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Optimizing photovoltaic systems performance under partial shading using an advanced cuckoo search algorithm

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ABSTRACT

Partial shading negatively impacts power output in photovoltaic systems (PVs), causing multiple local maximum power points (LMPP) instead of a single global maximum power point (GMPP). The cuckoo search (CS) technique utilizes the maximum power point tracking (MPPT) technique to extract the global maximum power (GMP) from shaded PVs. CS is a metaheuristic technique that has gained widespread recognition. Moreover, the CS algorithm is associated with several challenges, including a failure rate, long response time, and noticeable oscillations during steady-state operation. To address these limitations, our proposed advanced cuckoo search (ACS) algorithm is designed to overcome the shortcomings of the standard CS algorithm. The algorithm iteratively evaluates individual solar panels and collectively explores the solution space using levy flight operations. Persistent variables are used to store and track the current state and previous iterations. Where the duty cycles of the solar panels are optimally set to enhance the overall power generation efficiency. We also evaluate and analyze the results obtained from the performance of our proposed technique and compare them to the performance of the four most recent CS optimization techniques. for all test cases, the tracking efficiency was improved to 99.98% with a fast-settling time of <44 ms.

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1. INTRODUCTION

In recent times, there has been an increasing global demand for clean and sustainable energy sources driven by concerns over climate change and the limited availability of fossil fuels. Solar energy has gained significant recognition as a promising solution among various renewable energy options, offering abundant power generation that is both environmentally friendly and sustainable. Nevertheless, the efficiency of photovoltaic (PV) systems can be notably influenced by partial shading (PS), a phenomenon that arises when one or more solar panels are obstructed by objects such as clouds, trees, buildings, or other structures [1]. PS can result in the appearance of several local maximum power points (LMPP) making it difficult to pinpoint the global maximum power point (GMPP), which leads to significant energy losses, reduced system efficiency, and a shortened lifespan of PV systems [2], [3]. In this context, researchers have put out several optimization methods in recent years to address the problems with GMPP in partially shaded solar panels. These techniques encompass genetic algorithms [4], fuzzy logic controller (FLC) [5], grey wolf optimization (GWO) [6], and model predictive control (MPC) [7]. However, these methods have limitations in computational efficiency, speed response, and accuracy. This means that these traditional methods are inadequate in such scenarios and may only locate a local MPP, resulting in reduced output from the solar array [8], [9].

To address the aforementioned challenges, researchers have put forward several GMPP techniques based on soft computing and metaheuristic [10]. These approaches encompass genetic algorithms [4], particle swarm optimization (PSO) [11], cuckoo search (CS) [12], artificial neural networks [13], firefly algorithm [14], artificial bee colony [15], and slap swarm optimization (SSO) [16]. While these soft computing methods demonstrate the capability to conduct global searches, they often exhibit increased complexity and slower execution due to the random nature of the search [17], [18]. To overcome this problem, a cuckoo search algorithm technique has been developed to address these challenges by changing parameters like modified cuckoo search (MCS) [19], in which the random parameter Lévy is replaced by a coefficient. However, despite the effectiveness of this technology, it has limitations in combining the fast-settling time and ensuring stable MPP tracking during continuous operation (reliability), as well as achieving high efficiency in energy production. In response to these challenges, the research introduces an advanced cuckoo search (ACS) algorithm controller to optimize PV systems under partial shading conditions (PSC). The ACS algorithm effectively optimized the performance of the photovoltaic system by combining fast settling time, reliability, and accurate GMPP Tracking, thereby improving the efficiency and lifespan of PV systems.

This paper proposes a new method that enhances performance and efficiency and achieves accurate the global maximum power point tracking (GMPPT) with a fast-settling time. The algorithm iteratively evaluates individual solar panels and collectively explores the solution space using levy flight operations. Persistent variables are used to store and track the current state and previous iterations. The main objective is to obtain the best solution, where the duty cycles of the solar panels are optimally set to enhance the overall power generation efficiency. The technique is examined through computer simulations conducted with the utilization of MATLAB/Simulink software. We also evaluate the results obtained from the performance of our proposed technique and compare them to the performance of the four most recent cuckoo search (CS) optimization techniques. The outcomes demonstrate that the proposed technique is superior in terms of computational efficiency, accuracy, stability, and fast settling time. Thereby improving the efficiency and lifespan of PV systems.

The presented work is divided into five sections: i) Section 2, we delve into the electrical modeling and characteristics of a PV system under PSC; ii) Section 3 elaborates on the proposed algorithm; iii) Section 4 is dedicated to the simulation results, analysis, and comparison of the obtained results of the proposed technique with the four most recent CS optimization techniques; and iv) Lastly, in the concluding section, we draw the final conclusion.

2. ELECTRICAL MODELING OF A PV SYSTEMS

2.1. PV systems performance under PSC

Partial shading is a major challenge for PV systems, as it can cause significant energy losses and reduce the efficiency of the entire system [20]. To address this challenge, several optimization techniques have been proposed. For example, the genetic algorithm (GA) [4], was applied to position PV systems as efficiently as possible under PSC [21]. The power output of PV systems under PS was optimized via particle swarm optimization [22]. In addition, ant colony optimization has been used to optimize the placement and configuration of PV systems to lessen the impact of PSC [23]. Despite their effectiveness, these techniques have limitations in terms of computational efficiency, speed response, stability, and accuracy. Their combination may be challenging.

2.2. Modeling of the PV system under PSC

The photovoltaic (PV) system comprises four photovoltaic panels, a control system ACS, a DC-DC converter (boost), and a load, as depicted in Figure 1. Photovoltaic systems often encounter PSC due to factors such as nearby buildings, trees, or cloud cover, which can significantly impact their efficiency. To comprehend the behavior and optimize the overall PV system performance under PSC, it is crucial to model the power-voltage (P-V) and current-voltage (I-V) curves. Figures 2(a) and 2(b) depicts these curves, providing valuable insights into the system's characteristics.

2.2.1. The DC-DC boost converter

Boost converters, commonly referred to as choppers, encompass various types of configurations. In this discussion, we will focus on the Step-up chopper, also known as a boost converter. Its primary function is to elevate the input DC voltage to the required output DC value. The DC-DC boost converter comprises several essential components, including a diode represented by D, two capacitors C_{int} and C_{out}, a source of DC input voltage labeled as V_A, Out Voltage V_0 , a switch referred to as S, an inductor denoted as L, and a diode represented by D as depicted in Figure 3. V_A and V_0 are given by the equations (1) and (2) respectively. The DC-DC converter serves as a crucial interface that facilitates the adjustment between the load and the PV panel, enabling the extraction of the panel's maximum power [24].

$$\frac{dI_L}{dt} = \frac{V_A}{L} \tag{1}$$

$$\frac{dV_0}{dt} = -\frac{V_0}{C_{out}R_L} \tag{2}$$

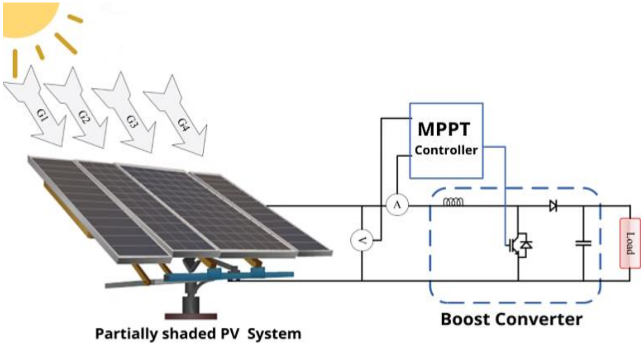
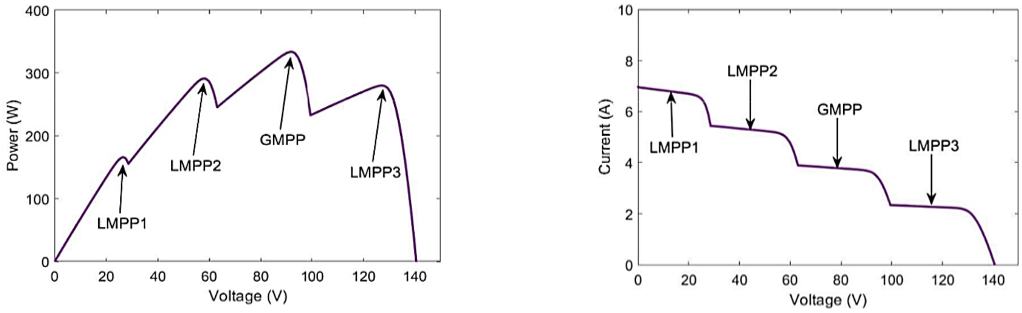


Figure 1. PV System under PSC



(a) (b)

Figure 2. The PV system curves when it is partially shaded (a) the P-V and (b) the I-V

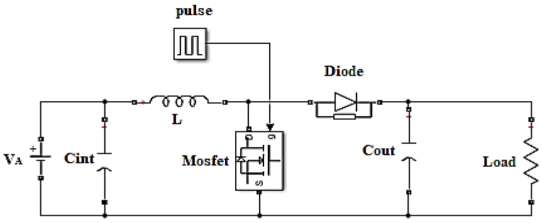


Figure 3. Step-up chopper

Duty cycle (D), The inductance (L) and Capacitance (C) of the boost converter are calculated as in (3), (4), (5) respectively.

$$D = 1 - \frac{V_A}{V_0} \tag{3}$$

$$L \geq \frac{V_A D}{f_s \Delta I_0} \tag{4}$$

$$C \geq \frac{I_0 D}{f_s \Delta V_0} \tag{5}$$

The PWM pulse generator provides the duty pulses necessary for the DC-DC converter operation. During the time interval between [αT, T], the transistor is in a blocked state. Here, T is the static converter time period, and α denotes the duty cycle. To describe the behavior of the DC-DC converter, (6) and (7) can be utilized in its modeling. The converter is controlled by a K switch this is typically implemented using a transistor (MOSFET). This switch has the ability to be either opened or closed, depending on the duty cycle that the MPPT algorithm generates.

$$\frac{dV_0}{dt} = \frac{i_L}{C_{out}} - \frac{V_0}{C_{out} R_L} \tag{6}$$

$$\frac{dI_L}{dt} = \frac{V_A - V_0}{L} \tag{7}$$

3. PROPOSED METHOD

3.1. Cuckoo search (CS) algorithm

The CS algorithm (CSA), originally introduced by Yang and Deb [25], is a metaheuristic approach that draws inspiration from the reproductive behavior of cuckoo birds. Cuckoos are renowned for their parasitic nature, as they deposit their eggs in the nests of other bird species rather than constructing their own. To enhance the likelihood of successful hatching and ensure the survival of their offspring, cuckoos engage in a stochastic search process by hopping from one nest to another.

During the search, cuckoos evaluate the quality of potential host nests and select the best one for egg placement. They strategically lay their eggs in favorable positions within the chosen nest, sometimes cuckoos may even remove the host bird's eggs to raise their chances of successfully hatching. Some cuckoo species have evolved to mimic the eggs of specific bird species, further increasing their chances of successful hatching. However, there is an inherent risk that the host bird may detect the presence of foreign eggs, leading to the abandonment of the nest and consequent failure of the cuckoo's eggs.

Drawing inspiration from this natural behavior, the CSA was developed as an optimization technique. When applied to single-objective problems such as GMPP, the CSA adheres to three fundamental rules: i) Random search: Cuckoos explore the search space by generating random solutions or candidate nests; ii) Levy flights: Cuckoos perform levy flights, a type of random walk, to enhance search efficiency and cover a broader space; and iii) Host detection and egg laying: Cuckoos identify promising nests based on fitness evaluation and lay their eggs strategically, taking into account the quality of the nests.

3.2. Advanced cuckoo search algorithm

The proposed methodology aims to optimize photovoltaic system performance under PSC using an ACS algorithm control method with fast response and accurate GMPPT. The methodology comprises the following sequential steps:

- Initialization: The algorithm initializes persistent variables to track the state and previous iterations. These variables include u (current iteration step), $d_{current}$ (current duty cycle value), p (power output), dc (the duty cycle value), d_{best} (the duty cycle value of the best-performing solar panel), counter (a variable used for keeping track of iterations), i_{worst} (a variable representing the index of the worst-performing solar panel), and discover (a variable indicating whether the algorithm should discover a new nest).
- Input: The algorithm takes input values V_{pv}, and I_{pv}.
- Iterative evaluation: The algorithm iterates through each solar panel (u = 1 to 4) and calculates the power output (p(u)) for each panel based on the current duty cycle (DC(u)). The duty cycle with the highest power output is stored in d_{best}.
- Levy flight exploration: The algorithm explores the solution space by applying levy flight operations to update the duty cycles of the solar panels. If u = 5, there is a chance of discovering a new nest. The duty cycle of the worst-performing solar panel (i_{worst}) is updated using levy flight with d_{best} as a parameter. If a random value is greater than 0.25, a new nest is discovered. Otherwise, the duty cycles of all solar panels are updated based on the best-performing panel (d_{best}).
- Convergence check: The algorithm checks if the counter is between 1 and 9. If true, it sets D to the current $d_{current}$ value and increments the counter. Otherwise, it proceeds to the next step.

- Output: The algorithm outputs the current value of u and sets D to a default value of 0.2 if u is not between 1 and 4.
- Termination: The algorithm stops after completing the required iterations.

The ACS algorithm distinguishes itself from existing cuckoo search-based GMPPT methods through several key innovations. It employs a sequential panel-by-panel approach, refining duty cycles individually, and enhancing accuracy. A unique levy flight exploration strategy, including a chance for nest discovery, bolsters solution space exploration. ACS also features a dynamic convergence check that adapts the algorithm's behavior during iterations. This check ensures that if the counter is between the predefined min and max values, it sets D to the current $d_{current}$ value and increments the counter; otherwise, it proceeds to the next step, as shown in Figure 4. Furthermore, ACS provides clear output information and follows a specified termination criterion. These elements collectively make ACS a more adaptive and potentially efficient tool for optimizing photovoltaic system performance under PSC compared to prior research. Proposed advanced cuckoo search algorithm parameters: i) Fraction K = 0.85, population size = 4, β = 3/2, and Pa = 0.25 and ii) Initial population = [0.4, 0.5, 0.6, 0.8] (duty cycle ratio).

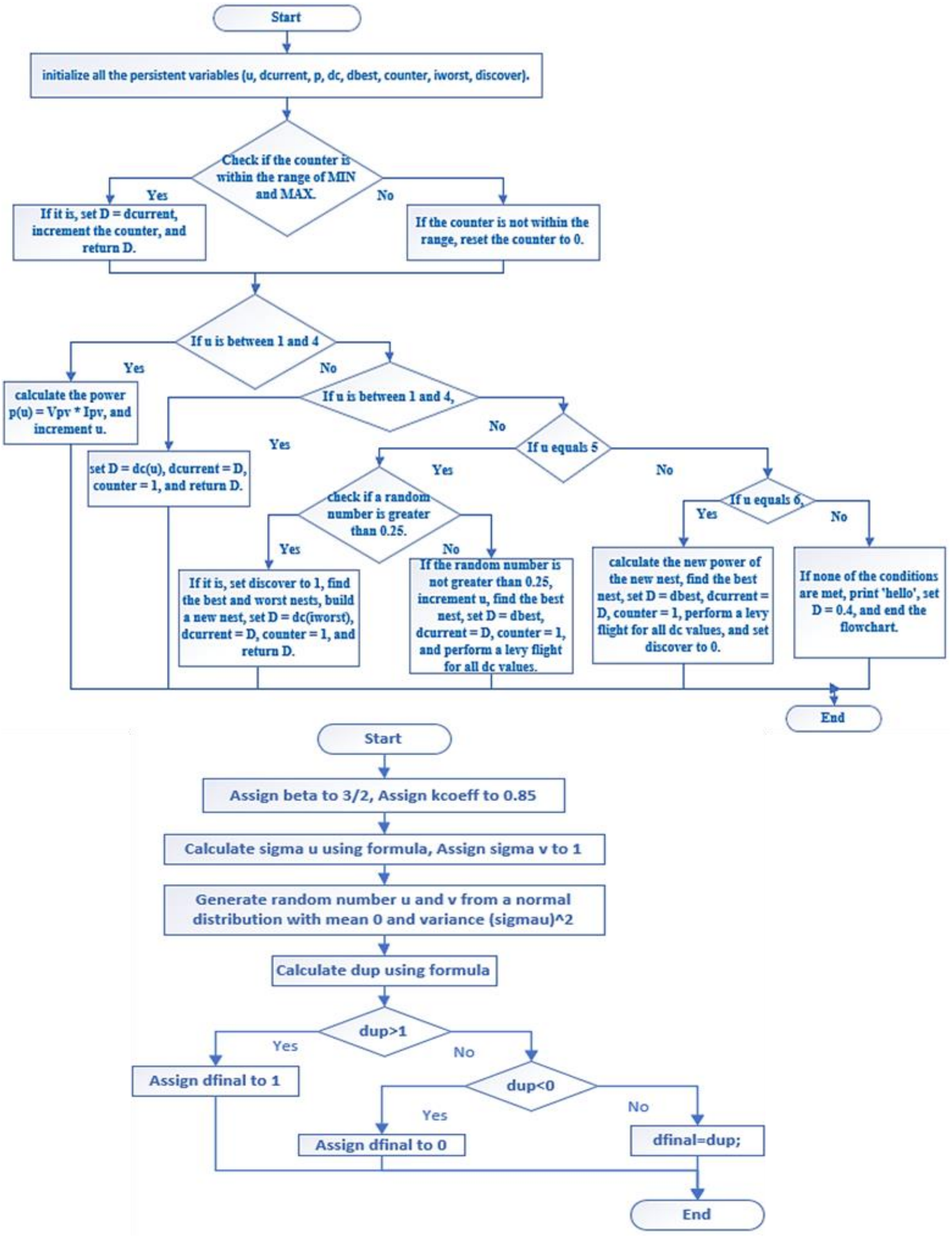


Figure 4. Flow chart of the ACS algorithm

4. SIMULATION RESULTS AND DISCUSSION

In this study, we conducted an evaluation of maximum power extraction techniques utilizing the proposed ACS method in MATLAB/Simulink. To simulate the impact of PSC on a solar PV system, we employed the API156P200 PV panels to model the PV string. A boost converter was used to adapt the load. The characteristic curves of the PV modules were simulated by adjusting the irradiance of the four PV panels series-connected as shown in Figure 5, along with the step-up chopper, such as illustrated in Figure 6. The simulation was conducted with a 25 °C constant temperature. Table 1 provides detailed specs regarding the solar PV modules and the DC-DC converter. Table 2 presents the comprehensive outcomes of the simulation. Table 3 showcases various performance metrics, including tracking efficiency, settling time, and other relevant parameters, comparing them with the results of four recent CS optimization techniques. The findings in Table 3 demonstrate the superiority of the ACS algorithm in enhancing power generation efficiency and its potential for practical implementation in real-world PV applications. Efficiency: $\eta = \frac{P_o}{P_{GMPP}} \times 100$, where P_o represents the PV panels output power, which is tracked by the ACS algorithm, while P_{GMPP} denotes the global maximum real power.

Table 1. API156P200 PV module, and step-up chopper specs

Parameters	Value
API156P200 solar PV module	
Number of cells per module	60
V_{oc} (V)	36 V
I_{SC} (A)	7.75 A
V_{Mpp} (V)	28.7 V
I_{Mpp} (A)	6.97 A
P_{Mpp} (W)	200.039 W
Step-up chopper specs	
Inductance (L)	10 mH
Capacity (C_{int})	4 µF
Capacity (C_{out})	20 µF
Frequency (fs)	50 kHz
Load	120 Ω

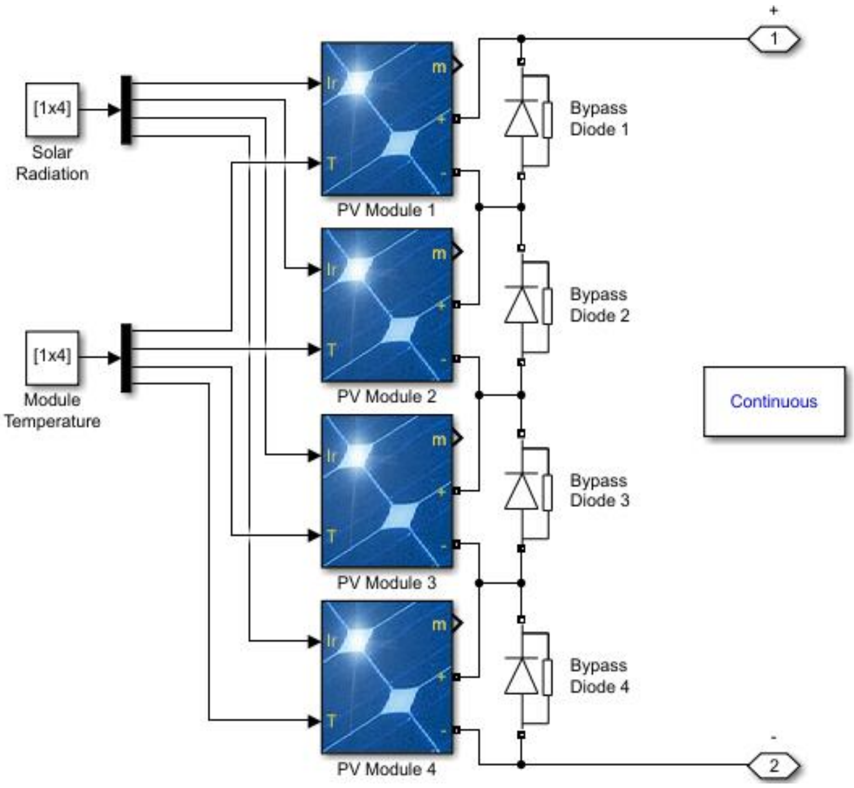


Figure 5. PSC on PV panels series-connected

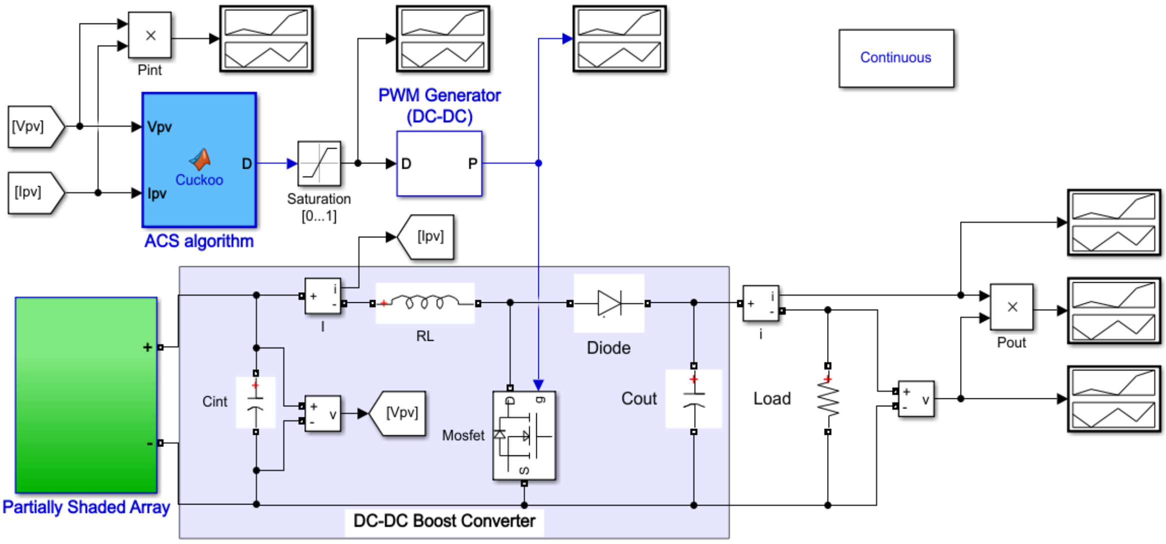


Figure 6. Simulation models of four series-connected API156P200 PV panels in various shading patterns were developed using the ACS algorithm

4.1. Various shading patterns: examining four cases

4.1.1. Case 1

This shading pattern consists of irradiation values 1000 w/m^2, 800 w/m^2, 600 w/m^2 and 400 w/m^2 for each module, respectively. The system operates with a 25 °C constant temperature. Figure 7 illustrates the characteristic power-voltage plots, providing insights into the behavior of the photovoltaic strings under this specific PSC. The plots clearly depict four distinct peaks, indicating the presence of both global and local MPP within the characteristic curve. The GMPP is precisely measured at 397.45 W. The outcomes for this case are represented in Figures 8 and 9. Figure 8(a) shows the efficiency, Figure 8(b) depicts the stability, Figure 9(a) illustrates ST, and Figure 9(b) illustrates the steady-state oscillations. In this case simulation, the proposed advanced cuckoo (ACS) algorithm successfully demonstrates superior tracking efficiency for the global MPP and fast settling time (ST) under PSC. It achieves an impressive efficiency of 99.95% with a fast ST of 18 ms, as depicted in Table 2.

Table 2. Results of the four cases of studies

Irradiance pattern $(\mathbf{w/m^2})$	$P_{GMPP}(w)$	$I_{out}(A)$	$V_{out}(V)$	$P_{out}(w)$	Duty cycle (%)	Settling time (sec)	Efficiency (%)
Case 1	397.45	1.819	218.38	397.24	48.66	0.018	99.95
Case 2	333.68	1.665	200.30	333.5	54.19	0.025	99.95
Case 3	268.64	1.496	179.54	268.59	58.29	0.044	99.98
Case 4	210.65	1.324	159.07	210.61	63.18	0.022	99.98

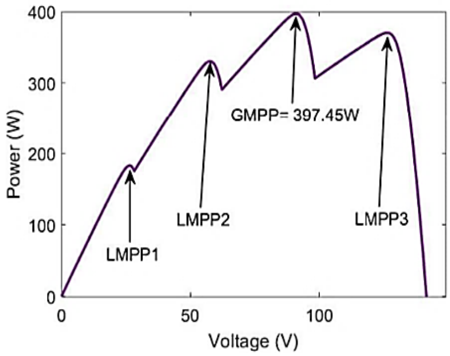
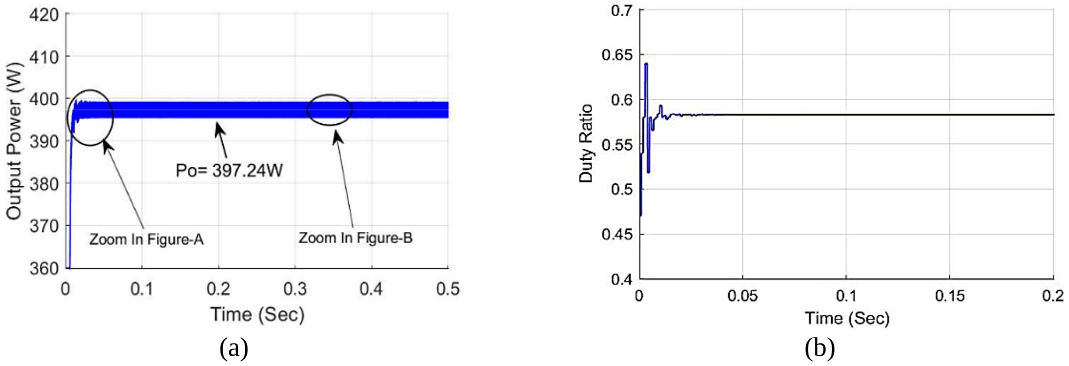
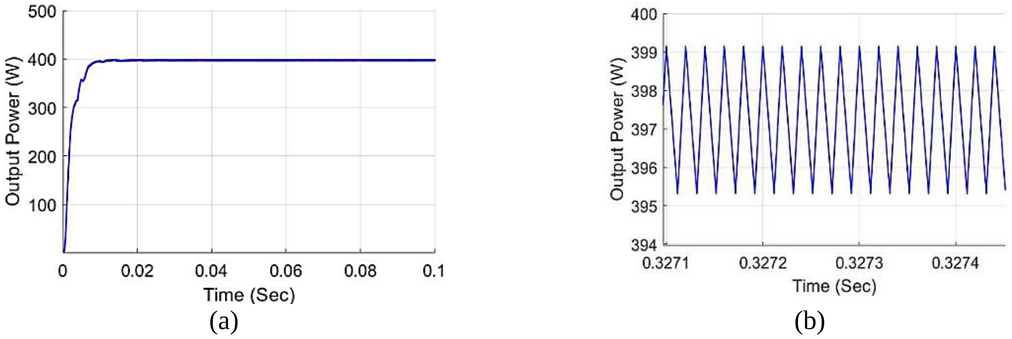


Figure 7. The P-V curve represents the response of the PV module under the specific PS pattern, with irradiation values of [1000, 800, 600, and 400] w/m^2 applied respectively



(a) (b)

Figure 8. The simulation results using ACS for pattern 1: (a) the output power and (b) duty ratio



(a) (b)

Figure 9. The zoomed images of the output power provide a closer look at two important aspects: (a) the settling time and (b) the steady-state oscillations of the output power

4.1.2. Case 2

In this second shading pattern, consists of irradiation values 900 w/m^2, 700 w/m^2, 500w/m^2, and 300w/m^2, for each module, respectively. The system operates with a 25 °C constant temperature. Figure 10 illustrates the characteristic power-voltage plots, providing insights into the behavior of the photovoltaic strings under this specific PSC. The plots clearly depict four distinct peaks, indicating the presence of both global and local MPP within the characteristic curve. The GMPP is precisely measured at 333.68. The outcomes for this case are represented in Figures 11 and 12. Figure 11(a) shows the efficiency, Figure 11(b) depicts the stability, Figure 12(a) illustrates ST, and Figure 12(b) illustrates the steady-state oscillations. In this case simulation, the proposed ACS algorithm successfully demonstrates superior tracking efficiency for the global MPP and fast ST under PSC. It achieves an impressive efficiency of 99.95% with a fast ST of 25 ms, as depicted in Table 2.

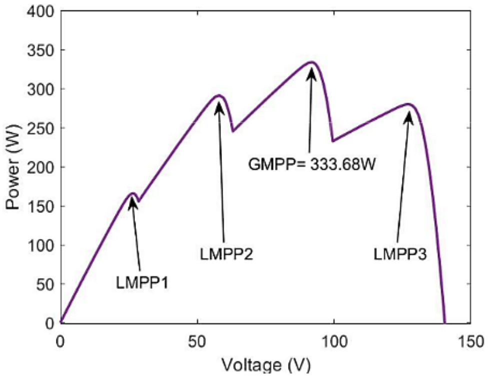
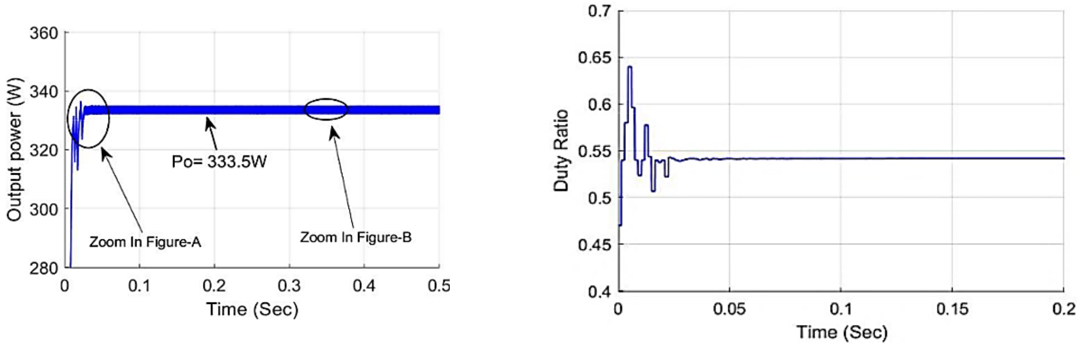
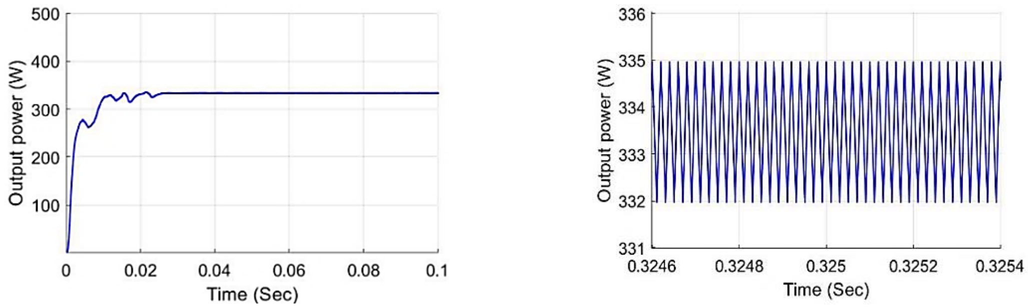


Figure 10. The P-V curve represents the response of the PV module under the specific PS pattern, with irradiation values of [900, 700, 500, and 300] w/m^2applied respectively



(a) (b)

Figure 11. The simulation results using ACS for pattern 2: (a) the output power and (b) duty ratio



(a) (b)

Figure 12. The zoomed images of the output power provide a closer look at two important aspects: (a) the settling time and (b) the steady-state oscillations of the output power

4.1.3. Case 3

In this particular shading pattern, consists of irradiation values 800 w/m^2, 600 w/m^2, 400 w/m^2, and 200 w/m^2, for each module, respectively. The system operates with a 25 °C constant temperature. Figure 13 illustrates the characteristic power-voltage plots, providing insights into the behavior of the photovoltaic strings under this specific PSC. The plots clearly depict four distinct peaks, indicating the presence of both global and local MPP within the characteristic curve. The GMPP is precisely measured at 268.58 W. The outcomes for this case are represented in Figures 14 and 15. Figure 14(a) shows the efficiency, Figure 14(b) depicts the stability, Figure 15(a) illustrates ST, and Figure 15(b) illustrates the steady-state oscillations.

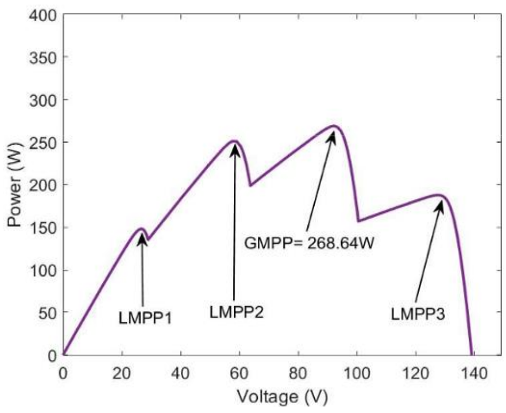
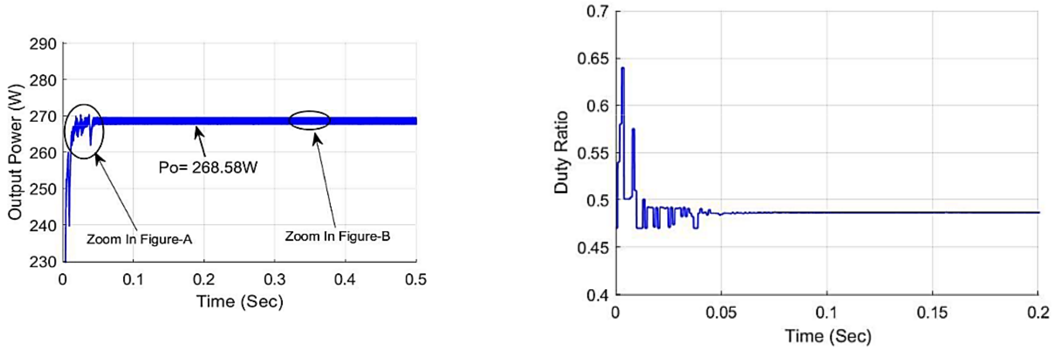
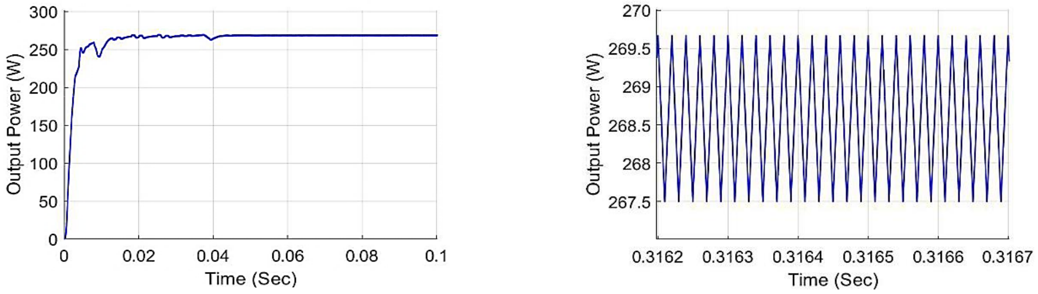


Figure 13. The P-V curve represents the response of the PV module under the specific PS pattern, with irradiation values of [800, 600, 400, and 200] w/m^2 applied respectively



(a) (b)

Figure 14. The simulation results using ACS for pattern 2: (a) the output power and (b) duty ratio



(a) (b)

Figure 15. The zoomed images of the output power provide a closer look at two important aspects: (a) the settling time and (B) the steady-state oscillations of the output power

4.1.4. Case 4

In this particular shading pattern, consists of irradiation values 700 w/m^2, 500 w/m^2, 300 w/m^2, and 100 w/m^2, for each module, respectively. The system operates with a 25 °C constant temperature. Figure 16 illustrates the characteristic power-voltage plots, providing insights into the behavior of the photovoltaic strings under this specific PSC. The plots clearly depict four distinct peaks, indicating the presence of both global and local MPP within the characteristic curve. The GMPP is precisely measured at 210.62 W. The outcomes for this case are represented in Figures 17 and 18. Figure 17(a) shows the efficiency, Figure 17(b) depicts the stability, Figure 18(a) illustrates ST, and Figure 18(b) illustrates the steady-state oscillations. In this case simulation, the proposed ACS algorithm successfully demonstrates superior tracking efficiency for the global MPP and fast ST under PSC. It achieves an impressive efficiency of 99.98% with a fast ST of 44 ms, as depicted in Table 2.

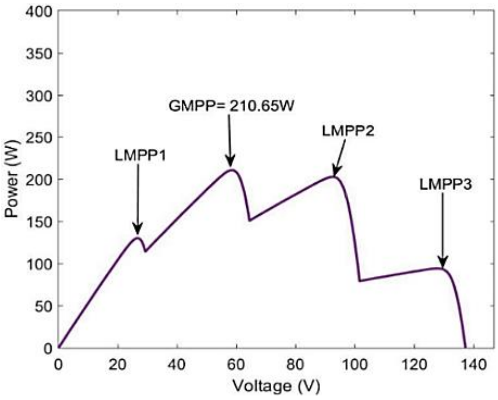
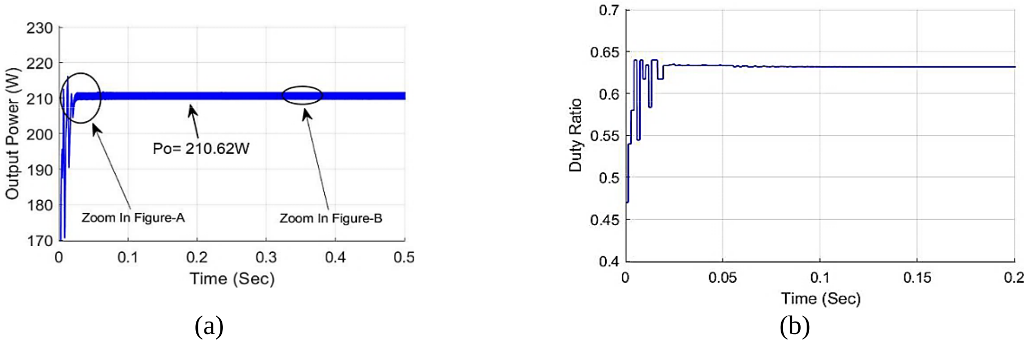
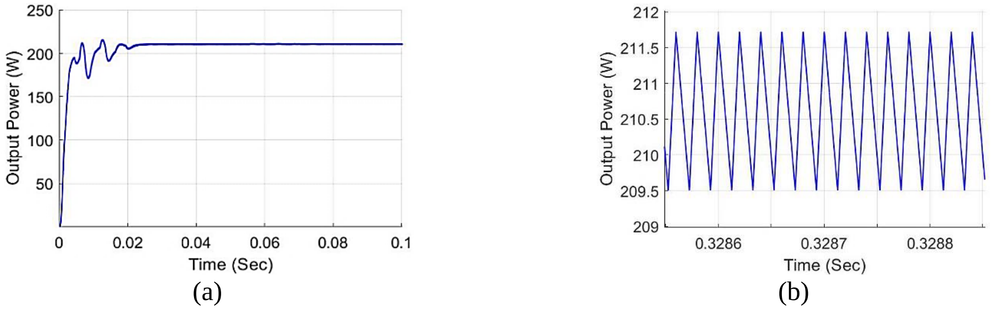


Figure 16. The P-V curve represents the response of the PV module under the specific PS pattern, with irradiation values of [700, 500, 300, and 100] w/m^2applied respectively



(a) (b)

Figure 17. The simulation results using ACS for pattern 4: (a) the output power and (b) duty ratio



(a) (b)

Figure 18. The zoomed images of the output power provide a closer look at two important aspects: (a) the settling time and (b) the steady-state oscillations of the output power

4.2. Comparison of test results

The results obtained from the proposed technique, ACS algorithm, are compared with the four most recent CS optimization techniques. This comparative study specifically focuses on shading models utilizing four photovoltaic panels with different irradiance levels. Notably, the (P-V) curve exhibits quadruple-peaks values within the shading pattern. The evaluation of this comparative study encompasses several aspects, including efficiency accuracy, settling time speed, and reliability, as shown in Table 3. The remarkable results achieved by our proposed technique, the ACS algorithm, compared to other CS optimization techniques, are evident regarding failure rate, steady-state oscillations, settling time, and tracking efficiency. These results demonstrate the absolute superiority of (ACS) when employed for GMPPT in photovoltaic energy systems under PSC.

Table 3. Comparison results between the proposed ACS and four other CS optimization techniques under PSC

CSA technique	Proposed in [26]	Proposed in [27]	Proposed in [19]	Proposed in [28]	(ACS)
Efficiency (%)	99.09	99.88	99.9	99.7	99.98
Settling time (sec)	0.16	0.061	3.1	0.7	0.025
Tracking speed	Moderate	Fast	Low	Low	Fast
Tracking accuracy	Good	Good	Excellent	Good	Excellent
Steady-state oscillations	Moderate	Low	High	High	Low

5. CONCLUSION

This paper proposes an advanced cuckoo search algorithm for GMPPT in photovoltaic systems under PSC. By iteratively evaluating individual solar panels and employing levy flight-based exploration of the solution space, combined with optimal duty cycle settings. The technique is examined through computer simulations conducted using the MATLAB/Simulink software. The ACS algorithm demonstrates significant improvements in power generation efficiency with fast settling time compared to the four most recent CS optimization techniques. The comparison was conducted by evaluating the capacity to achieve the actual GMPP, the settling time speed, and overall efficiency while considering their combination. The outcomes demonstrate that the proposed technique is superior in terms of computational efficiency, accuracy, stability, and fast settling time. Thereby improving the efficiency and lifespan of PV systems. The ACS algorithm achieves a tracking efficiency all higher than 99.95% with a fast-settling time of less than 44ms for all test cases under PSC.

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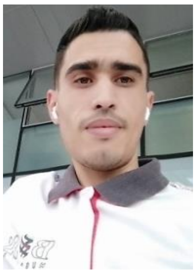

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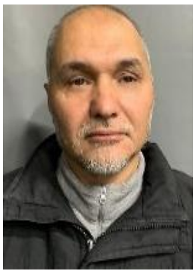

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