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Ilyas MIMOUN[1], Youcef MIHOUB[2], Aicha ASRI[3], Said HASSAINE[4]
ORCID: [1]0009-0007-5251-1936, [2]0009-0005-5693-6494, [3]0000-0002-2575-1009, [4]0000-0002-2827-1414
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Coot optimizer algorithm-based GMPPT to extract maximum power under partial shading conditions

Algorytm optymalizatora Coot oparty na GMPPT w celu uzyskania maksymalnej mocy w warunkach częściowego cieniowania

[1] Ilyas Mimoun, University of Tiaret, Department of Electrical Engineering, E-mail: ilyas.mimoun@univ-tiaret.dz
[2] Dr. Youcef Mihoub, University of Tiaret, Department of Electrical Engineering, E-mail: youcef.mihoub@univ-tiaret.dz
[3] Dr. Aicha Asri, University of Tiaret, Department of Electrical Engineering, E-mail: aicha.asri@univ-tiaret.dz
[4] Prof. Dr Said Hassaine, University of Tiaret, Department of Electrical Engineering, E-mail: said.hassaine@univ-tiaret.dz
correspondence address: ilyas.mimoun@univ-tiaret.dz

Abstract: Partial shading conditions (PSCs) complicate the power-voltage (P-V) curve of photovoltaic (PV) systems, featuring a single global maximum power point (GMPP) alongside multiple local maxima. Traditional MPPT algorithms often is unable to locate the GMPP under these conditions. This study proposes a Coot Optimization Algorithm (COA) as an innovative approach for tracking the GMPP in PV systems. The drawbacks of conventional MPPT algorithms under PSCs are addressed by the suggested COA algorithm, as well as those of particle swarm optimization (PSO), including reduced tracking efficiency and prolonged tracking times. A comparative analysis conducted using MATLAB R2023b/SIMULINK evaluated the performance of the COA-MPPT in a PV array during complex PSCs, with results compared to those obtained using the PSO-MPPT. The simulation outcomes demonstrate that the COA technique consistently achieves efficiencies exceeding 95% under various conditions, underscoring its efficacy in enhancing the performance of PV systems. Furthermore, the findings indicate that COA surpasses the PSO technique in both tracking efficiency and speed.

Keywords: Photovoltaic Systems (PV), Partial Shading Conditions (PSCs), Global Maximum Power Point (GMPP), Coot Optimization Algorithm (COA)

Streszczenie: Warunki częściowego zacienienia (PSC) komplikują krzywą mocy i napięcia (PV) systemów fotowoltaicznych (PV), charakteryzującą się jednym globalnym punktem maksymalnej mocy (GMPP) i wieloma lokalnymi maksimami. Tradycyjne algorytmy MPPT często nie są w stanie zlokalizować GMPP w takich warunkach. W niniejszym badaniu zaproponowano algorytm optymalizacji Coot (COA) jako innowacyjne podejście do śledzenia GMPP w systemach fotowoltaicznych. Sugerowany algorytm COA rozwiązuje wady konwencjonalnych algorytmów MPPT w ramach PSC, a także wady optymalizacji roju cząstek (PSO), w tym zmniejszoną wydajność śledzenia i wydłużony czas śledzenia. Analiza porównawcza przeprowadzona przy użyciu MATLAB R2023b/SIMULINK oceniła wydajność COA-MPPT w układzie PV podczas złożonych PSC, a wyniki porównano z wynikami uzyskanymi przy użyciu PSO-MPPT. Wyniki symulacji pokazują, że technika COA konsekwentnie osiąga wydajność przekraczającą 95% w różnych warunkach, co podkreśla jej skuteczność w zwiększaniu wydajności systemów PV. Co więcej, wyniki wskazują, że COA przewyższa technikę PSO zarówno pod względem wydajności, jak i szybkości śledzenia.

Słowa kluczowe: Systemy fotowoltaiczne (PV), warunki częściowego zacienienia (PSC), globalny maksymalny punkt mocy (GMPP), algorytm optymalizacji Coot (COA)

Introduction

The growing depletion of conventional energy resources, coupled with intensifying global environmental challenges, underscores the urgent need to increase the adoption of renewable energy sources. This demand has driven the widespread implementation of distributed generation systems globally. Solar energy, due to its abundant availability, limitless supply, and environmental benefits, has emerged as a leading renewable energy source. Compared to traditional energy sources, renewables like solar energy offer significant advantages, including reduced greenhouse gas emissions and air pollution, which contribute to climate change mitigation. Solar energy's abundance and universal accessibility make it an appealing option for electricity generation, utilizing technologies such as solar thermal and PV systems to meet diverse energy needs [1, 2].

While solar thermal systems use the sun's heat to generate steam or heat water, photovoltaic PV systems use solar panels to convert sunlight directly into electricity [3]. These technologies have shown significant advancements in efficiency, cost-effectiveness, and scalability, positioning solar energy as an increasingly viable and competitive alternative to conventional energy sources.

MPPT techniques are essential in PV systems to optimize solar energy utilization. MPPT's main objective is to effectively control the PV panel's power extraction in order to satisfy the demands of the load. MPPT continuously monitors the MPP on the solar panel's (I-V) curve, improving system performance and overall efficiency [4].

Partial Shading (PS) results in uneven sunlight distribution across a PV system, reducing its maximum power output. This uneven solar irradiance causes multiple MPPs on the I-V curve, hindering power generation efficiency. Mitigating partial shading effects is crucial for maximizing power output and overall PV system performance. PV panels with parallel-connected bypass diodes create multiple local peaks on the I-V curve, challenging traditional MPPT algorithms in tracking the global peak (GP) under PS conditions. AI-based MPPT approaches are among the most promising methods for moderating PV solar systems and accurately tracking the GP under various PS patterns [5, 6, 7].

To address the issues caused by partial shading, numerous metaheuristic optimization approaches have been proposed for GMP tracking, including the Grey Wolf Optimization (GWO) [8], Particle Swarm Optimization (PSO) [9], Salp Swarm Optimization (SSA) [10], Flower Pollination Algorithm (FPA) [11], and Ant Colony Optimization (ACO) [12]. Among these bioinspired algorithms, the Coot Optimization Algorithm (COA) [13] is a swarm intelligence method based on the cooperative behaviors of coots. It uses four main movements—random, chain, leader-following, and leader-directed adjustment—enable robust search capabilities while mitigating premature convergence risks. Furthermore, COA's reduced dependency on parameter tuning simplifies implementation compared to conventional methods. Despite these advantages, existing literature lacks comprehensive studies on COA's direct application to MPPT control in PS scenarios. This work addresses this research gap by evaluating COA's efficacy in navigating complex P-V curves under non-uniform irradiance conditions.

This work presents a simulation-based validation of a direct control method integrated with a COA-based MPPT technique under PSCs. The method eliminates the need for a linear controller, as the algorithm directly adjusts the duty cycle. Key advantages of the COA algorithm include its simplicity, low computational cost, high solution accuracy, fast convergence independent of initial conditions, and effective avoidance of local minima.

This study holds the following contributions:

1. A new COA-based MPPT controller for PV systems, improves GMPPT efficiency and tracking accuracy while minimizing tuning parameters to prevent agent position redundancy.
2. Evaluation of the COA-based approach under complex PSCs, demonstrating its resilience and effectiveness in capturing the GMPP.
3. A comparative analysis of the proposed COA-based MPPT algorithm with the PSO algorithm through simulation.

The paper structure is as follows: The modeling of partially shaded PV systems is comprehensively discussed in Section II. The MPPT method based on COA is demonstrated in Section III. The numerical simulations are shown in Section IV. Section V culminates with conclusions and suggestions for additional study.

Characteristics of a PV system under PSCs

Fig. 1 illustrate the PV structure. It is composed of a current source, a diode, a series resistor (R_s), and a shunt resistor (R_{sh}). The mathematical model of single-diode representation is mentioned above. The PV cell current is defined in Eq. (1).

$$I_{pv} = I_{ph} - I_{sat}\left(e^{\frac{q(V_{pv}+R_s.I_{pv})}{n.K.T}} - 1\right) - \frac{V_{pv}+R_s.I_{pv}}{R_{sh}} \tag{1}$$

where: I_{ph} represents the photocurrent, I_{sat} is the saturation current, V_{pv} and I_{pv} are the voltage and current of the PV cell, T is the temperature (in Kelvin), K is the Boltzmann constant.

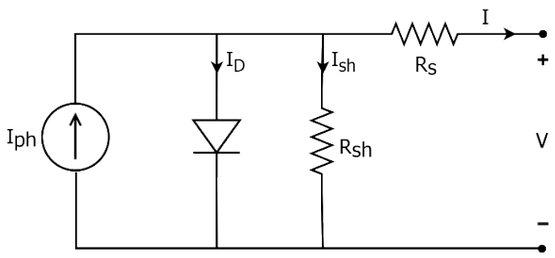

Fig. 1. PV cell modeling.

The impact of PSCs on MPPT

PV systems exhibit intrinsically low conversion efficiency, necessitating continuous operation at their MPP to optimize energy harvest. Conventional PV architectures consist of interconnected solar cells arranged in series or parallel configurations to form modules and arrays. output power and voltage shaded modules suffer significant reductions under PSCs. In order to counteract these effects, bypass diodes are implemented in parallel with individual modules. This solution facilitates uninterrupted current flow and minimizes shading-induced losses. These diodes are critical for preventing hotspot formation caused by mismatched module performance. Additionally, series-connected blocking diodes are employed to inhibit reverse current flow within the system.

Advanced MPPT algorithms are adapted to identify the GMPP under PSCs, thereby enhancing system efficiency and ensuring optimal PV operation. Fig. 2(a) depicts a series configuration of three PV modules integrated with bypass diodes. Under uniform irradiance, modules exhibit uniform voltage characteristics, as demonstrated by the P-V and I-V curves in Fig. 2(b). PS induces multiple Local Maximum Power Points (LMPPs) and a single GMPP in these curves, where LMPPs represent lower power peaks and the GMPP corresponds to the highest attainable power output.

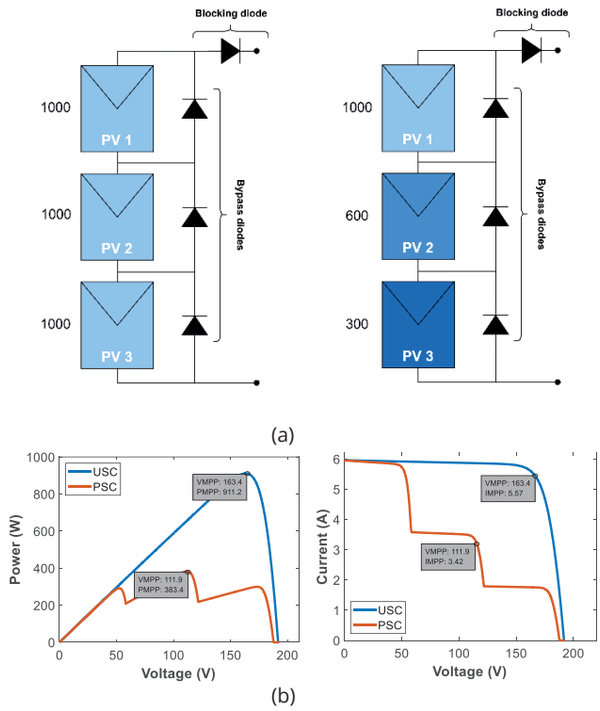

Fig. 2. Impact of PS on PV array performance: (a) configuration of bypass diodes within the PV array, (b) comparison of P-V and I-V curves under USC and PSC.

Coot optimization algorithm

In 2021, Iraj Naruei [13] introduced the COA, a metaheuristic optimization approach inspired by the social behaviors of coots, a species of waterfowl in the Rallidae family. The algorithm models a population of virtual coots that modify their positions according to a set of rules designed to emulate the natural foraging behaviors observed in coot flocks. COA operates in two main phases: an initial phase of random, exploratory movements, and a subsequent phase of more focused and directed motion.

The COA framework analyzes four distinct movement patterns exhibited by coots on the water surface: (1) random motion, (2) chain motion, (3) positional shifts of group leaders, and (4) leader-driven movement to guide the group toward the optimal location.

Eq. (2) is used to determine the population in space that is generated at random.

$$X(k) = rand(1,d) \times (ub - lb) + lb \tag{2}$$

The position at iteration k is denoted by $X(k)$, where d is the search space's dimensionality (i.e., the number of optimization variables). ub and lb stand for the upper and lower bounds of the search space, respectively. The framework for the four different movement phases in the COA model is defined by these factors.

Random motion

Eq. (3) defines the movement of the coot particle within the search space is randomly.

$$W = rand(1,d) \times (ub - lb) + lb \tag{3}$$

By exploring diverse regions within the search space, coots facilitate a more comprehensive search, allowing the algorithm to bypass local optima where it might otherwise get trapped. As the algorithm departs from these local points, Eq. (4) is applied to update the coots' positions.

$$X(k) = X(k) + Z \times R_2 \times (W - X(k)) \tag{4}$$

Here, R_2 represents a random value between 0 and 1, while Z is computed according to Eq. (5).

$$Z = 1 - L \times \left(\frac{1}{I_{ter}}\right) \tag{5}$$

L indicates the current iteration step, and the variable I_{ter} indicates the maximum number of iterations.

Changing the position following the group leaders

Coots position is adjusted depending on selected leaders, based on Eq. (6) to move toward leaders.

$$X(k) = G(M) + 2 \times R_1 \times cos(2\pi R) \times (G(M) - X(k)) \tag{6}$$

The coot's current location is shown by $X(k)$, the position of the chosen leader is indicated by G(M), R_1 is a random number between [0,1], R is a random value between [-1, 1], π is the constant 3.14.

Movement of the leaders to direct a group to the best location

During this phase, when the coots move toward the leaders' positions, the leaders themselves move to find

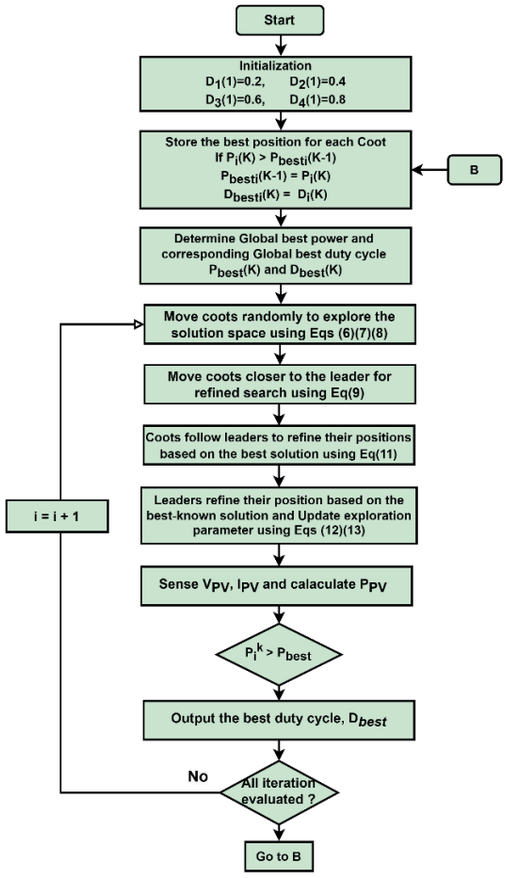

Fig. 3. The proposed algorithm flowchart.

the best spot for the coots to follow. Eq. (7) is used to determine the leaders' optimal position.

(7)
$$G(k) = \begin{cases} B \times R_3 \times cos(2R\pi) \times \left(g_{Best} - G(k)\right) + g_{Best} & R_4 < 0.5 \\ B \times R_3 \times cos(2R\pi) \times \left(g_{Best} - G(k)\right) - g_{Best} & R_4 > 0.5 \end{cases}$$

Eq. (8) variables are defined as follows: random values in the interval [0, 1] make up R_3 and R_4, R falls within the interval [-1, 1], and B is represented accordingly.

(8)
$$B = 2 - L \times \left(\frac{1}{I_{ter}}\right)$$

Where L is the current iteration and I_{ter} indicates the maximum iteration.

In the implementation of the MPPT algorithm grounded in the COA for PV systems operating under PSCs, the algorithm employs a direct control strategy to optimize the duty cycle (D) of the boost converter. This method focuses on the fine-tuning of a solitary parameter. Fig. 3 shows the flowchart of the COA steps that are mentioned. Initially, n random duty cycles (d_1, d_2,..., d_n) are generated within a specified range using (9):

(9)
$$d_i = d_{min} + rand[0,1](d_{max} - d_{min})$$

The boost converter is subjected to these duty cycles in order to assess the goal function. PV voltage (V_{PV}) and current (I_{PV}) are monitored in order to determine the corresponding power (P_{PV}) for every di. To guarantee reliable sampling, the interval between assessments must be longer than the settling time of the power converter.

Simulation results

To highlight the advantages and effectiveness of the Coot Optimizer Algorithm (COA) in GMPPT techniques, simulations were performed in the MATLAB R2023b/SIMULINK environment. The system includes a boost converter, an MPPT controller, and a load, as depicted in Fig. 8.

The input and output capacitances, Cin and Cout, are set to 90 µF and 190 µF, respectively, the inductance L is set to 160 µH, and the load resistance (R_{load}) is maintained at 100 Ω. A MOSFET with a switching frequency of 15 kHz is used. The evaluation incorporates the parasitic parameters of the PV panels provided in Table 1.

Table 1. SunPower PL-SUNP-SPR-305W under STCs

Parameter	Value
P_{MPP}	305.226
V_{MPP}	54.7
I_{MPP}	5.58
V_{OC}	64.2
I_{SC}	5.96

Table 2. Tuning parameters of PSO, and COA

Metaheuristic methods	Tuning parameter
PSO [9]	$C_{1max} = 2, C_{1min} = 1, C_{2max} = 2, C_{2min} = 1$ $w_{max} = 1, w_{min} = 0.1$
COA	$B = 2 - L \times \left(\frac{1}{I_{ter}}\right)$

Validation is conducted on the proposed technique on three PSCs, each exhibiting multiple and distinct peaks, as depicted in Figs. 4–7 which show both the shading patterns and the corresponding theoretical power output.

The PV panel is configured with the following three complex PSCs:

1. PS-1: 200, 400, 1000, 1000, 1000 and 1000 W/m^2
2. PS-2: 300, 600, 900, 1000, 1000 and 1000 W/m^2
3. PS-3: 900, 800, 700, 500, 400 and 200 W/m^2

The proposed COA technique was evaluated against Particle Swarm Optimization (PSO) [9] were analyzed in terms of tracking efficiency, and resilience under PSCs. Table 2 provides a summary of the tuning parameters used for each algorithm.

Both PSO and COA-based MPPT algorithms were used to track the GMP. To enable GMP tracking from

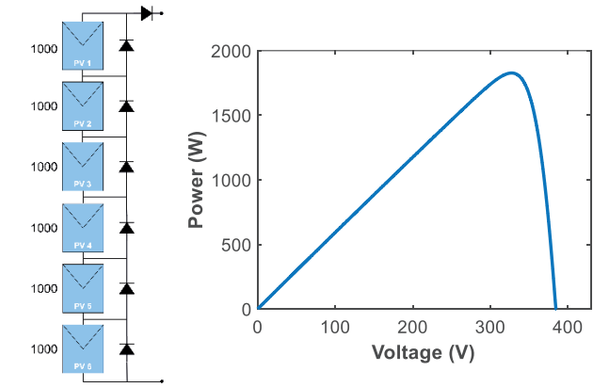

Fig. 4. Explanation of the STC scenario.

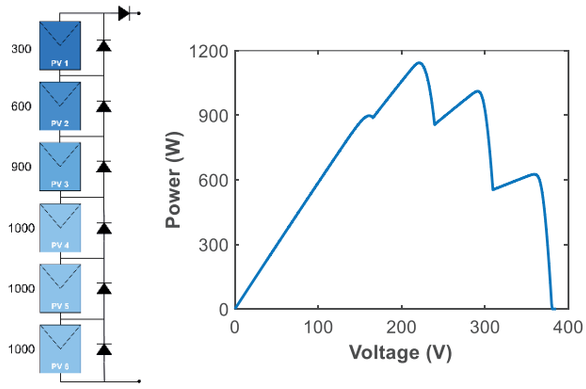

Fig. 6. Explanation of partial shading pattern (2).

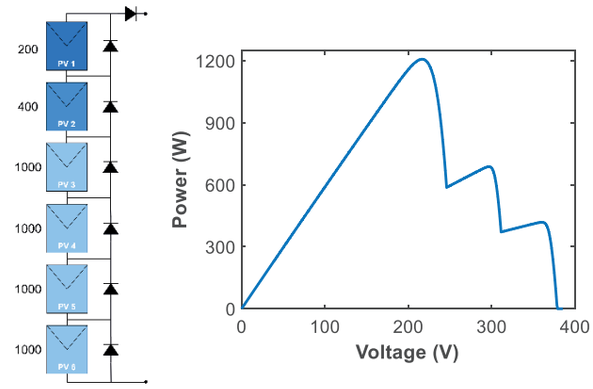

Fig. 5. Explanation of partial shading pattern (1).

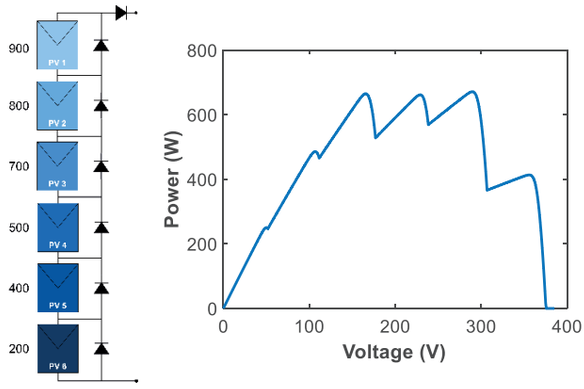

Fig. 7. Explanation of partial shading pattern (3).

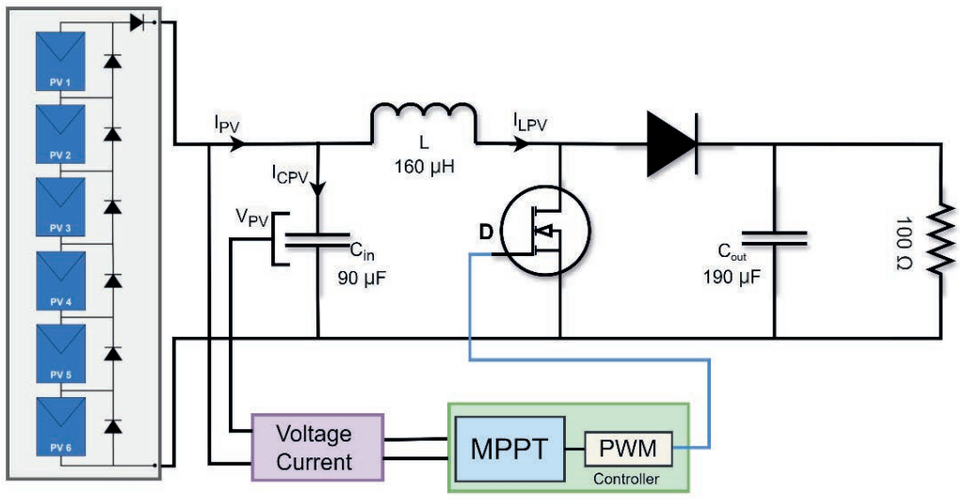

Fig. 8. The considered PV system under study.

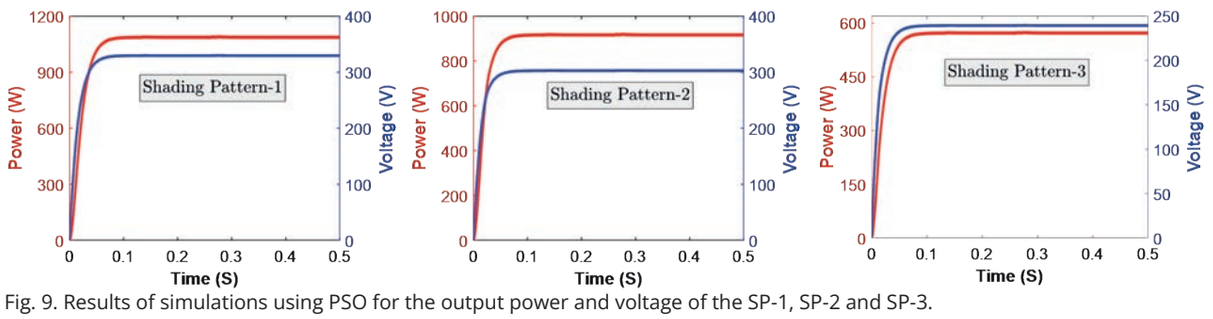

Fig. 9. Results of simulations using PSO for the output power and voltage of the SP-1, SP-2 and SP-3.

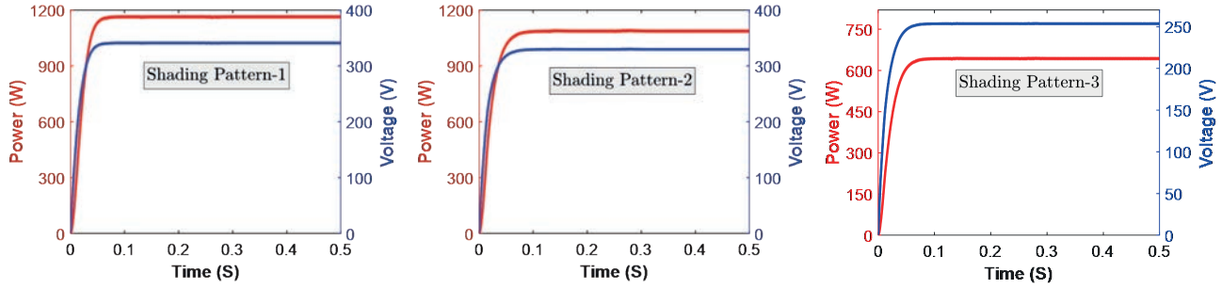

Fig. 10. Results of simulations using COA for the output power and voltage of the SP-1, SP-2 and SP-3.

Table 3. COA and PSO techniques capturing of the simulation results

Shading Pattern	MP(W) from P-V curve	Algorithm	PGMP (W)	IGMP (A)	VGMP (V)	Efficiency (%)
SP-1	1207.51	COA	1163	3.41	341.0	96.31
		96.31	1086	3.29	329.6	89.93
SP-2	1143.53	COA	1086	3.29	329.5	94.96
		PSO	916	3.02	302.7	80.10
SP-3	671.251	COA	642.4	2.53	253.5	95.70
		PSO	571.9	2.39	239.1	85.19

a PV array, the duty cycle (0.2, 0.4, 0.6, and 0.8) of a boost converter was first tuned to random values. The halting condition was then attained by adjusting the duty cycle using the MPPT algorithms. The results, as illustrated by Figs. 9, 10, show the PV array's power output using both COA and PSO techniques. A qualitative analysis of GMP extraction during various shading conditions is provided in Table 3.

The parameters at GMP—VGMP, IGMP, and PGMP—were analyzed. The COA algorithm demonstrated superior tracking speed and efficiency compared to the PSO algorithm across all shading patterns.

Under shading pattern SP-1, the COA algorithm achieved a tracking efficiency of 96.31%, significantly higher than the PSO algorithm 89.93%. For shading pattern SP-2, the COA algorithm achieved a PGMP of 1086 W with an efficiency of 94.96%, whereas the PSO algorithm attained a PGMP of 916 W with an efficiency of 80.10%. Similarly, under shading pattern SP-3, the COA algorithm recorded a PGMP of 642.4 W and an efficiency of 95.70%, in contrast to the PSO algorithm PGMP of 571.9 W and efficiency of 85.19%.

The results indicate that the GMP may be found using both the COA and PSO techniques in a variety of shading scenarios. In addition, the COA technique performs better overall in terms of tracking efficiency and speed.

Conclusion

This paper proposes a new MPPT technique for PV system operating under complex PSCs, utilizing the COA with direct duty cycle control. Also, PSO-based MPPT was tested. The performance of the proposed algorithm was evaluated through simulations under various shading patterns to assess its feasibility and effectiveness. The simulation demonstrates the COA-based MPPT technique's superior performance over the PSO technique in terms of shorter convergence times and higher tracking efficiency under various SPs. Notably, the suggested algorithm doesn't rely on presumptions about the beginning conditions, and doesn't require knowledge of the technical details or features of PV arrays beforehand. Future work will focus on comparative analyses of new advanced metaheuristic algorithms under PSCs to provide a comprehensive understanding of PV system performance. Additionally, experimental validation using low-cost commercial microcontrollers is recommended to confirm the practical applicability and robustness of the proposed approach.

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