0.9
Length scale of attraction, l	2.0

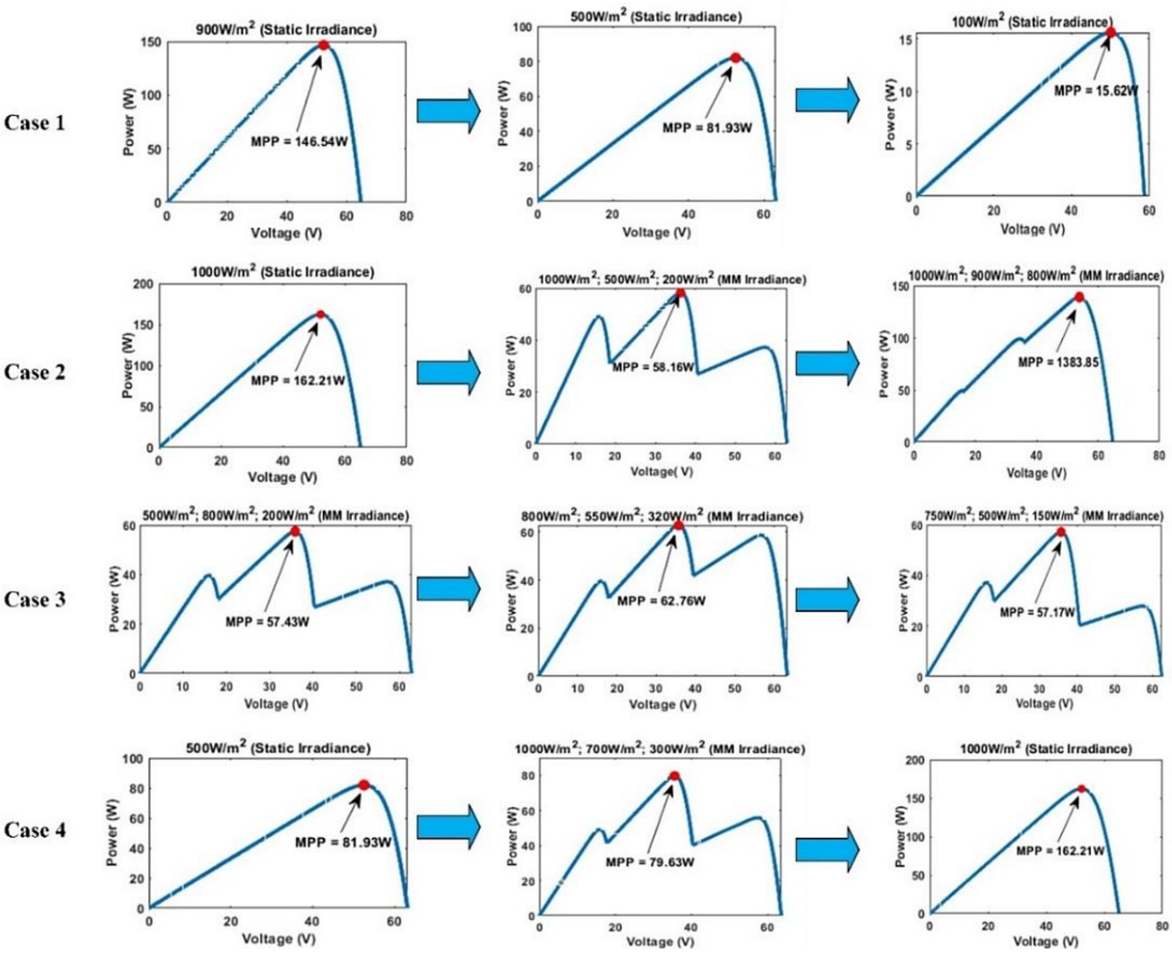

Figure 4. Dynamic changing of solar irradiance tests

All measurement outcomes for varying solar irradiances are recorded in Table 4. Simultaneously, the tracking response of the proposed GOA technique, in comparison with PSO and GWO, is depicted in Figure 5 and Figure 6. Figure 5 illustrates the tracking response when the MPPT algorithm transitions from one static irradiance level to another. In contrast, Figure 6 depicts the tracking response of the MPPT algorithm as it moves from one MM irradiance mode to another. The power results in Table 4 undoubtedly indicate that the MPPT technique based on GOA surpasses the other algorithms by adeptly tracking the MPP in a minimal amount of time across all solar irradiance conditions. In relation to the other two algorithms, it's evident that the new algorithm has advanced significantly, managing MPP tracking with negligible to zero oscillation, and eliminating issues of significant oscillation. Figures 5 and 6 corroborate this observation; after tracking the MPP, the GOA method displays only minor duty cycle disturbances and no duty cycle perturbations, respectively. The data in Table 4 further underscores the proficiency with which the recommended algorithm tracks the MPP in diverse, shifting scenarios, as the overall efficiency rates of the GOA technique range between 93% and 96%.

Table 4. Results of the MPPT algorithm track the MPP in dynamic changing static and mismatch irradiance

Cases	Algorithms	Solar irradiance condition						Overall efficiency (%)
		1		2		3		
		Power (W)	Tracking time (s)	Power (W)	Tracking time (s)	Power (W)	Tracking time (s)	
1	GOA	145.50	0.57	81.42	0.49	15.47	0.43	93.66
	PSO	146.30	1.01	81.84	1.74	14.95	0.77	90.81
	GWO	146.60	1.03	81.53	1.07	12.98	1.16	86.57
2	GOA	162.10	0.47	58.09	0.53	138.80	0.44	95.65
	PSO	161.80	0.88	58.08	1.11	138.80	1.92	92.53
	GWO	162.30	1.17	58.05	1.27	138.90	1.17	90.24
3	GOA	57.43	0.53	62.73	0.51	57.14	0.69	95.54
	PSO	57.42	1.01	62.63	1.89	56.27	1.93	90.27
	GWO	57.34	0.91	62.78	0.95	57.22	1.40	87.39
4	GOA	81.46	0.50	79.58	0.63	162.10	0.49	95.24
	PSO	81.84	1.22	79.63	1.62	162.20	1.63	93.73
	GWO	81.87	0.85	79.70	1.04	162.40	1.07	90.51

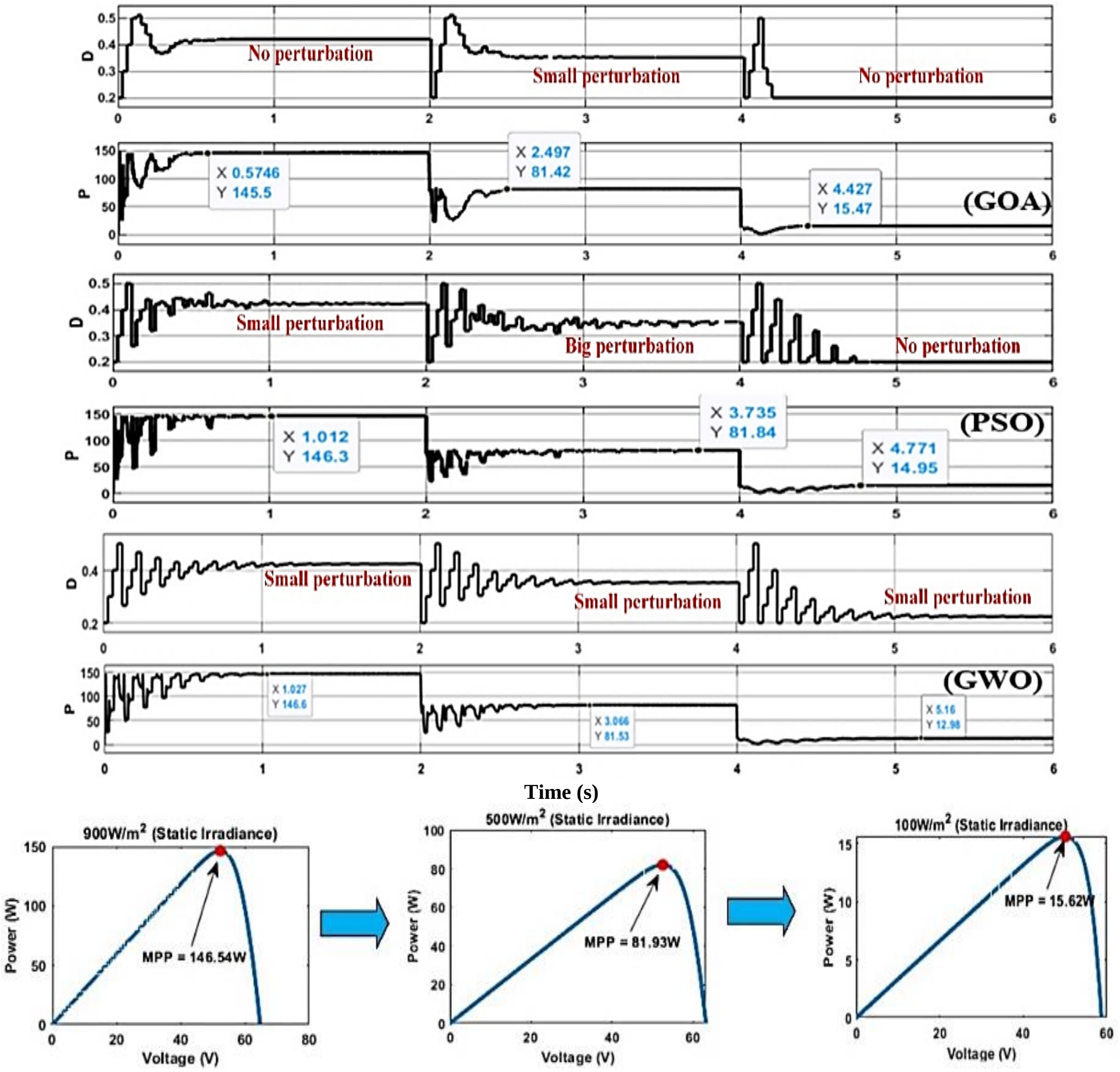

Figure 5. Tracking responses of GOA, PSO, and GWO during dynamic solar irradiance changes in Case 1

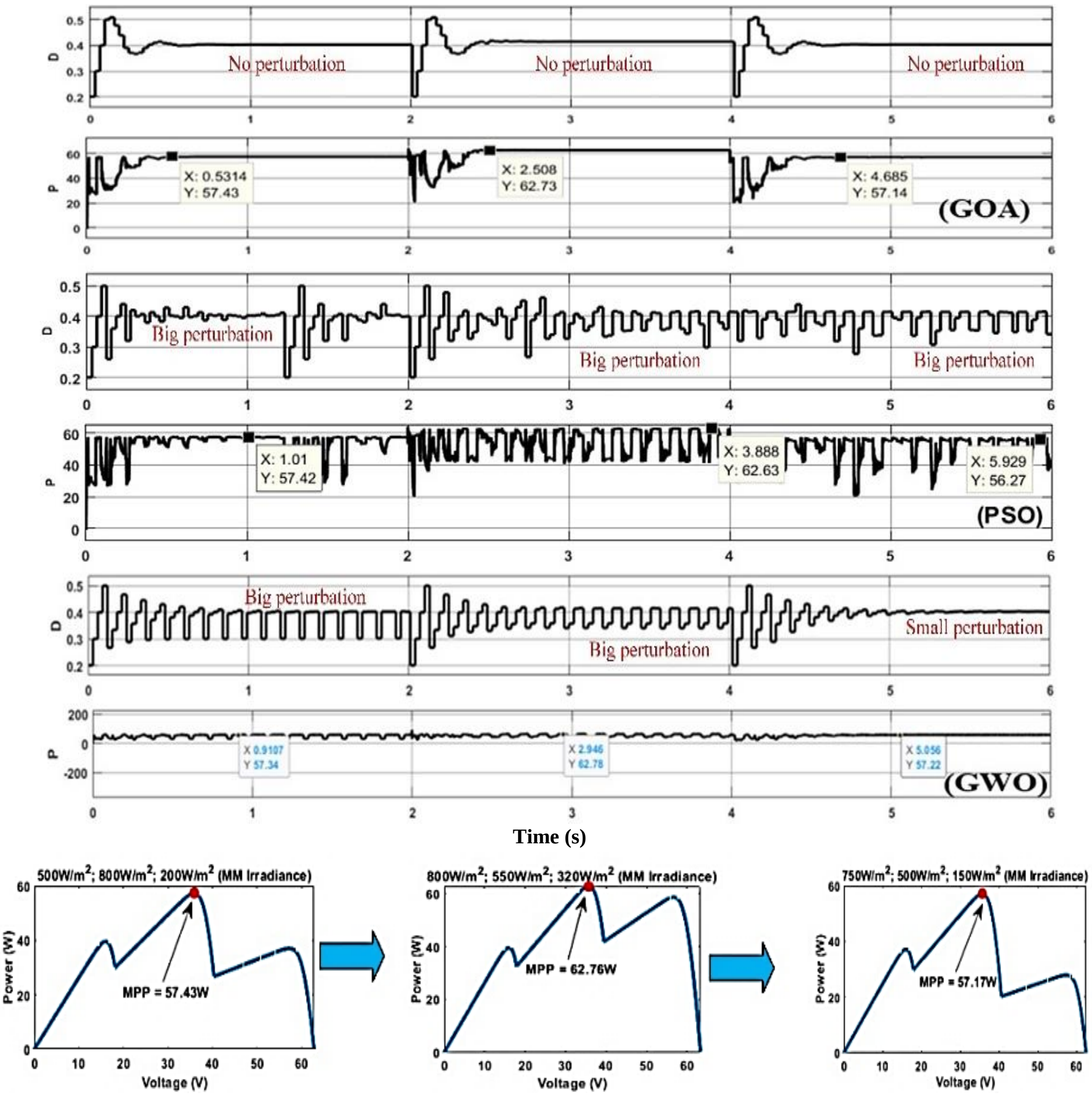

Figure 6. Tracking responses of GOA, PSO, and GWO during dynamic solar irradiance changes in Case 3

4. CONCLUSION

In their practical and experimental work, the researchers' primary focus has been on effectively tracking the maximum power of photovoltaic (PV) systems. In this study, the grasshopper optimization algorithm (GOA), a nature-inspired MPPT algorithm, has been proposed. The GOA technique aims to address the problem of mismatch loss (MML) by tracking the maximum power of PV arrays under dynamic mismatch (MM) solar irradiance conditions. The results indicate that the proposed GOA algorithm surpasses well-known methods like grey wolf optimization (GWO) and particle swarm optimization (PSO). It is superior in rapid tracking and exhibits fewer fluctuations near the steady-state curve. Simulation results underscore the algorithm's commendable efficiency, which lies between 93% and 96% under different environmental conditions. However, additional research is essential to affirm the algorithm's supremacy, especially in scenarios involving gradual weather transitions.

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