

# A Hybrid of Meta-Heuristic Techniques Based on Cuckoo Search and Particle Swarm Optimizations for Solar PV Systems Subjected to Partially Shaded Conditions

Aiman Nouh<sup>1\*</sup>, Alhasan H Almalih<sup>1</sup>, Moneer A Faraj<sup>1</sup>, Alhusayn Almalih<sup>2</sup>,  
Faisal Mohamed<sup>3</sup>.

<sup>1</sup>Department of Electrical and Electronic Engineering, University of Omar Al-Mukhtar, Al-Bayda, Libya.

<sup>2</sup>Department of Renewable and Sustainable Energy Engineering, University of Derna, Derna, Libya .

<sup>3</sup>Libyan Authority for Scientific Research, Tripoli, Libya.

**E-mail:** [aiman.nouh@omu.edu.ly](mailto:aiman.nouh@omu.edu.ly), [alhasan.almalh@omu.edu.ly](mailto:alhasan.almalh@omu.edu.ly), [moneer.a.faraj@omu.edu.ly](mailto:moneer.a.faraj@omu.edu.ly),  
[a.almalih@uod.edu.ly](mailto:a.almalih@uod.edu.ly), [faisal.mohamed@omu.edu.ly](mailto:faisal.mohamed@omu.edu.ly).

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## ABSTRACT

Solar energy has a significant role in meeting rising energy demand while reducing environmental impact. Solar radiation and temperature are important factors on which PV energy production depends, but its optimal operation point is influenced by variations in the aforementioned environmental factors. The nonlinear behavior of the solar system and the variable nature of environmental conditions make determining the optimal operation point difficult. To overcome these difficulties, maximum power point tracking (MPPT) finding techniques are used to extract the optimal power from the photovoltaic energy system.

The behavior of MPPT varies for different weather conditions, such as partial shading conditions (PSC), and uniform irradiance conditions. Conventional techniques are simple, quick, and efficient for tracing the MPP quickly, but they are limited to uniform weather conditions. In addition, these techniques don't achieve the Global Maxima (GM) and mostly stay stuck at the Local Maxima (LM). The Meta-Heuristic techniques aid in finding the GM, but their primary disadvantage is that they take a longer time to trace the Global Maxima. This study addresses the problem by combining Cuckoo Search (CS) and Particle Swarm Optimization (PSO) algorithms, leading to a hybrid (CSPSO) technique to extract the global maximum (GM).

\*Corresponding author.



To verify the effectiveness of the suggested technique, its performance is examined under three different irradiance patterns for different PV array configurations (such as 3S and 4S3P) through MATLAB simulation. The outcomes of CSPSO are compared with the prior well-known Meta-Heuristic techniques such as Cuckoo Search (CS), Particle Swarm Optimization (PSO), and Crow Search Algorithm (CSA). The results show the suggested technique excels over other techniques in terms of accuracy, tracking efficiency, and tracking speed. The suggested technique is capable of tracking GMPP with an average efficiency of 99.925% and an average tracking time of 0.13 s in all shading patterns studied.

### خليط من تقنيات الاستدلال الفوقي القائمة على بحث الوقواق وتحسينات سرب الجسيمات لمنظومات الطاقة الشمسية الكهروضوئية المعرضة لظروف مظلمة جزئياً

أيمن عبدالرحمن نوح، الحسن حمد المالح، منير عبدالله فرج، الحسين حمد المالح، فيصل عبدالعظيم العبدلي.

**ملخص:** يمكن للطاقة الشمسية ان تلعب دوراً مهماً في تلبية الطلب المتزايد على الطاقة وتقليل الضرر البيئي. ويعتبر الإشعاع الشمسي ودرجة الحرارة الهواء الجوي من العوامل الجوية المهمة التي تؤثر في إنتاج الطاقة الكهروضوئية وكذلك نقطة التشغيل المثالية. كما يجعل السلوك الغير خطي للخلايا الشمسية والظروف الجوية المتغيرة من تحديد موضع التشغيل المثالي تحدياً تقنياً. وللتغلب على هذه الصعوبات، يتم استخدام تقنيات تتبع موضع القدرة القصوى (MPPT) للحصول على أكبر قدر من الطاقة من نظام الطاقة الكهروضوئية. يختلف سلوك MPPT باختلاف الظروف الجوية، مثل ظروف التظليل الجزئي، وكمية الإشعاع الشمسي. وتعتبر التقنيات التقليدية بسيطة وسريعة وفعالة لتتبع موضع القدرة القصوى بسرعة، ولكنها تقتصر على الظروف الجوية الموحدة. بالإضافة إلى ذلك، لا تحقق هذه التقنيات الحد الأقصى الكلي وتبقى في الغالب عالقاً عند الحد الأقصى الموضعي. تساعد تقنيات Meta-Heuristic في العثور على القيمة القصوى الكلية، غير أنها تستغرق وقتاً أطول للتتبع وهذا يمثل القصور الأساسي لهذه التقنيات. تحاول هذه الدراسة حل هذه المشكلة من خلال الجمع بين خوارزميات (Cuckoo Search - CS) وخوارزميات (Particle Swarm Optimization - PSO)، وبشكل هذا النهج تقنية هجينة جديدة (CSPSO) للحصول القيمة القصوى الكلية. وللتحقق من فعالية التقنية المقترحة، تم اختبار أداؤها تحت ثلاثة أنماط إشعاع مختلفة وتوصيلات مختلفة للصفيف الكهروضوئي مثل التوالي والتوازي والتضاعف، وذلك باستخدام برنامج المحاكاة MATLAB. حيث تم مقارنة نتائج التقنية الهجينة المقترحة مع التقنيتين. أظهرت النتائج أن التقنية المقترحة تتفوق على التقنيتين السابقتين، حيث بلغ متوسط كفاءة التتبع حوالي 99.925% ومتوسط مدة التتبع 0.13 ثانية لجميع أنماط التظليل التي تمت دراستها.

**الكلمات المفتاحية:** بحث الوقواق، تحسينات سرب الجسيمات، حالات التظليل الجزئي.

## 1. INTRODUCTION

The usage of solar photovoltaics is expanding worldwide since it is one of the most economical methods for producing power. The installed capacity of photovoltaic solar energy has been growing continuously since 2000, and a high of 1177 GW is expected in 2022. Markets throughout the world are moving significantly toward sustainable and renewable energy sources as a result of the photovoltaic solar energy sector's expanding trend. Notably, with installed capacities of 307 GW and 122 GW, respectively, China and the United States emerged as leaders in the global photovoltaic solar energy business. In addition, Chile and Honduras stated in 2022 that their whole energy mix included the highest percentage of photovoltaic solar energy [1-3].

PV solar energy fields are quite important, especially considering how well they work in hybrid energy systems as an ideal complement to conventional and renewable energy sources. These systems are extensively used across the world because of their dependability and resilience

in producing electricity from a variety of sources, such as PV/grid, PV/wind, PV/diesel, PV/concentrated solar power (CSP), PV/wind/diesel, and PV/wind/battery combinations [4-8]. Moreover, solar photovoltaic has many qualities, including its clean energy, ease of installation, and environmentally friendly nature; however, despite these qualities, it also faces challenges. As the output of the photovoltaic system is not constant, it varies according to the position of the sun, temperature, shadows, and irradiance level, which is sufficient to place the system in partial and complex shading conditions [9-11]. Under these conditions, the system's performance degrades because many peaks appear on the P-V curve. Among these peaks, only one is the global peak or global maximum (GM); and the rest are known as local peaks. Therefore, tracking the global peak is essential for maximum power point extraction and ensuring the optimum operation of a PV system under PSCs [12].

In the literature, several tracking (MPPT) techniques have been suggested. The complexity, accuracy, and cost-effectiveness of these techniques differ greatly by the type of control strategy [13]. Traditional techniques such as hill climb (HC), perturb and observe (P&O), and incremental conductance (INC), work on similar principles. The insertion of a minor change into the present operating point is a feature of these techniques. If the outcome improves, the change is kept, and the process of increasing continues in this direction. If the alteration has a negative outcome, the motion is continued in the reversed direction [14, 15]. These techniques are fairly efficient and easy to implement. However, these techniques are incapable of distinguishing between global maxima (GM) and local maxima (LM). These techniques mostly stay stuck at the local maxima (LM). Consequently, the system's overall performance decreases.

To address this issue, several researchers by applied artificial intelligence techniques, such as fuzzy logic controller (FLC), artificial neural network (ANN), and neural fuzzy (NF). These strategies are efficient in addressing the shaded PV panel's nonlinear output characteristic. However, the FLC technique needs the creation of a full fuzzy rule table, the ANN method demands the training of parallel grids in neural network models, and the NF method requires the proper construction of a neuro-fuzzy model [16]. As a result, these techniques need more memory space as well as massive amounts of data for training.

In recent years, a new category of meta-heuristic optimization-based MPPT techniques that effectively solve PSC. The behavior and performance of these techniques depend on many factors, namely the number of iterations, parameter tuning, convergence speed, objective function, population size, and computational time [17]. In [18], a particle swarm optimization (PSO)-based MPPT technique shares information through the social iteration of swarm particles. The velocity vectors of the personal and global best solutions along the current exploration's direction are used to share this information. The impact of velocity vectors is governed by random and fixed weights. The addition of randomization to velocity vectors increases exploration, but as a side effect, the particle's tracks in the GMPPT are slowed. The equilibrium optimization (EO) in [19] utilizes more than one random variable, which causes unnecessary exploring of the same position, thus increasing the tracking time. In [20], cuckoo search (CS) is used for the MPPT application, where the particle's position is updated using Levy flight. Although CS can effectively search the GMPP and avoid the LMPP trap, it still takes a long time to locate the global MPP. The grey wolf optimization (GWO) algorithm presented in [21] has the capability of tracking GMPP effectively under PSC but remains trapped on the LMPP trap under complex partial shading because of the grey wolves' slow motion as the number of iterations increases. The slow motion is caused by a tuning parameter that decreases with iteration. The artificial bee colony (ABC) in [22] is used as an MPPT controller where the scout bee group is randomly selected. This random solution is useful for maximizing exploration, however, it results in undesirable slow convergence and energy loss. In [23], the grasshopper optimization (GHO)-based MPPT technique uses

the comfort zone parameter to balance the optimization process's exploration and exploitation stages, which causes random oscillation and slow tracking toward the GMPP. The squirrel search algorithm in [24] uses the random relocation notion to enhance exploring ability. However, random exploration results in abrupt changes and a slower convergence speed to the GMPP. The pattern search (PS) optimization in [25] was studied to achieve faster tracking, but the duration among track and settling time at the global MPP is still longer and required a significant number of iterations. The slap swarm optimization (SSO) presented in [26] uses a leader-follower strategy that divides the population into two groups. This grouping restricts initial exploration and may result in a longer iteration period, which causes slow tracking toward the GMPP.

According to the above-mentioned literature survey, no technique provided the best results in terms of convergence, accuracy, and tracking efficiency. Therefore, a hybrid technique (CSPSO) based on cuckoo search and particle swarm optimization is suggested in this study for MPPT application [27]. From the literature review, it has been noticed that none of the publications have concentrated on the execution of CSPSO for MPPT applications. Therefore, based on this research gap, the suggested technique (CSPSO) is used as the MPPT controller for tracking the GMPP under PSC conditions. The suggested technique benefits from the search advantage of PSO and combines it with CS. Thus, the population of individuals in the CSPSO evolves using two different mechanisms and then exchanges information with each other, which leads to improved solutions during the tracking process. Consequently, accelerating the convergence towards GMPP. The prime contributions of this study are summarized as follows:

1. A new hybrid MPP tracking technique is introduced using CS and PSO to handle the PSC problems for the solar PV system.
2. To verify the efficacy of the proposed hybrid technique, it is comparing their out-put results to CS, PSO, and CSA.
3. The proposed technique effectively avoids the drawbacks of traditional MPPT techniques, which can easily fall into local MPP rather than GMPP.
4. The proposed technique tracks GMPP with a quicker convergence rate, consequently, considerably minimizes power losses.
5. A prominent attribute of the proposed technique is the absence of oscillation around the GMPP.

## 2. PV CELL CIRCUIT

The electrical configuration of a PV cell is studied using two or a single diode. The single-diode PV cell, which was utilized in this work, is the most often used mathematical model, since it uses fewer parameters and is relatively accurate [20]. Figure 1 depicts the equivalent circuit single-diode model of the PV cell.

The characteristic equation of a PV cell is given as follows [20].

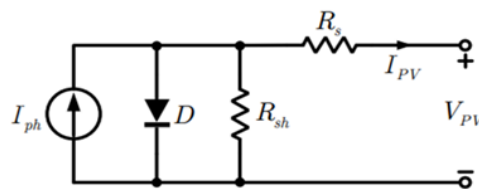


Figure 1. shows an illustration of the PV cell circuit model.

$$I_{PV} = I_{ph} - I_0 \left[ \exp \left( \frac{q}{nkT} (V_{PV} + I_{PV} R_s) \right) - 1 \right] - \frac{V_{PV} + I_{PV} R_s}{R_{sh}} \quad \dots (1)$$

where  $I_{ph}$  represents the photoelectric current,  $q$  the electron charge, and  $I_0$  the diode's reverse saturation current  $V_{PV}$  denotes the panel voltage.  $R_s$  and  $R_{sh}$  are the series and shunt resistance

of the PV cell in (ohm), respectively.  $T$  denotes the absolute temperature;  $k$  denotes Boltzmann's constant. The ideality factor of the diode is represented by  $n$ . The detailed specifications of the PV module are shown in Table 1.

Table 1. Electrical parameter specifications of the LA361K51S [20].

Description	Value
Maximum power ( $P_{max}$ )	51W
Maximum voltage ( $V_{max}$ )	16.9V
Maximum current ( $I_{max}$ )	3.02A
Short circuit current ( $I_{sc}$ )	3.25A
Open circuit voltage ( $V_{oc}$ )	21.20V
Series-connected cells	36
Temperature coefficient of $I_{sc}$ ( $A/^{\circ}C$ )	0.063805
Temperature coefficient of $V_{oc}$ ( $V/^{\circ}C$ )	-0.33

### 3. EFFECT OF PARTIAL SHADING ON PV SYSTEM

A PV module is composed of several identical solar cells that are linked in series and/or parallel to increase the voltage and output power [20]. Therefore, as a consequence of changing climatic conditions like precipitation, clouds, and storms, achieving constant uniform irradiance is not feasible. Furthermore, trees and building that cast shade cause partial shading. The photovoltaic array does not receive uniform irradiation under PSC. As a demonstration to show the influence of shading on PV modules, two various designs are used in this study. One of the user configurations (3S configuration) is made up of three modules in series, as shown in Fig 2. As a result, hot spots form, causing severe cell damage. The use of a bypass diode prevents the impact of the hot spot problem. Therefore, multiple peaks make P-V and I-V curves, as shown in Figure 3 which contains a global peak and two local peaks for each pattern of partial shading patterns. The shading patterns for this configuration are listed in Table 2. The second one (4S3P configuration) consists of twelve modules, four modules per string, as shown in. Table 3 and Figure 4 show the various shading patterns for this configuration.

The Simulink model depicted in Figure 5 describes the configurations of the tested PV arrays (3S) and (4S3P) under partially shaded conditions. Three simulated patterns for each configuration with a constant temperature of 25 °C, as illustrated in Tables 2 and 3. to show the characteristics of P-V and I-V for every configuration, as shown in Figs. 3 and 4.

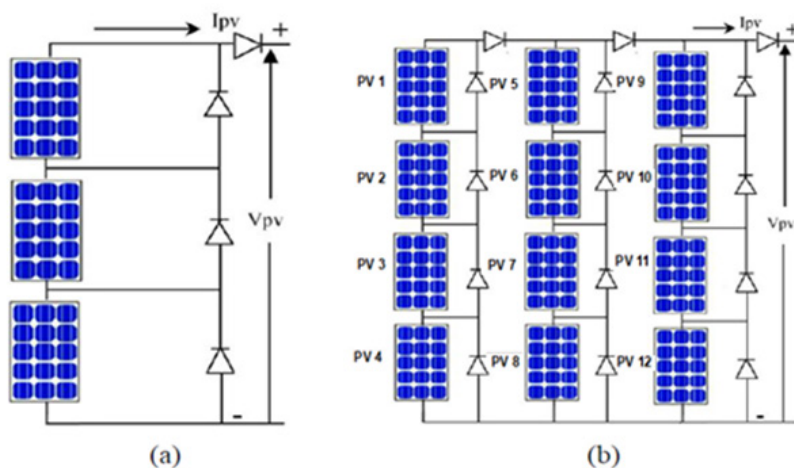


Figure 2. PV array configurations (a) series 3S, (b) Series-Parallel 4S3P.



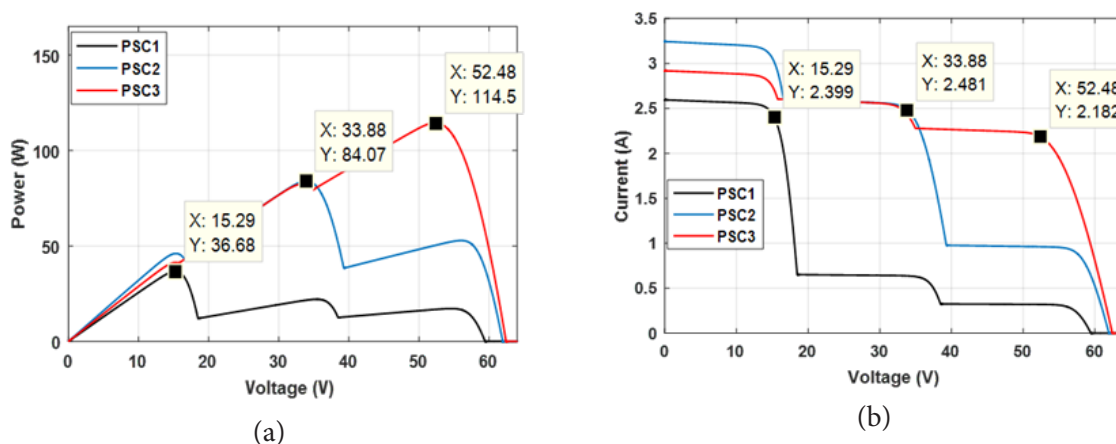


Figure 3. Characteristics under different shading patterns for 3S configuration (a) P–V curve, and (b) I–V curve.

Table 2. Different shading cases for the (3S) configuration

Cases	Solar irradiance (W/m <sup>2</sup> )	Power (W) at GMPP	Voltage (V) at GMPP	Current (A) at GMPP
PSC 1	PV1=100 PV2=200 PV3=800	2.399	15.29	36.68
PSC 2	PV1=1000 PV2=800 PV3=300	2.481	33.88	84.07
PSC 3	PV1=800 PV2=900 PV3=700	2.182	52.48	114.5

The purpose of altering the six irradiation patterns is to shift the GMPP position from the left to the right. Moreover, choosing difficult cases in which the local peak is close to the global peak is a trip to assess and measure the suggested algorithm’s performance in capturing the global peak under these circumstances. In these cases, conventional means are stuck around the local peak, which reduces the energy of the PV system.

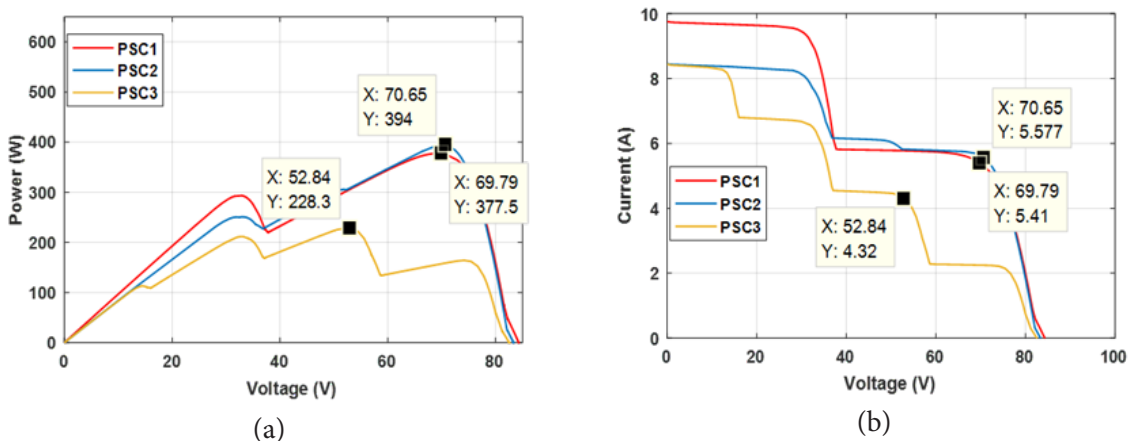


Figure 4. Characteristics under different shading patterns for 4S3P configuration (a) P–V curve, and (b) I–V curve.

Table 3. Different shading cases for the (4S3P) configuration.

Cases	Solar irradiance (kW/m <sup>2</sup> )	Power (W) at GMPP	Voltage (V) at GMPP	Current (A) at GMPP
PSC 1	PV1 =1.0 PV5 =1.0 PV9 =1.0 PV2 =1.0 PV6 =1.0 PV10=1.0 PV3= 0.4 PV7= 0.4 PV11=1.0 PV4= 0.4 PV8= 0.4 PV12=1.0	377.5	69.79	5.41
PSC 2	PV1 =0.9 PV5 =0.5 PV9 =0.6 PV2 =0.9 PV6 =0.5 PV10=0.6 PV3 =0.8 PV7= 0.7 PV11=1.0 PV4 =0.7 PV8= 0.7 PV12=1.0	394	70.65	5.577
PSC 3	PV1 =0.8 PV5 =1.0 PV9 =0.3 PV2 =0.6 PV6 =0.7 PV10=0.8 PV3 =0.3 PV7 =0.4 PV11=0.7 PV4 =0.2 PV8 =0.2 PV12=0.8	228.3	52.84	4.32

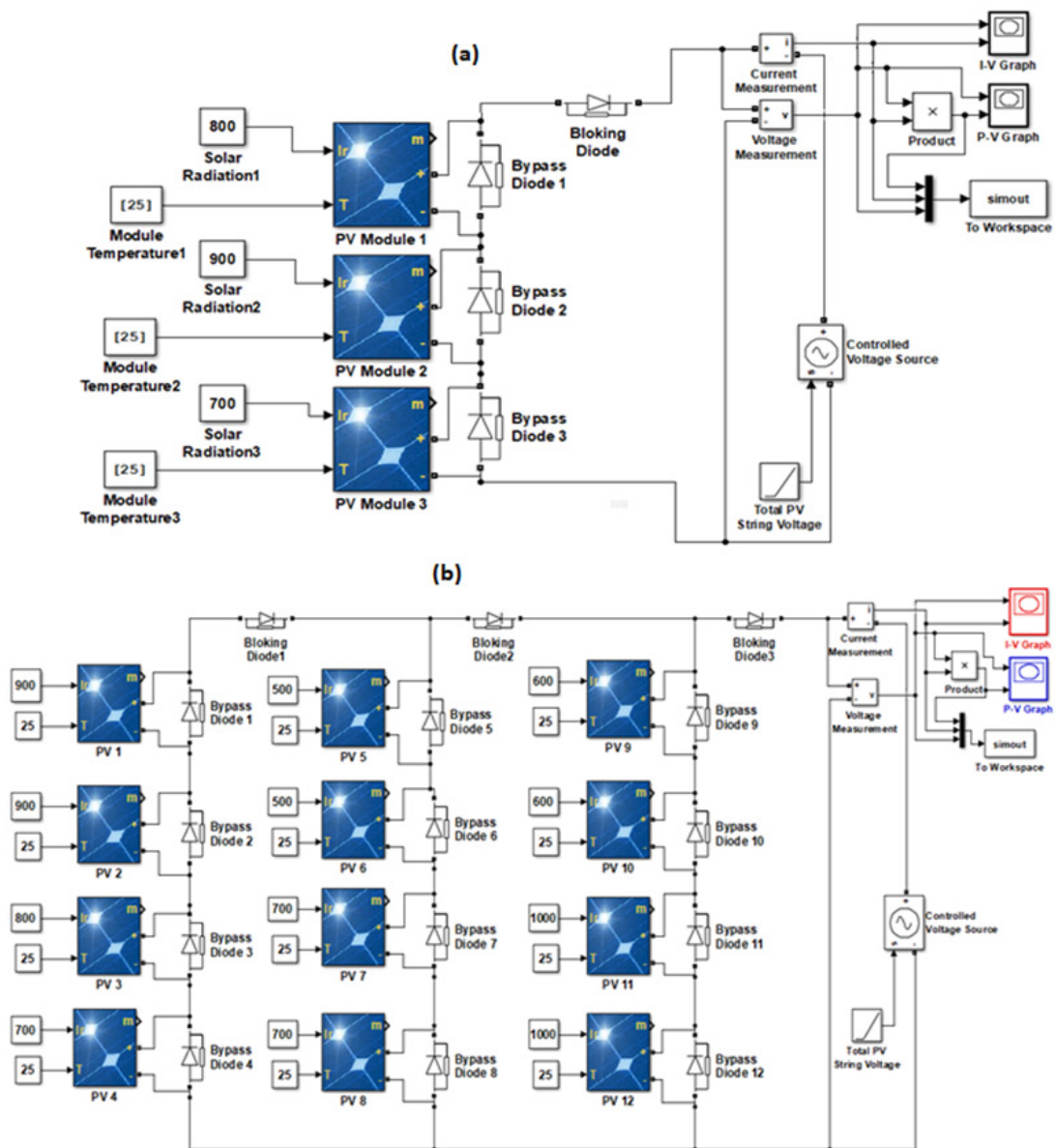


Figure 5. Simulink model of the tested PV array under PSC (a) S3 and (b) 4S3P.

## 4. META-HEURISTIC OPTIMIZATION TECHNIQUES

### 4.1. An overview of CS algorithm

Cuckoo search is a meta-heuristic optimization technique that was suggested in Ref. [28]. In this technique, the Lévy flight individual mechanism is used for updating the swarm's position within the search space. This technique was created by the breeding behavior of the cuckoo bird (CB). As a consequence, brood parasitism sums up the fundamental idea of CS. Therefore, brood parasitism sums up the basic concept of CS. They are categorized as follows: cooperative, nest takeover, and interspecies [27, 29]. CB lay their eggs in other birds' nests. Whenever the host bird observes a CB egg in its nest, it either leaves or damages the egg and produces a new one in a different place. Consequently, cuckoos improve their chances of survival by laying their eggs in various nests. They also mimic the host birds' colors to improve their chances of getting a new cuckoo. The model outlined in ref. [30] used the three laws listed below.

- 1 CB only ever generates one egg.
- 2 Only the best nests have high-quality eggs.
- 3 The host nest has remained unchanged.

The new eggs are produced using Lévy's flight. It is a random process in which the Lévy distribution step size is determined by Eq. (2) [29].

$$Le'vy(\beta) = l^{-\beta} \quad \dots\dots(2)$$

where  $l$  indicates the length of flight  $1 < \beta < 3$ .

The new egg is represented by the coordinates obtained at the end of the flight. A coefficient  $\alpha$  has been used to predict flight size in Ref. [28]. On the other hand, the proportion of rejected eggs ( $P_a$ ) was identified as a critical variable that must be considered. The major objective of the current work is to attain the optimum duty cycle of the boost converter regarding the GMPP under PSC. The following equation is used to update the duty cycle [29].

$$d_i^{k+1} = d_i^k + \alpha \oplus Le'vy(B) \approx d_i^k + k_{Le'vy} \left( \frac{u}{|v|^{1/\beta}} \right) (d_{best}^k - d_i^k) \quad \dots\dots(3)$$

Where  $\beta=1.5$ ,  $k_{Le'vy}$  indicates the Lévy multiplication coefficient,  $u$  and  $v$  may be determined by the normal distribution curves shown in (4) [29].

$$u \approx N(0, \sigma_u^2) \quad \text{and} \quad v \approx N(0, \sigma_v^2) \quad \dots\dots(4)$$

Where  $\sigma_u$  and  $\sigma_v$  are defined as follows [29]:

$$\sigma_u = \left[ \frac{\Gamma(1+\beta) \sin\left(\Pi \frac{\beta}{2}\right)}{\Gamma\left(\frac{(1+\beta)}{2}\right) \times \beta \times 2 \frac{(\beta-1)}{2}} \right] \quad \text{and} \quad \sigma_v = 1 \quad \dots\dots(5)$$

where  $\Gamma$  denotes the integral gamma function.

### 4.2. An overview of PSO algorithm

PSO is a stochastic computation algorithm, first suggested by Kennedy and Eberhart in 1995 [31]. The fundamental idea of PSO can be visualized in the conduct of crowded birds or schooling fishes [32]. PSO involves some particles establishing a swarm of wandering wasps that roams the search space to find the most effective solution. Each particle attempts to adjust its traveling velocity as a consequence of its flying experiences. The PSO method uses few particles or agents to conduct searches. Throughout the search process, these particles or agents to conduct searches.



Throughout the search process, these particles or agents can exchange information with each other. Each particle must follow two rules throughout the search process. First, the best-performing particle is calculated and must be followed by each particle. Second, the better particle's location is determined by the objective of each particle for the following search and direction. These two rules are applied to every particle during the search process until the optimum solution is discovered. Specifically, Equations (6) and (7) are used to update the particle's position and velocity [11, 29, 30].

$$x_i^{k+1} = x_i^k + v_i^{k+1} \quad \dots\dots\dots(6)$$

$$v_i^{k+1} = wv_i^k + c_1r_1(p_{best} - d_i^k) + c_2r_2(G_{best} - d_i^k) \quad \dots\dots(7)$$

Where  $r_1$  and  $r_2$  represent random values drawn from the range [0, 1],  $x_i, w, c_1$  and  $c_2$  represent a particle's position, the inertial weight constant, and the coefficients of inertia, respectively;  $P_{best}$  represents the particle's individual best position, and  $G_{best}$  indicates the global best position.

### 4.3. Hybrid CSPSO algorithm

The CS-PSO algorithm has been introduced in [27]. It has been seen in [27] that there are three enhancements to the presented algorithm. The first enhancement is that the hybrid algorithm's initial individuals are generated using orthogonal Latin squares. The second enhancement is that the CS step size is dynamically modified rather than a fixed value. The third enhancement is the hybridization of the CS and PSO to create a new hybrid optimization algorithm. The suggested technique has been validated using twenty benchmark functions and two engineering optimization problems. In this study, the third enhancement, a hybridization of cuckoo search and particle swarm optimization (CSPSO), has been utilized to solve GMPPT problems in PSC conditions.

In the cuckoo search, there is no information interchange between each cuckoo, and each cuckoo actually conducts its search independently [27]. In this algorithm, we will combine the good search ability of CS with the global search advantage of PSO in order to improve the population variety and convergence rate of the suggested hybrid algorithm. In this instance, rather than using a single pattern known as Lévy flight to generate new solutions in CS, we employ a combination of two distinct methods to create the solutions in CSPSO. The first method is the classic pattern of Lévy flight in CS as described in Eq (3), and the second method is the updating method as shown in Eqs (6–7) in PSO. Each cuckoo executes Lévy flight to create a new solution  $d_i^{(k+1)}$  and then follows the PSO-based updating methods to generate a new solution  $x_i^{(k+1)}$ . A new solution of the CSPSO is created by combining  $d_i^{(k+1)}$  and  $x_i^{(k+1)}$ , and the formula for updating the new solutions is suggested in Eq. (8).

$$H_i^{(k+1)} = R \times d_i^{(k+1)} + (1 - R) \times x_i^{(k+1)} \quad \dots\dots(8)$$

where  $H_i^{(k+1)}$  is the new solution of the CSPSO,  $R$  ( $R \in [0, 1]$ ) is a random number.

Figure 6 shows the flowchart for the CSPSO-based tracker.

Initially, duty cycles are created at random. After that, each is utilized for the boost converter. PV power is determined by calculating the voltage and the current. The duty cycle supplied to the boost converter is chosen as the optimization task's objective function for tracking the global MPP of the photovoltaic system.

The following step is to compare the new power to the old one recorded in history. If the new power is greater than the prior value, the duty cycle is deemed to be superior. Then, each cuckoo performs a Lévy flight based on Eq. (3) to generate a new solution. and then follows the updating ways PSO shown in Eqs. (6) and (7) to generate another solution. Subsequently, a new solution

for the CSPSO is generated as shown in Eq (8). After finishing all iterations, when the stopping criterion is met, the CSPSO-based tracker stops and provides the optimum solution, which is the duty cycle's optimal value in relation to the GMPP.

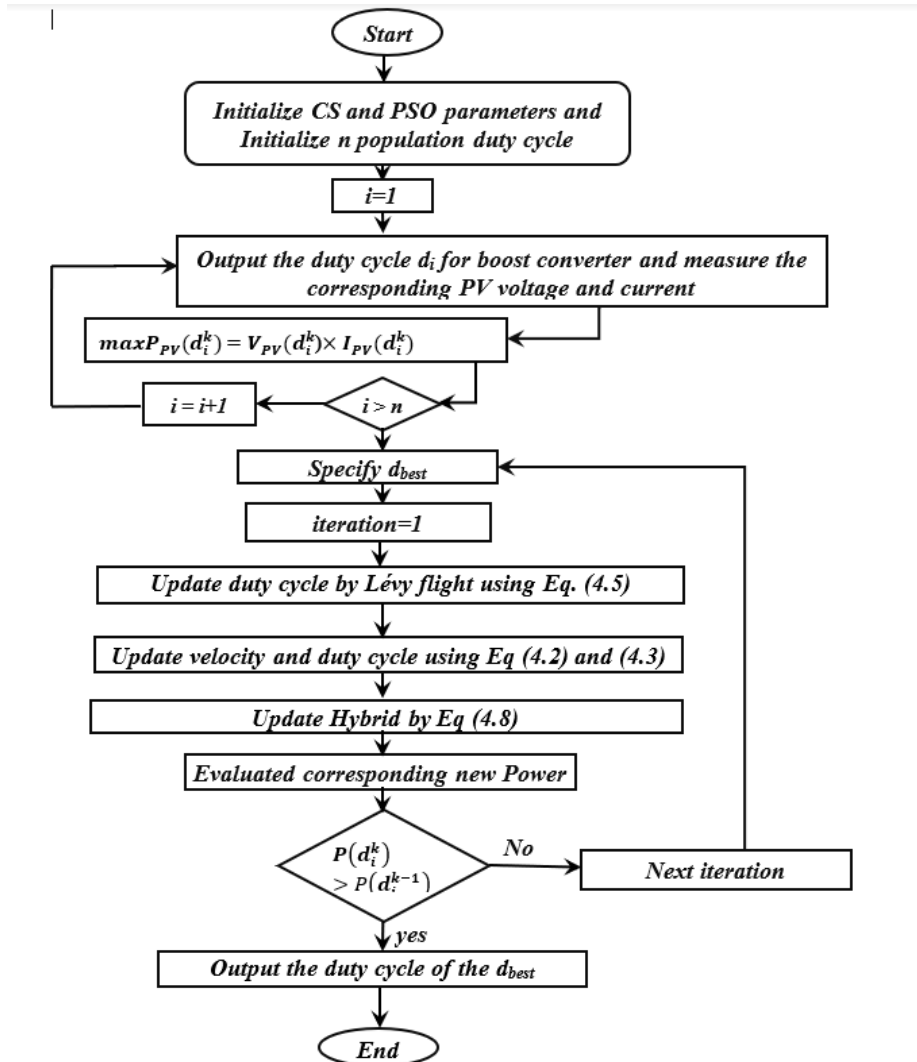


Figure 6. The flowchart for the CSPSO-based tracker.

## 5. RESULTS AND DISCUSSION

In this section, a simulation MATLAB is performed to validate the suggested MPPT technique's ability to track the GMPP under PSC patterns. Due to the difficulty of testing multiple configurations, only two configurations were chosen to evaluate the performance of the suggested technique in this study.

The comprehensive SIMULINK diagram of the proposed system is depicted in Figure 7. This system consists of three modules connected in series with a boost converter as an interface between load and modules, and the duty cycle is controlled by MPPT control, which takes  $V_{pv}$  and  $I_{pv}$  as inputs and generates the duty cycle. The primary parameters of the boost converter are  $C_{in} = 10 \mu F$ ,  $C_{out} = 47 \mu F$ ,  $L = 1 m$ , and  $R = 60 \Omega$ . Table 4. illustrates the parameters of the algorithms used in this study.

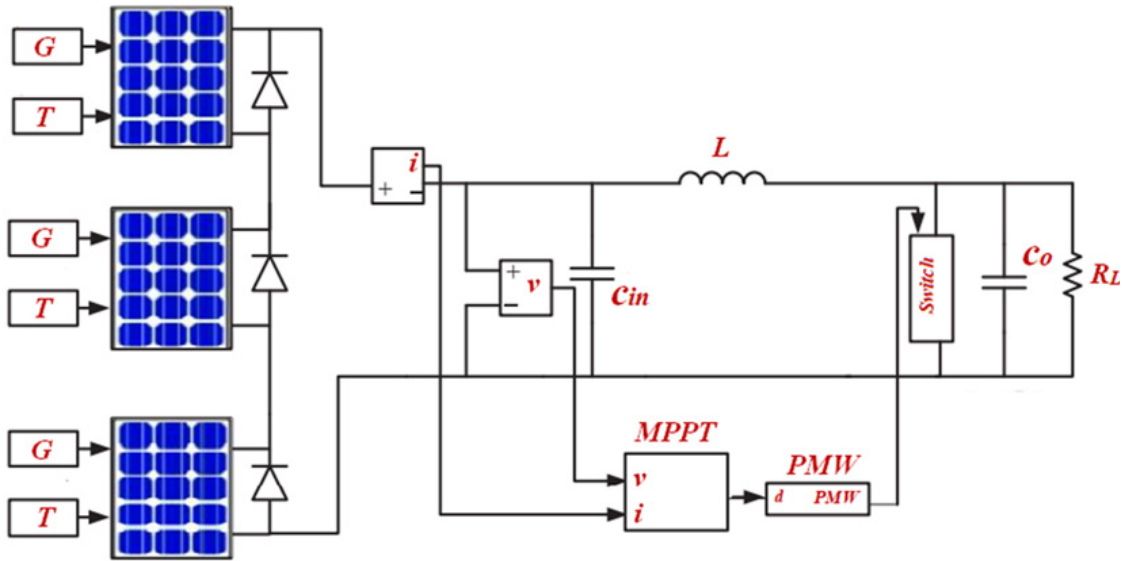


Figure 7. Diagram of the total tested system.

The four MPPT algorithms under study are compared in terms of accuracy, tracking efficiency, and tracking speed for every pattern of irradiance. The simulations were conducted under identical conditions to ensure the fairness of the comparison. In this study, three various irradiance patterns with a constant temperature of 25 °C for every configuration were employed. The purpose of altering the radiation patterns is to move the GMPP from the left to the right or to the center to evaluate the performance of MPPT algorithms under varying environmental conditions. In addition, ensure the dependability of each MPPT approach for capturing GMPP in the event of any shading impact.

For the first case of PSC1, the irradiance levels are given in Table 2. The V–I and P–V were previously shown in Fig 3. In this case, there are three peaks, and the GMPP of 36.68 W is located at the first peak of the P–V curve. Figure 8 depicts the simulation results (output PV power and duty cycle) of a PV system using four various MPPT algorithms under PSC.

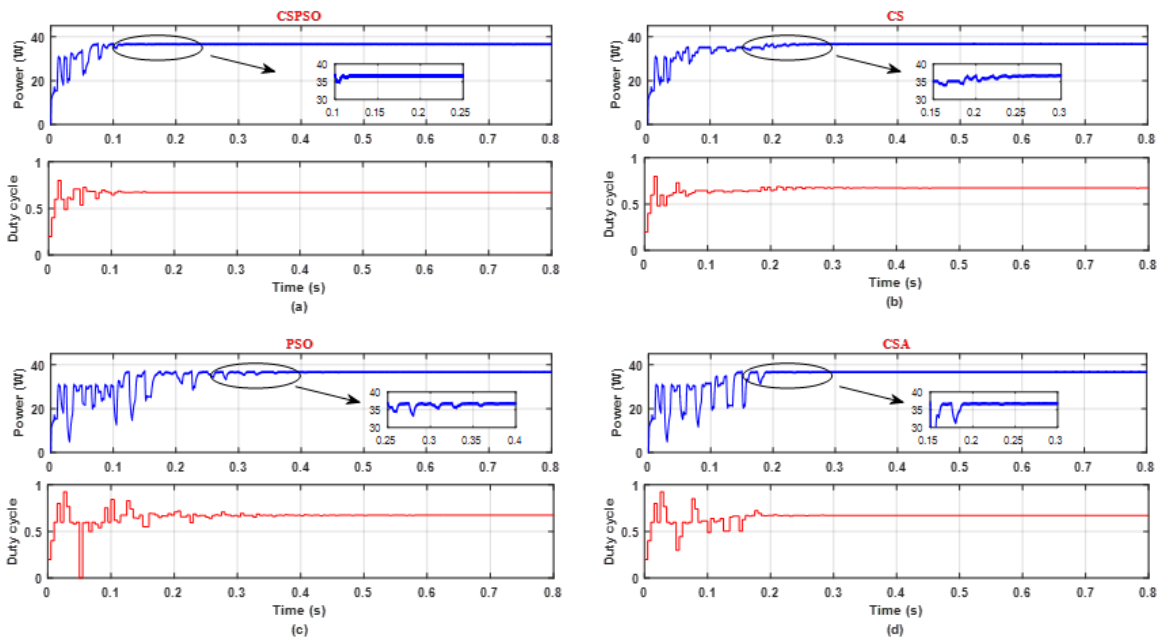


Figure 8. The simulation results for a PV system under PSC1 for 3S configuration (a) CSPSO, (b) CS, (c) PSO, and (d) CSA.

Based on such results, CSPSO, CS, PSO, and CSA achieve steady powers of 36.67, 36.66, 36.65, and 36.65 W, respectively. CSPSO achieves the greatest efficiency of 99.97%, followed by CS. These findings confirm the superiority of the suggested MPPT algorithm. In terms of convergence speed, CSPSO, CS, PSO, and CSA can effectively track GMPP after 0.12 s, 0.25 s, 0.37 s, and 0.2 s respectively. This suggests that the proposed algorithm decreases the tracking time by 52%, 67.57%, and 40% compared with the CS, PSO, and CSA algorithms, in order. It is clear from the outcomes that the CSPSO has fewer power fluctuations than the CS, PSO, and CSA, it outperforms these algorithms because of the decreases random of the duty cycles during iterations. In the second case, PSC2, the GMPP of 84.07 W is located at the second peak of the P–V curve. The obtained simulation findings are exhibited in Figure 9. The power achieved by the CSPSO, CS, PSO, and CSA is 84.07 W, 84.058 W, 84.065 W, and 84.065 W, respectively. Based on these findings, it can be seen that the proposed CSPSO technique effectively obtains the global MPP with superior tracking efficiency. Furthermore, this technique tracks the GMPP in 0.13 s while CS, PSO, and CSA require, 0.25 s, 0.33 s, and 0.18 s to reach the GMPP. Hence, it should be noted that using the suggested ICPSO minimizes tracking time by 48%, 60.60%, and 27.77%, as compared to CS, PSO, and CSA, respectively. It is clear from the outcomes that the CSPSO has fewer power fluctuations than the CS, PSO, and CSA. The PSO was more precise than the CS. However, considerable power swings are noticeable throughout the first 0.3 seconds, which causes her to take longer to converge toward GMPP.

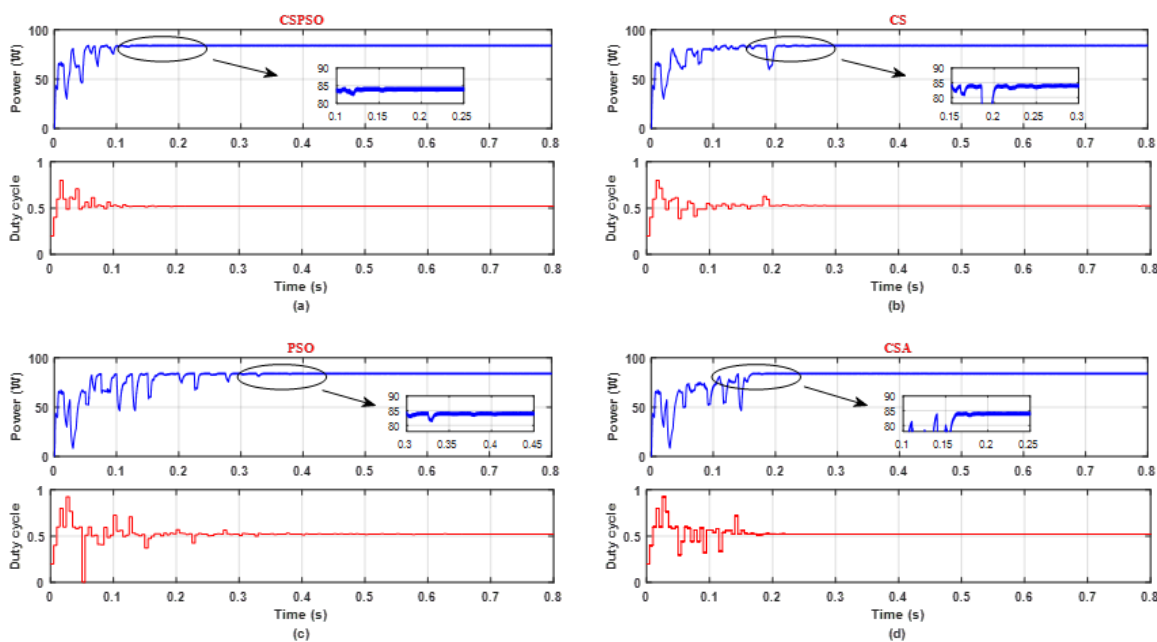


Figure 9. The simulation results for a PV system under PSC2 for 3S configuration (a) CSPSO, (b) CS, (c) PSO, and (d) CSA.

While in the third case of PSC3, the GMPP was 114.5 W, as shown in Fig 3. The simulation findings for the four algorithms are displayed in Figure 10. Based on such results, it can be noticed that the four techniques successfully achieve the GMPP with excellent tracking efficiency. In terms of convergence speed, the CSPSO was faster to arrive at the global MPP within 0.12 s, followed by the CS within 0.14 s, the CSA with-in 0.19 s, and then the PSO within 0.3 s. This suggests that utilizing a CSPSO-based tracker lowers the tracking time by 14.28%, 60%, and 36.84%, as compared to CS, PSO, and CSA, respectively. One can observe from Figure 9, that the PSO and CSA have some significant power fluctuation over the first 0.15 s, which causes them to take longer to converge towards GMPP. This is due to the sudden changes in the duty cycle generated

by the random relocation. The CSPSO and CS exhibit some minor power fluctuation over the first 0.1s before convergent with the GMPP.

Table 5 summarizes the extensive simulation findings of the comparison of various MPPT algorithms for the 3S configuration. From this table, we can deduce that metaheuristic methods are quite efficient at rapidly tracking the optimal energy point GMPP.

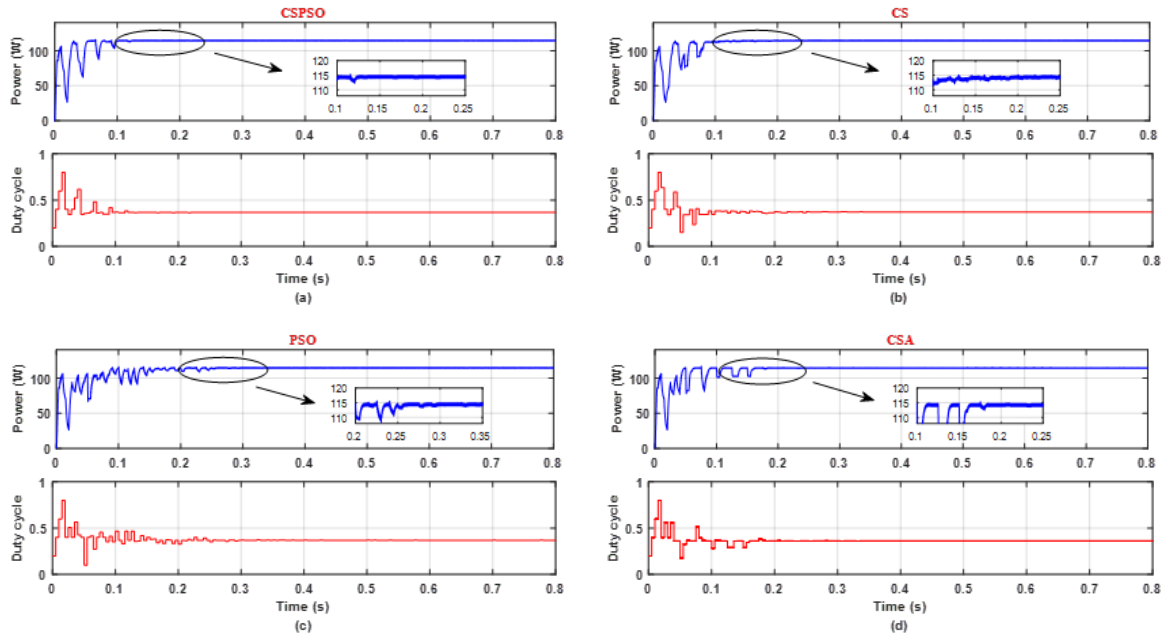


Figure 10. The simulation results for a PV system under PSC3 for 3S configuration (a) CSPSO, (b) CS, (c) PSO, and (d) CSA.

Table 4. The parameters of algorithms.

algorithm	Parameter Utilized
PSO	$w = 0.4, C1 = 1.2, C2 = 1.6$
CS	$K = 0.8$
CSA	$AP = 0.1, fl = 2$

Table 5. Results comparison of the various MPPT algorithms for 3S configuration.

Cases (sec)	Technique	Power (W)	Tracking Speed	Global Power(W)	Efficiency $\frac{P_{out}}{P_{max}} \times 100$
PSC 1	CSPSO	36.67	0.12	36.68	99.97
	CS	36.66	0.25		99.94
	PSO	36.65	0.37		99.91
	CSA	36.65	0.2		99.91
PSC 2	CSPSO	84.07	0.13	84.07	100
	CS	84.058	0.25		99.985
	PSO	84.065	0.33		99.994
	CSA	84.065	0.18		99.994
PSC 3	CSPSO	114.5	0.12	114.5	100
	CS	114.5	0.14		100
	PSO	114.5	0.3		100
	CSA	114.5	0.19		100



Nonetheless, the CSPSO-based tracker has a speed priority for reaching the GMPP than other trackers. As a result, the improved performance of the CSPSO-based MPPT method can decrease the loss of power while also lowering implementation costs.

To verify the efficacy of the suggested CSPSO technique in minimizing the negative impacts of partially shadowing conditions on a PV system, a simulation utilizing MATLAB has been performed on the 4S3P configuration under three different shading patterns.

For the first case of PSC1, the irradiance levels are given in Table 3. The P–I and V–I were previously displayed in Fig 4. In this case, there are two peaks, and the GMPP of 377.5 W is found at the second peak of the P–V curve. Figure 11 depicts the simulation results (output PV power and duty cycle) of a PV system using four various MPPT algorithms under PSC. According to the results, the CSPSO algorithm reached a rapid GMPP at 377.18 W after 0.11Sec, while the CS, PSO, and CSA algorithms reached 377.03, 377.13, and 377.105 after 0.2 s, 0.32 s, and 0.17 s, in order. This suggests that the proposed algorithm lowers the tracking time by 45%, 65.62%, and 35.29%, compared with the CS, PSO, and CSA algorithms, respectively. It can be noticed from the results that the CSPSO, CS, and CSA algorithms showed only minor power fluctuations over the first 0.1 s, but the CSPSO achieved GMPP quicker and with greater efficiency. The PSO has several and great power fluctuations over the tracking time because of the considerable difference in duty cycle values.

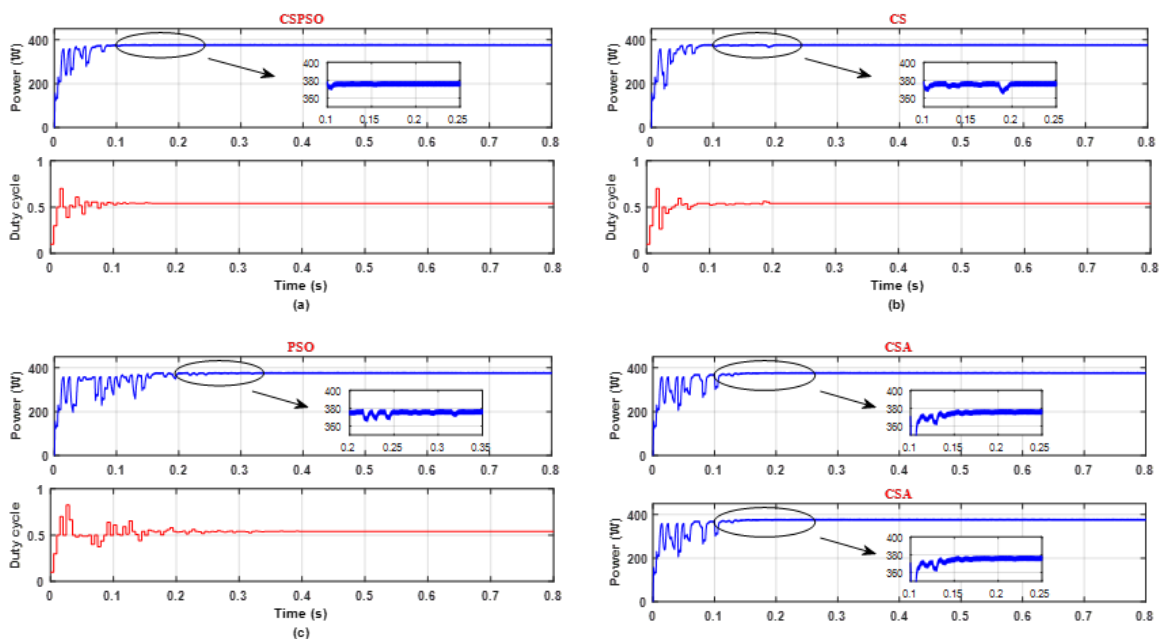


Figure 11. The simulation results for a PV system under PSC1 for 4S3P configuration (a) CSPSO, (b) CS, (c) PSO, and (d) CSA.

In the second case, PSC2, The GMPP of 394 W is located at the third peak of the P–V curve. The simulation findings are exhibited in Figure 12. CSPSO, CS, PSO, and CSA achieve steady powers of 393.32, 392.83, 393.22 W, and 393.18 W, respectively. CSPSO obtains the greatest efficiency of 99.83% and is followed by PSO and CSA, whereas CS obtains the least efficiency of 99.70%. Based on these results, it may be observed that the suggested CSPSO technique achieves the GMPP with greater efficiency. Furthermore, this technique tracks the GMPP in 0.16 seconds, whereas CS, PSO, and CSA require 0.2 seconds, 0.25 seconds, and 0.22 seconds, respectively, to reach the GMPP. Thus, it should be noted that using the suggested ICPSO minimizes tracking time by 20%, 36%, and 27.27%, as compared to CS, PSO, and CSA, respectively. It can be noticed from the results that these CSPSO, CS, and CSA showed only minor power fluctuations over the first 0.1 s,

but the CSPSO achieved GMPP faster and with greater efficiency. The PSO was more precise than the CSA and CS. However, large oscillations in power were noticeable over the first 0.2 seconds.

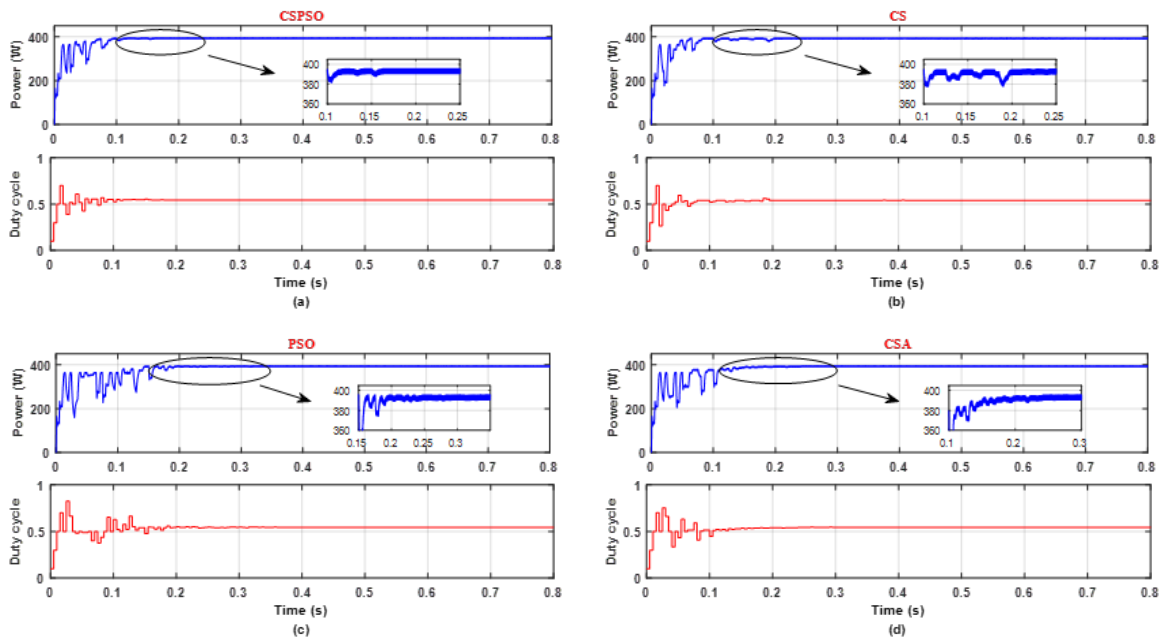


Figure 12. The simulation results for a PV system under PSC2 for 4S3P configuration (a) CSPSO, (b) CS, (c) PSO, and (d) CSA.

While in the third case of PSC3, the GMPP of 228.3W, as shown in Fig 4. The simulation findings for the four algorithms are displayed in Figure 13.

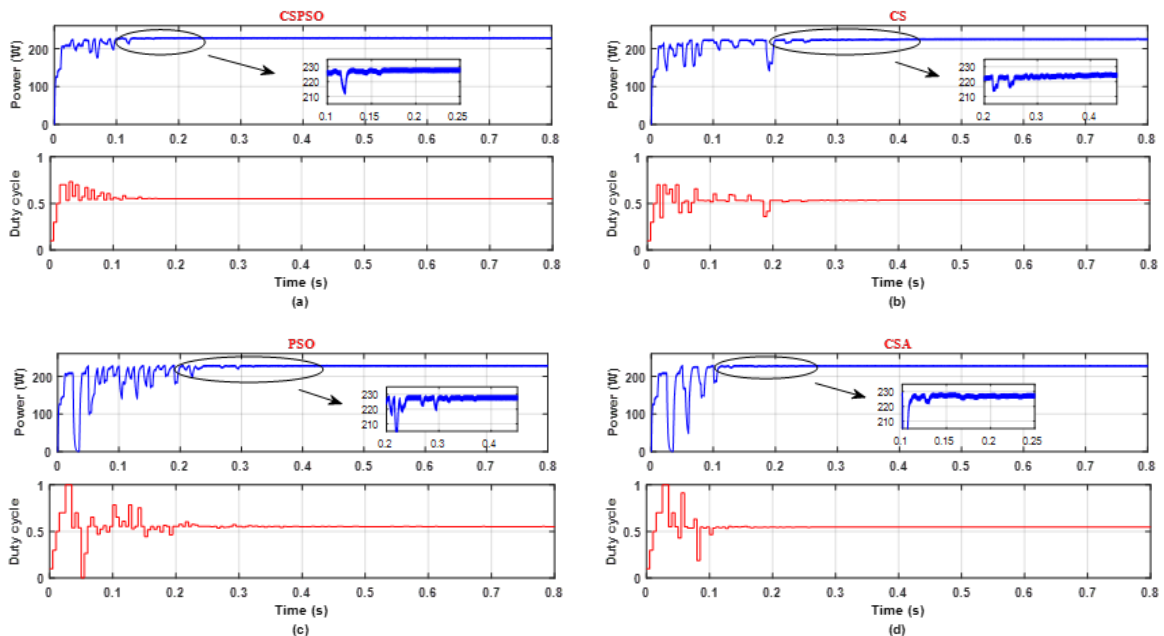


Figure 13. The simulation results for a PV system under PSC3 for 4S3P configuration (a) CSPSO, (b) CS, (c) PSO, and (d) CSA.

Based on such findings, it can be observed that the CSPSO algorithm reached rapidly a GMPP at 227.91W after 0.16 sec, while the CS, PSO, and CSA algorithms reached 224.9, 227.79, and

227.79 after, 0.38 s, 0.37 s, and 0.18 s, respectively. CSPSO obtains the greatest efficiency of 99.83 % while CS has the least efficiency of 98.51 %. Hence, it should be noted that using the proposed ICPSO minimizes tracking time by 57.89%, 56.75%, and 11.11%, as compared to CS, PSO, and CSA, respectively. The results show that the CSPSO and CSA have lower power fluctuations throughout the tracking time than other algorithms. While the PSO and CS have shown some high power fluctuation over the first 0.2 s, which causes them to take longer to converge toward GMPP. According to prior findings, we can conclude that the performance of the CSPSO-based tracker is superior compared with other trackers in terms of tracking speed, accuracy, and tracking efficiency for all studied shading patterns. Table 6 provides a comparison of the various MPPT algorithms studied for the 4S3P configuration. From this table, one can observe the outperformance of the CSPSO-based tracker over the other algorithms.

Table 6. Results comparison of the various MPPT algorithms for 4S3P configuration.

Cases (sec)	Technique	Power (W)	Tracking Speed	Global Power(W)	Efficiency $\frac{P_{out}}{P_{max}} \times 100$
PSC 1	CSPSO	377.18	0.11	377.5	99.92
	CS	377.03	0.2		99.87
	PSO	377.13	0.32		99.90
	CSA	377.105	0.17		99.89
PSC 2	CSPSO	393.32	0.16	394	100
	CS	392.83	0.2		99.985
	PSO	393.22	0.25		99.994
	CSA	393.18	0.22		99.994
PSC 3	CSPSO	227.91	0.16	228.3	99.83
	CS	224.90	0.38		98.51
	PSO	227.79	0.37		99.776
	CSA	227.79	0.18		99.776

## 6. CONCLUSION

This paper proposes a hybrid (CSPSO) MPPT technique to extract the most power from solar PV energy systems. The presented technique is intended to enhance the efficiency of partially shaded PV systems. The CSPSO is comprehensively evaluated against CS, PSO, and CSA with two various PV array configurations. The initial PV arrangement (3S configuration) consists of three modules connected in series. The second one (4S3P configuration) consists of twelve modules, four modules per string. The suggested photovoltaic system includes an MPPT system, a boost converter, and a PV array, which was simulated using MATLAB simulation to validate the proposed technique's tracking performance. The obtained results suggest that the suggested CSPSO algorithm is very effective. The suggested algorithm greatly excels the over-mentioned algorithms in terms of accuracy, tracking efficiency, and tracking speed. The suggested algorithm can track GMPP within 110–160 ms as compared to the time taken by competing algorithms in all tested patterns, regardless of the GMPP position. For the 3S configuration, it was found that the CSPSO-based tracker is much faster than the CS, PSO, and CSA. The tracking time decreased by an average of 38.09%, 62.72%, and 34.87% when compared to the CS, PSO, and CSA, respectively. Whereas in the 4S3P configuration, the suggested technique reduces the tracking time by an average of 40.96%, 52.79%, and 24.55% compared with the CS, PSO, and CSA algorithms, respectively, in all tested shading patterns. Finally, it is concluded that the proposed technique minimized power losses due to the rapid search capacity of a GM, which improved the performance of PV energy systems.

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