International Journal of Electrical, Energy and Power System Engineering
Vol. 09, No. 03, October 2026
e-ISSN: 2654-4644

Cuckoo Search-Based MPPT Design for PV Optimization Under Partial Shading

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Abstract— Partial shading conditions (PSC) give a major challenge to photovoltaic (PV) systems by producing multiple local maximum power points (LMPPs) and a global maximum power point (GMPP), which can cause conventional maximum power point tracking (MPPT) methods such as Perturb and Observe (P&O) to converge at an LMPP. This study aims to design and evaluate a Cuckoo Search (CS) based MPPT method using a buck-boost converter for PV battery charging under PSC. The proposed method uses Lévy flight and nest-updating mechanisms to optimize the converter duty cycle. CS and P&O were compared via MATLAB/Simulink simulations under uniform irradiance and PSC scenarios. The optimal CS parameters were obtained as Pa = 0.25, α = 0.4, and β = 1.5. Under uniform irradiance, P&O achieved 99.90% tracking efficiency with a 0.028 s tracking time, while CS achieved 99.95% efficiency with a 0.148 s tracking time. Under PSC, P&O achieved 52.55-99.85% efficiency and failed to track the GMPP under complex shading, whereas CS consistently tracked the GMPP with 99.30-99.91% efficiency. The average overall efficiency was 73.24% for P&O and 93.35% for CS. These results demonstrate that CS is able to provide reliable GMPP tracking and high overall system efficiency under PSC.

Keywords: Buck-Boost Converter, Cuckoo Search, MPPT, Partial Shading, Photovoltaic.

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INTRODUCTION

Over the past decade, Indonesia's national electricity consumption has increased significantly, reaching 1,411 kWh per capita in 2024, reflecting the rapid growth in energy demand driven by technological advancements and changes in consumer behavior [1]. However, the national energy mix remains fossil fuel dominated, which contributes significantly to greenhouse gas emissions, potentially hindering the achievement of the Net Zero Emissions target [2]. As an equatorial tropical country, Indonesia has high solar energy potential, with an average daily radiation intensity of approximately 4.5 kWh/m² per day, indicating massive potential for the expansion of solar power plants as a clean and sustainable energy source [3], [4]. The performance of photovoltaic (PV) based solar power systems is greatly influenced by variations in environmental conditions, such as changes in solar radiation intensity, temperature, and the presence of partial shading, which can affect the efficiency, stability, and continuity of the power generated [5], therefore, appropriate

Received: Sept 15, 2026, Revised: Oct 11, 2026, Accepted: Oct 28, 2026
https://doi.org/10.31258/ijeepse.9.3.184-201

control and optimization strategies are necessary to ensure that solar power systems can operate optimally under various operating conditions [6]. Furthermore, the variability and intermittency of PV systems drive the use of batteries as energy storage media, particularly in off-grid systems and solar home systems, to store energy generated when solar radiation is available and use it when PV generation decreases or is unavailable [7], [8], [9]. In order to improve the utilization of power generated by PV, the Maximum Power Point Tracking (MPPT) method is used to adjust the PV operating point so that it operates at the maximum power point, thereby increasing the extractable power and energy conversion efficiency. Various conventional MPPT methods have been developed, such as Constant Voltage, Open Circuit Voltage, Incremental Conductance, Hill Climbing, and Perturb and Observe (P&O) [10], [11].

Under partial shading conditions, the V-I and P-V characteristic curves of a PV system may have multiple power peaks [12]. This condition means that the global maximum power point is not always at the nearest peak, so conventional MPPT may get stuck at a local peak and fail to track the maximum power [13]. To address this issue, metaheuristic-based MPPT methods are used, as they can accurately track the maximum power point across multiple peaks under partial shading conditions [14]. Several metaheuristic methods that have been applied to MPPT include Particle Swarm Optimization (PSO), Genetic Algorithm (GA), Bat Algorithm (BA), Artificial Bee Colony (ABC), Grey Wolf Optimizer (GWO), and Cuckoo Search (CS) [15], [16], [17]. The CS algorithm offers high accuracy, low complexity, and good stability, although its convergence rate is slower than that of PSO and BA [18].

Several previous studies have applied the Cuckoo Search algorithm as an MPPT method in PV systems. A comparison of CS with Artificial Neural Networks (ANN) and IC using a boost converter showed that CS produced the highest power with the lowest power fluctuations [19]. In partial shading tests using a boost converter, CS also demonstrated a faster tracking time approximately 0.22 s and an efficiency of about 99% compared to Genetic Algorithms (GA) [20]. The development of the CS algorithm through the Improved Cuckoo Search (ICS) and its integration with Dynamic Particles in a boost converter also showed improved MPPT performance compared to other methods [21], [22]. Furthermore, the application of CS to an interleaved boost converter with a battery as the load demonstrated better performance compared to P&O [23]. These research results indicate that CS has good potential as an MPPT method to enhance maximum power point tracking capability in PV systems, particularly under partial shading conditions.

However, the studies in [19], [20], [21], [22], [23] use boost converters, which are limited to step-up voltage operation. In systems where the PV voltage is higher than the battery voltage, a buck converter is typically required. However, under partial shading conditions, the global maximum power point (GMPP) voltage can drop below the battery, which cannot be handled by a buck converter. A buck-boost converter can operate in both conditions, making it more suitable for partial shading conditions. In addition, most studies use resistive loads [19], [20], [21], [22], while real PV systems usually store energy in batteries, whose voltage changes during charging. All modules are also typically assumed to have the same temperature [22] , although shaded and unshaded modules have different temperatures in practice.

Therefore, this study designs a Cuckoo Search (CS)-based MPPT system with a buck-boost converter and a battery load to optimize PV power extraction under partial shading conditions while considering varying module temperatures. The CS algorithm parameters are optimized to achieve robust tuning, ensuring that the MPPT works quickly and accurately to determine the duty cycle for GMPP tracking. MPPT Performance is evaluated across PSC scenarios and compared to the conventional P&O method in terms of tracking time, tracking efficiency, and overall system efficiency during battery charging.

METHOD

A. System Configuration and Modeling

The system under study, illustrated in Figure 1, consists of a PV module, a buck-boost converter, an MPPT controller, and a battery as the load. The system configuration is based on the solar home system (SHS) concept [24], which has been adapted to the needs of this study. The MPPT controller receives PV voltage and current as inputs to determine the optimal duty cycle, which is used as the control signal for the buck-boost converter.

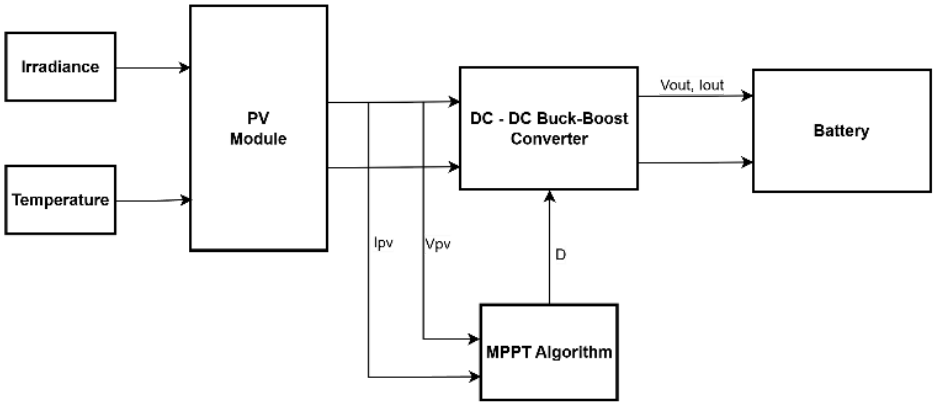


Figure 1. Proposed System Design

B. PV System Design

The PV system was designed based on the household's daily electricity needs [24], the total daily energy consumption was calculated at 2,750 Wh/day. Taking additional energy needs into account, the daily energy requirement was set at 4,500 Wh/day. The PV capacity was determined by considering peak sun hours (PSH) of 5 hours/day and a system efficiency of 80%, resulting in a required PV capacity of 1,125 Wp. The battery used as the charging load is a Lithium Iron Phosphate ($LiFePO_4$) battery with a nominal voltage of 48 V and a capacity of 50 Ah, as well as a charging operating voltage range of ± 48 - 53.5 V. The specifications of the panels used are shown in Table 1.

Table 1. PV Module Specifications

PV Module Parameter	SEP300	4S1P System
Maximum Power, P_{mpp}	300 Wp	1200.2952 Wp
Open-circuit Voltage, V_{oc}	44.71 V	178.84 V
Short-circuit current, I_{sc}	8.947 A	8.947 A
Voltage at MPP, V_{mpp}	37.23 V	148.92 V
Current at MPP, I_{mpp}	8.06 A	8.06 A
Temperature coefficient of, V_{oc}	- 0.34 (%/°C)	- 0.34 (%/°C)
Temperature coefficient of, I_{sc}	+ 0.05 (%/°C)	+ 0.05 (%/°C)

To obtain a total capacity of 1,200 Wp, the four 300 Wp modules were connected in series. The resulting string MPP voltage of 148.92 V is higher than the battery voltage, so the converter normally operates in buck mode. However, under partial shading, the GMPP voltage can drop below the battery voltage, which requires boost mode. Therefore, a buck-boost converter is used in this study.

C. Buck-Boost Converter Design

A buck-boost converter is used to regulate power extraction from the PV circuit to the battery by adjusting the duty cycle. In this study, the duty cycle is determined by the P&O and CS MPPT algorithms to achieve the PV operating point at maximum power. The converter can operate in buck mode to step down the PV voltage to match the battery charging voltage of 53.5 V, or in boost mode to step up the voltage when the PV voltage is below the battery voltage, as can occur under partial shading conditions. Figure 2 shows the buck-boost converter circuit model used in the simulation.

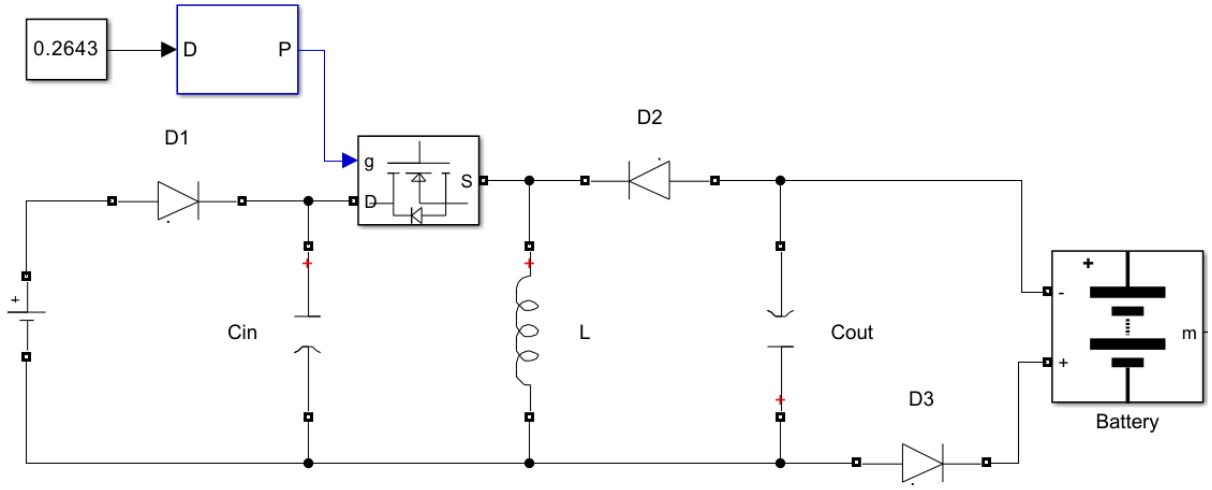


Figure 2. Buck-Boost Converter on Simulink

Designing a buck-boost converter circuit for MPPT requires determining the inductor and capacitor values using the following equations [25]:

Duty Cycle $D = \frac{Vo}{V_o + V_s}$ (1)

Inductor Value $L = \frac{D \cdot V_s}{\Delta I_L \cdot f_s}$ (2)

Capacitor Input Value $C_{in} = \frac{I_{in} D}{\Delta V_{in} f}$ (3)

Capacitor Output Value $C_{min} = \frac{D V_o}{V_r R f}$ (4)

where D is the duty cycle, V_s is the source voltage (V), V_o is the output voltage (V), L is the inductance (H), C_{in} is the input capacitance (F), C_{min} is the minimum output capacitance (F), I_{in} is the input current (A), ΔI_L is the inductor ripple current (A), ΔV_{in} is the input voltage ripple (V), V_r is the ripple voltage (V), R is the load resistance (Ω), and f_s is the switching frequency (Hz).

At the rated power of 1,200 W and an output voltage of 53.5 V, the output current is 22.43 A and the equivalent battery resistance is 2.39 Ω. At STC (V_{mpp} = 148.92 V), Eq. (1) gives a duty cycle of 0.264. With a switching frequency of 25 kHz, average inductor current of 30.5 A and a 20% current ripple (6.1 A), Eq. (2) gives a required inductance of 258 µH. For an input current of 8.06 A and an input voltage ripple of 1% (1.49 V), the required input capacitance is 57.2 µF. For a voltage ripple of 1%, Eqs. (3) and (4) give a minimum input capacitance of 57 µF and a minimum output capacitance of 442 µF. Based on these minimum values and the

availability of standard components, an inductor of 270 µH, an input capacitor of 220 µF, and an output capacitor of 680 µF were selected, as shown in Table 2.

Table 2. Buck-Boost Converter Parameters

Parameter	Value
Inductor, L	270 μH
Capacitor *Input*, C_{in}	220 µF
Capacitor *Output*, C_{out}	680 µF
Frequency Switching, f_s	25 kHz

D. Proposed CS MPPT Algorithm Design

The Cuckoo Search (CS) algorithm is inspired by the reproductive behavior of cuckoos and follows three main rules [26]. In each iteration, each cuckoo lays one egg in a randomly selected nest. The nest with the highest quality egg is retained to form the next generation, while foreign eggs can be recognized by the host bird, allowing the nest to be abandoned or rebuilt with probability Pa. The process of finding the best nest is carried out using a Lévy flight, which is a random walk mechanism with step lengths that follow a Lévy distribution to guide the search toward the optimal solution [22], [27].

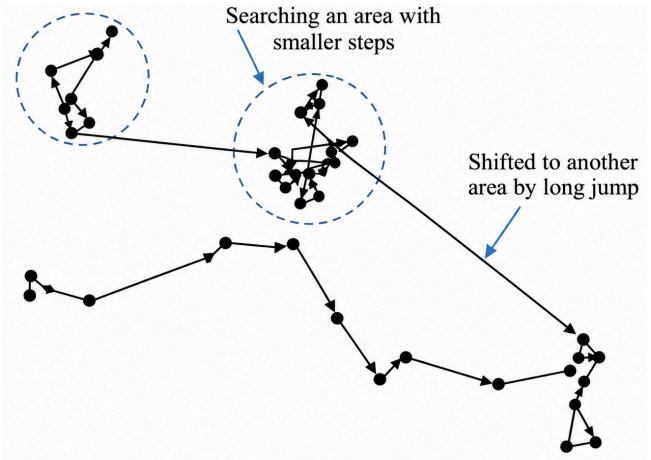


Figure 3. Lévy Flight

Based on the stable Lévy distribution, a Lévy flight is performed to generate a new solution as follows:

$$x_i^{best} = x_i^j + \alpha_0\left(x_{best}^j - x_i^j\right)\oplus Levy \quad (5)$$

where $x = [x_1.x_2.x_3.\ldots.x_N.]$ represents the sample positions in d dimensional space. Parameter α_0 is a coefficient related to the step size. This scheme can be summarized as:

$$x_i^{j+1} = x_i^j + k\left(\frac{u}{|v|^{\frac{1}{\beta}}}\right)\left(x_{best}^j - x_i^j\right) \quad (6)$$

where $\beta = 1.5$ and $k = \alpha$ is an adjustable coefficient. Random Variables u and v are drawn from normal distributions that define the random nature of the algorithm.

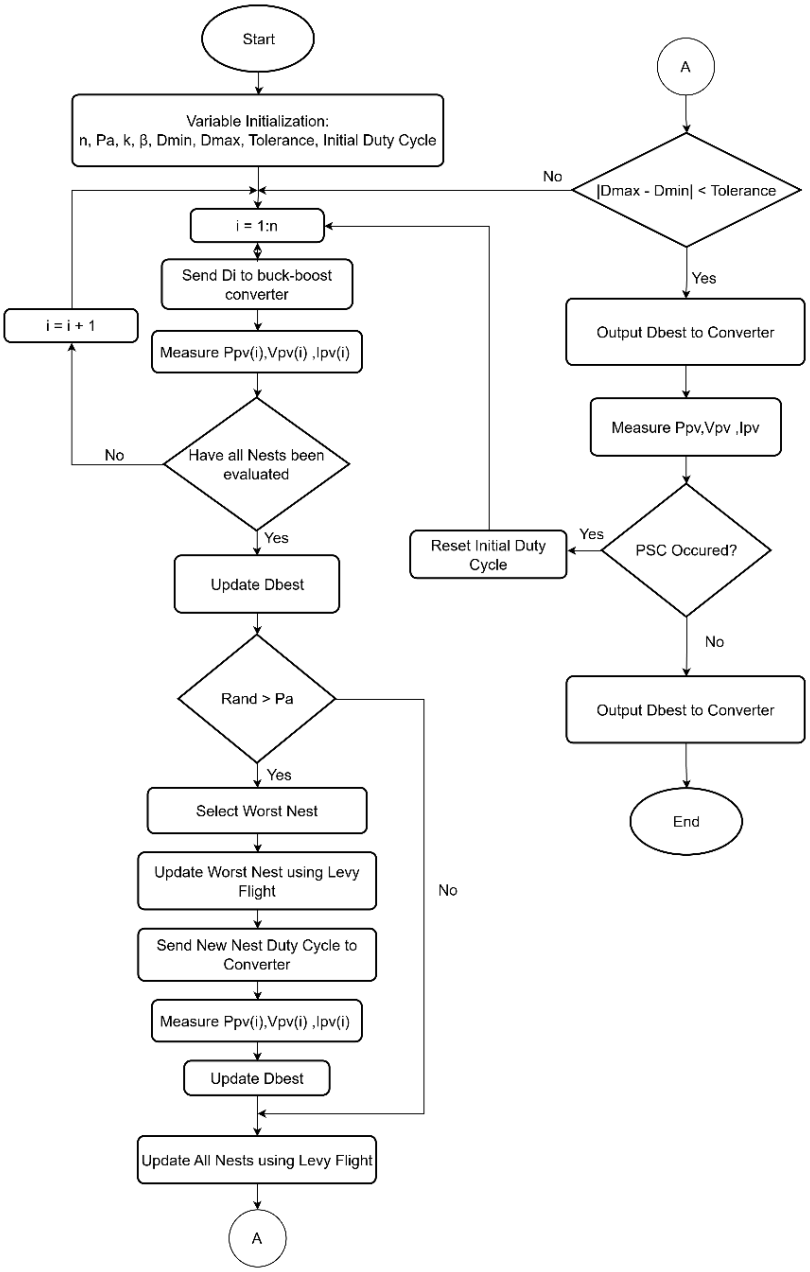


Figure 4. Flowchart of the Proposed CS-based MPPT

In the proposed MPPT, each nest represents a duty cycle value of the buck-boost converter, and the fitness of each nest is the PV output power measured when that duty cycle is applied. The objective of the algorithm is therefore to find the duty cycle that maximizes the PV power within the range of D_{min} and D_{max}.

As illustrated in Figure 4, the CS-MPPT algorithm initializes key parameters (n, P_a, k, β, D_{min}, D_{max}, error tolerance, and initial duty cycle) and sequentially evaluates each nest on the converter to determine the best duty cycle (D_{best}). If a random number exceeds P_a, the worst nest is updated via Lévy flight, after which all nests are iteratively updated using Lévy flight to track maximum PV power until convergence is reached ($D_{max} - D_{min} < Tolerance$). Upon convergence, the optimal D_{best} is applied to maintain maximum power output, while the

system continuously monitors for partial shading conditions (PSC) to reset duty cycles and re-trigger the optimization process whenever power variations are detected. To determine the appropriate CS parameters, a parameter tuning process was carried out by testing several candidate values of the discovery probability (Pa) and the Lévy flight step-size scaling factor (α). Each value was evaluated based on the tracking efficiency and tracking time, as shown in Figure 5 and Figure 6.

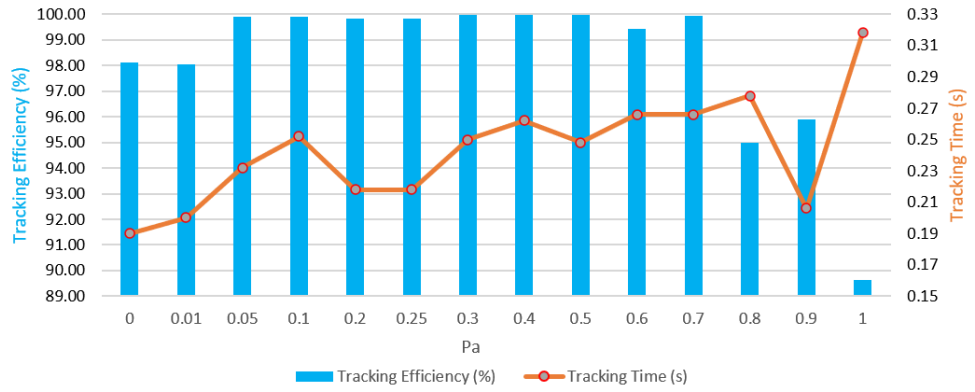


Figure 5. Effect of Parameter Pa on Tracking Efficiency and Time

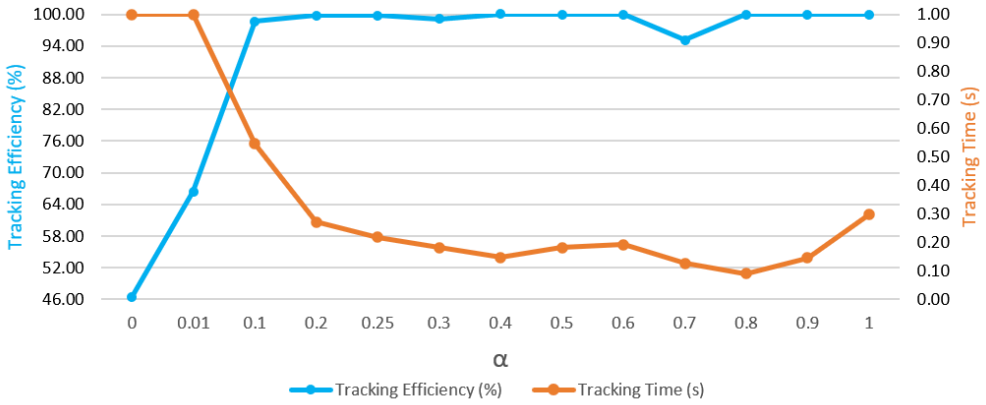


Figure 6. Effect of Parameter α on Tracking Efficiency and Time

As shown in Figure 5, Pa = 0.25 was selected because it yields near-maximum tracking efficiency with one of the shortest tracking times among the tested values, whereas larger values of Pa result in longer tracking. Likewise, Figure 6 shows that α = 0.4 was chosen as it consistently produces tracking efficiency above 99.95% while maintaining a relatively short and stable tracking time and the increasing tracking time observed as α approaches 1. The value β = 1.5 was adopted following the standard Lévy exponent commonly used in CS-based optimization.

E. Simulation Scenarios

The simulation was conducted on a PV string consisting of four series-connected modules with bypass diodes under varying irradiance and module temperatures. Two types of tests were carried out to evaluate the performance of the P&O and CS MPPT algorithms. In the static test, each of the four scenarios, consisting of uniform irradiance and three partial shading conditions (Case 1 to Case 3), was simulated separately. In the dynamic test, the same scenarios were applied sequentially in one simulation, changing every 1 s from No Shadow to Case 1, Case 2, Case 3, and back to No Shadow, to evaluate the ability of each

algorithm to track the GMPP when the shading pattern changes. The irradiance and temperature of each module for each scenario are presented in Figure 7.

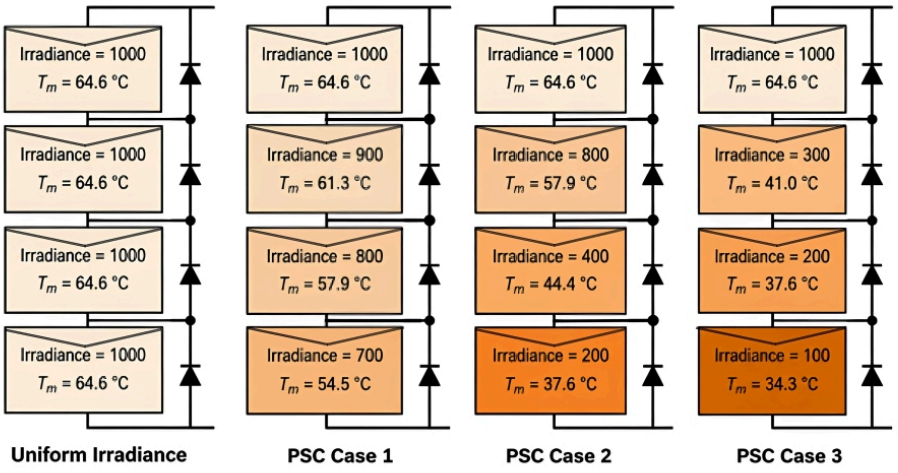


Figure 7. PV Strings Under Partial Shading Conditions

The PSC scenarios were designed using variations in irradiance intensity to represent shading severity, ranging from mild to severe. To simulate real-world conditions, panel temperature parameters were determined based on ambient temperature data obtained from the Renewable ninja website for a specific location in Indonesia. The module temperature for each irradiance level was then calculated using [28]:

$$T_m = T_{amb} + (NOCT - 20) \times \frac{G}{800} \quad (7)$$

where T_m is PV Module temperature (°C), T_{amb} is Ambient temperature (°C), NOCT is Nominal Operating Cell Temperature (°C), and G is Solar Irradiance (W/m²). With NOCT of 47 °C, the resulting module temperatures are summarized in Table 3.

Table 3. Effect of Input Irradiance Values on Panel Temperature

Irradiance Input Case	Irradiance Range (W/m^2)	T_{amb} (℃)	T_m (℃)
1000	≥ 1000	30.877	64.627
900	900-999	30.877	61.252
800	800-899	30.877	57.877
700	700-799	30.877	54.502
600	600-699	30.877	51.127
500	500-599	30.877	47.752
400	400-499	30.877	44.377
300	300-399	30.877	41.002
200	200-299	30.877	37.627
100	100-199	30.877	34.252
0	0-100	30.877	30.877

F. Performance Evaluation

The performance of the MPPT algorithms was evaluated using three efficiencies. The tracking efficiency (η_{MPPT}) measures the ability of the MPPT algorithm to extract the maximum available PV power, the converter efficiency (η_{conv}) measures the power loss in the

buck-boost converter, and the overall efficiency ($\eta_{overall}$) measures the power delivered to the battery relative to the maximum available PV power. For the dynamic test, the overall efficiency was calculated over the whole simulation period using the delivered and maximum available power at each time step. In addition, the tracking time was defined as the time required for the PV power to reach steady state.

Tracking efficiency $$\eta_{MPPT} = \frac{P_{tracked}}{P_{mpp}} \times 100\% \quad (8)$$

Converter efficiency $$\eta_{conv} = \frac{P_{out}}{P_{tracked}} \times 100\% \quad (9)$$

Overall Efficiency $$\eta_{MPPT} = \frac{P_{out}}{P_{mpp}} \times 100\% \quad (10)$$

Steady-state oscillation $$Oscillation_{ss}\,(\%) = \frac{P_{max} - P_{min}}{P_{MPP}} \times 100 \quad (11)$$

Overall Efficiency Under Dynamic PSC $$\eta = \frac{\int_0^{T_M} P(t)dt}{\int_0^{T_M} P_{mpp}(t)dt} \times 100\% \quad (12)$$

RESULT AND DISCUSSION

A. Simulation Setup

The system is designed and simulated using MATLAB/Simulink to analyze the performance of the maximum power point tracking (MPPT) method in a photovoltaic (PV) system based on a buck-boost converter. Figure 8 shows the simulation circuit used in this study. The simulation model consists of a PV module, buck-boost converter, MPPT algorithm, switching system, and battery load, which are integrated into a single system.

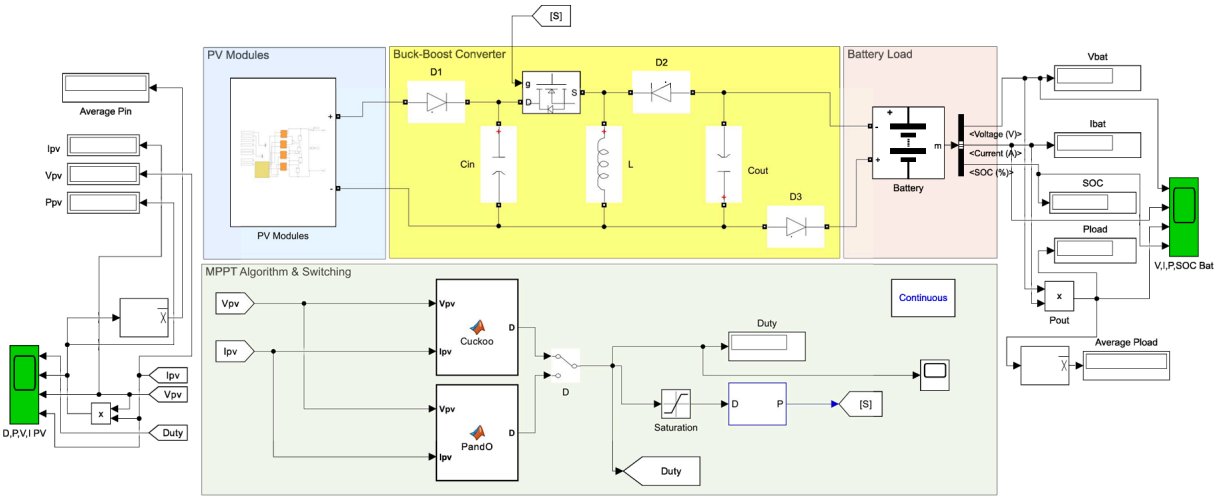


Figure 8. Simulink Model of the Proposed PV-MPPT System

B. Battery Charging Validation

To validate the proposed system, the battery voltage, charging current, charging power, and state of charge (SOC) were analyzed, as shown in Figure 9. The negative current and power indicate charging state. For both methods, the battery voltage maintained at about 52.1 V,

below the maximum charging voltage of 53.5 V, and the SOC increased continuously, confirming that the power tracked by the MPPT is delivered to the battery. With P&O, the system reached steady state almost immediately, while with CS, the battery current and power fluctuated at the beginning of the simulation, because CS evaluates each nest across the duty cycle range before converging.

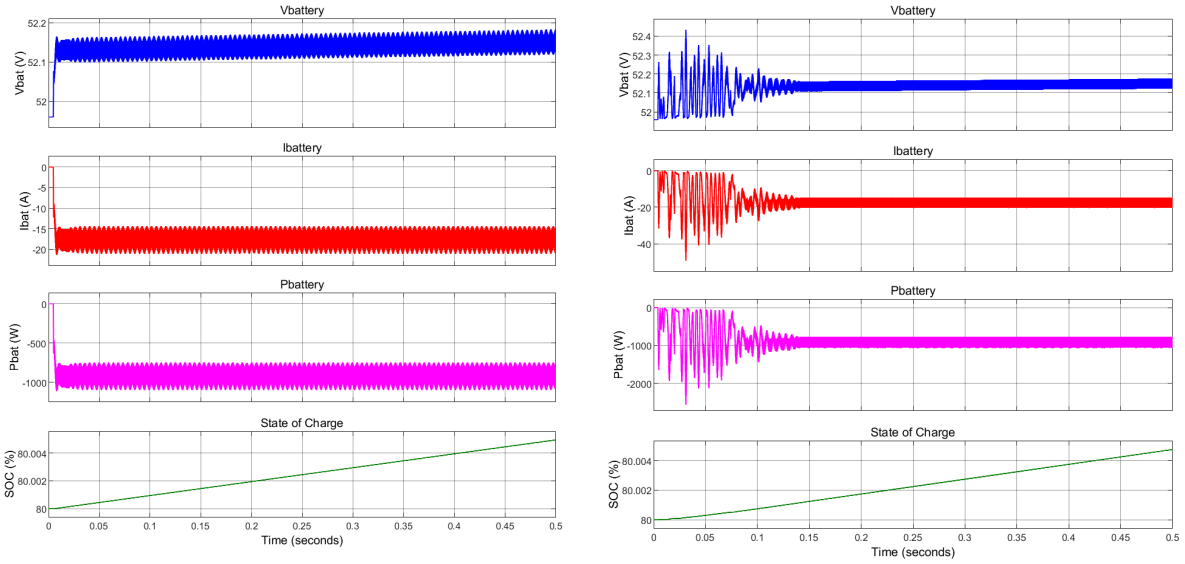


Figure 9. Battery Charging Performance Using (a) P&O and (b) CS Algorithm

C. Partial Shading Characteristic Curves

The difference in irradiance distribution under each partial shading condition (PSC) case results in significant changes in the I-V and P-V characteristic curves of the PV system. The simulation results illustrating the characteristic curves of the PV system under different PSC conditions are presented in Figure 10. The curves consist of the I-V characteristics on the left and the P-V characteristics on the right, with the global maximum power point (GMPP) indicated for each shading condition.

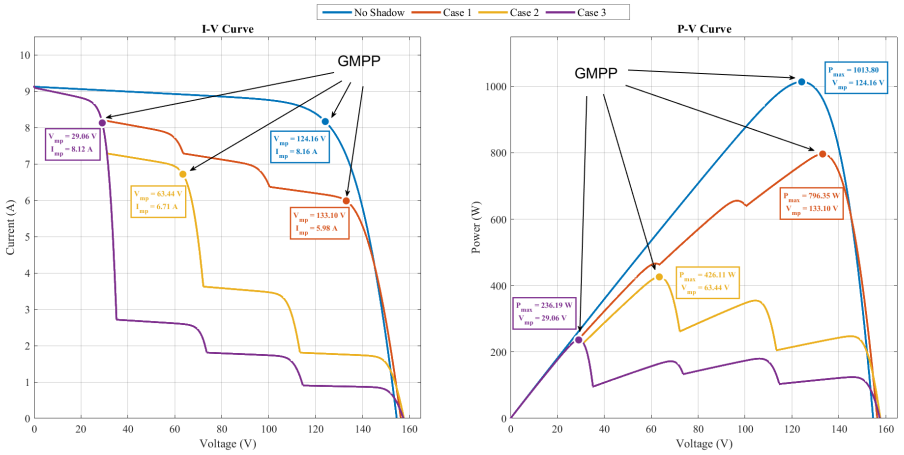


Figure 10. I-V and P-V Characteristic Curves

As shown in Figure 10, the uniform irradiance produces a smooth I-V curve and a single dominant peak on the P-V curve, corresponding to a GMPP of approximately 1013.80 W at 124.16 V. Under PSC, the non-uniform irradiance distribution causes multiple peaks to

appear in the I-V and P-V curves. As the shading condition becomes more severe from Case 1 to Case 3, the available maximum power decreases significantly, with the GMPP shifting to approximately 796.35 W, 426.114 W, and 236.197 W, respectively. The appearance of multiple peaks in the P-V curves indicates the presence of several local maximum power points, which makes GMPP tracking more challenging for conventional MPPT methods. The detailed I-V and P-V characteristic results for each case are shown in Table 4.

Table 4. Simulation Parameters and Results for All PSC Cases

PSCs Cases	Irradiance of PV Panel PSCs (W/m²)				Parameter			
	Panel 1	Panel 2	Panel 3	Panel 4	Duty Cycle	V_{mpp} (V)	I_{mpp} (A)	P_{mpp} (W)
Uniform Irradiance	1000	1000	1000	1000	0.301	124.16	8.165	1013.8
Case 1	1000	900	800	700	0.286	133.10	5.983	796.35
Case 2	1000	800	400	200	0.457	63.443	6.716	426.114
Case 3	1000	300	200	100	0.648	29.061	8.127	236.197

D. Evaluation of P&O-Based MPPT Performance

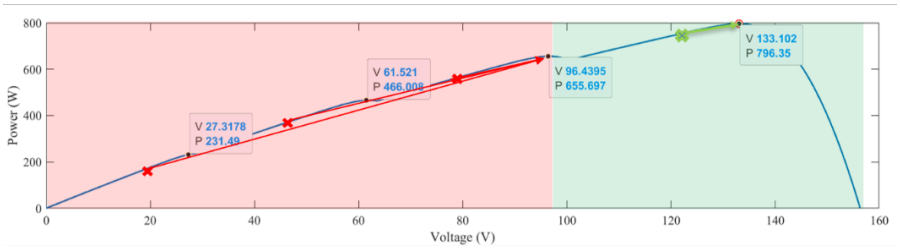


Figure 11. P&O Tracking of the GMPP and LMPP under PSC Case 1

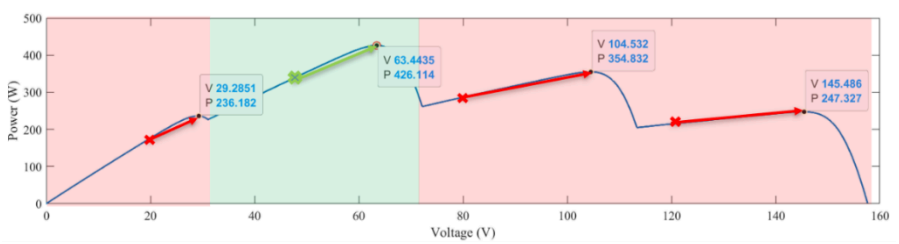


Figure 12. P&O Tracking of the GMPP and LMPP under PSC Case 2

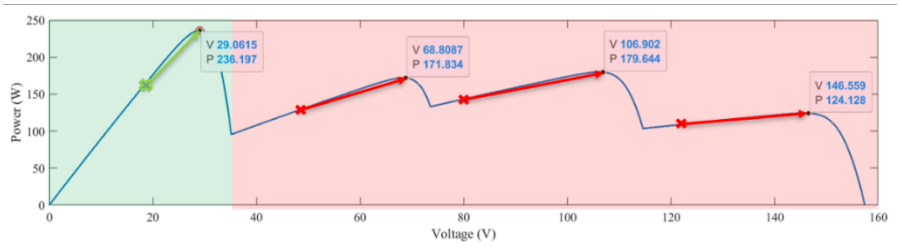


Figure 13. P&O Tracking of the GMPP and LMPP under PSC Case 3

The Perturb and Observe (P&O) algorithm was used as a comparison method to evaluate the performance of the proposed MPPT. This method works by applying a perturbation to the converter's duty cycle and observing the change in PV output power to determine the direction of the next operating point. Under uniform irradiance conditions, P&O is able to reach the MPP because the P-V curve has only one dominant peak, so the search process does not encounter LMPP. Under PSC, however, the result depends on the initial operating

point, as shown in Figure 11 to Figure 13. In these figures, the green region indicates initial points that converge to the GMPP, while the red region indicates initial points trapped at an LMPP. With an initial duty cycle of 0.3, P&O starts at the high-voltage side of the P-V curve, which lies in the green region in Case 1 but in the red region in Case 2 and Case 3. As a result, P&O reaches the GMPP in Case 1 but is trapped at an LMPP in Case 2 and Case 3. Because P&O only searches locally around its operating point, it cannot move from an LMPP to the GMPP. These results highlight the limitation of P&O to perform a global search. The performance of P&O in each case is summarized in Table 6 and compared with CS.

E. Evaluation of CS-Based MPPT Performance

Table 5. CS Parameter Settings

Parameter	Value
Number of nests	4
Pa	0.25
α	0.4
β	1.5
D_{min}	0.26
D_{max}	0.75
Tolerance	0.0005
Initial nest values	0.26; 0.35; 0.5; 0.75

Based on the results of the parameter variation analysis conducted by considering tracking efficiency, tracking time, and the algorithm's success in achieving GMPP, the most suitable parameter combination for this study was determined to be Pa = 0.25, α = 0.4, and β = 1.5. This combination of parameters will then be used to test each test case. The detail values applied are summarized in Table 5. The number of nests was set to four to keep the tracking time short, since each nest must be applied to the converter and evaluated one by one. The duty cycle search range is set based on the GMPP voltages that can occur, ranging from the worst partial shading conditions to maximum uniform irradiance at low temperatures. The initial nests (0.26, 0.35, 0.5, and 0.75) are spread across the duty cycle range so that the search starts from different regions of the P-V curve, as shown in Figure 14.

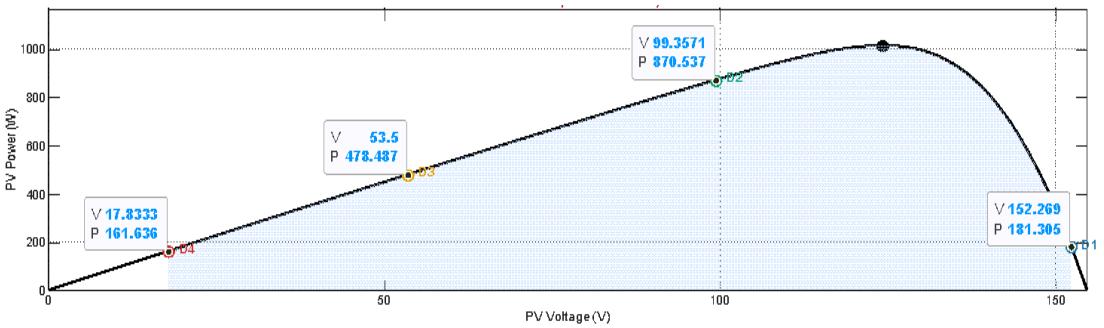


Figure 14. Initial CS MPPT Duty Position to the P-V Curve

The proposed MPPT system was simulated under four different PV operating conditions, including uniform irradiance and three partial shading scenarios. The duty cycle, PV power, voltage, and current during the tracking process are shown in Figure 15. Based on the simulation results, the Cuckoo Search-based MPPT algorithm was able to track the GMPP under all test conditions, both under uniform irradiation and partial shading conditions. The tracking efficiencies obtained sequentially from the unshaded condition to Case 3 were 99.95%, 99.91%, 99.30%, and 99.52%, with tracking times of 0.148 s, 0.182 s, 0.204 s, and 0.160 s, respectively. These results show that CS remains capable of finding the GMPP with

tracking efficiencies above 99% even though the P-V curve characteristics become increasingly complex due to changes in the irradiation pattern under PSC conditions, while maintaining relatively low steady-state oscillations. The detailed performance of CS in each case is summarized in Table 6.

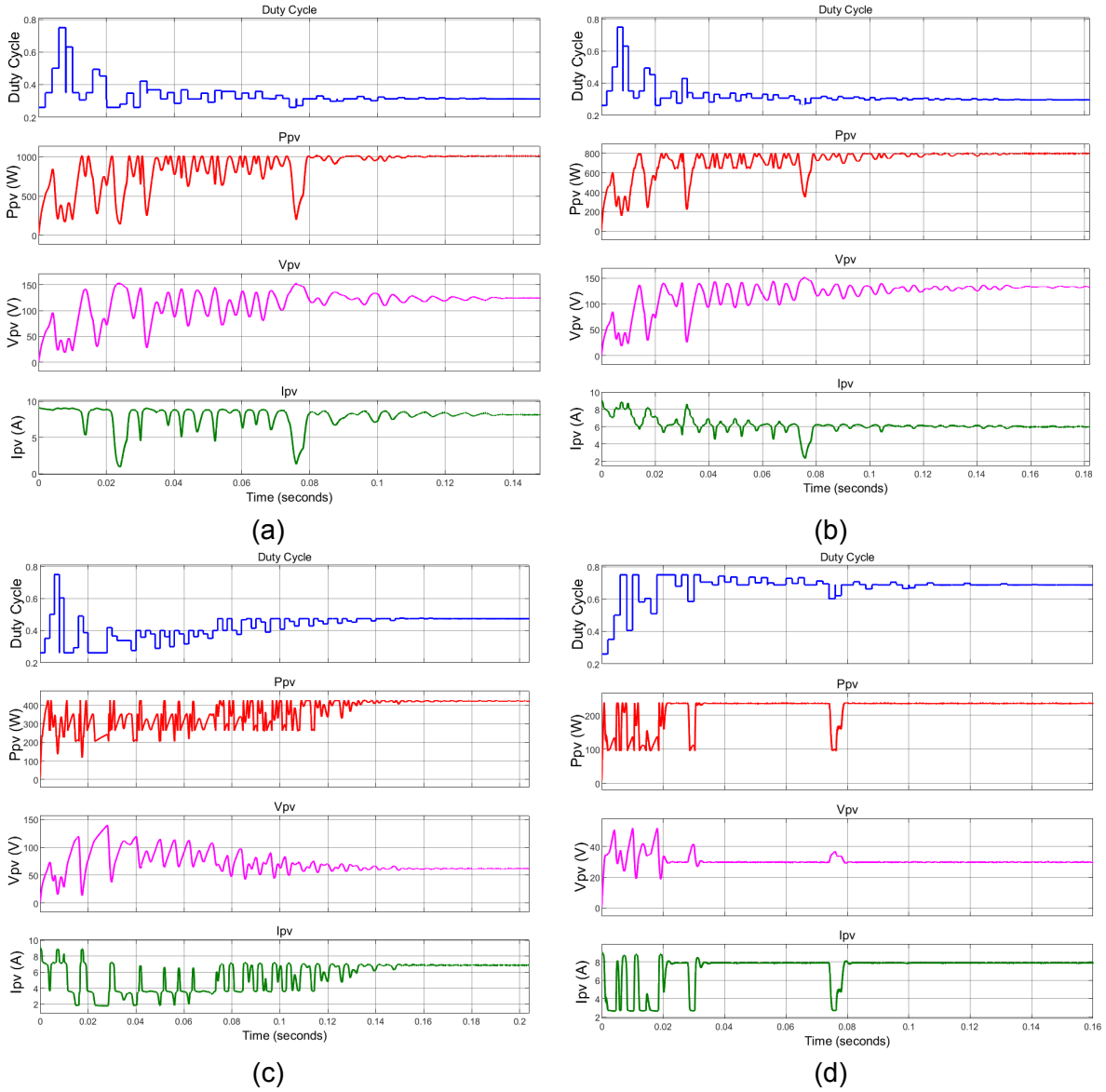


Figure 15. Simulation Result Under (a) Uniform Irradiance, (b) PSC Case 1, (c) PSC Case 2, and (d) PSC Case 3

F. MPPT Performance Under Dynamic PSC Conditions

Dynamic testing was conducted to evaluate the performance of the MPPT algorithm in maintaining GMPP tracking when irradiation conditions change periodically. The simulation scenario began with a no shadow condition, then transitioned sequentially to Case 1, Case 2, and Case 3, before returning to the no shadow condition, with each condition lasting 1 second. Figure 16 shows the results of the dynamic simulations using the P&O and CS MPPT algorithms. The simulation results show that the P&O algorithm fails to track the GMPP when more complex PSCs occur, particularly in Case 2 (t = 2 to 3 s) and Case 3 (t = 3 to 4 s), because the algorithm tends to get stuck at the LMPP. In contrast, the CS algorithm is able to track the GMPP with every change in conditions, although each change in the PSC

triggers a reset of the duty cycle and a search for a new best duty cycle value, resulting in a temporary drop in efficiency during the tracking process. During the simulation period, the CS algorithm achieved an overall efficiency of 90.19%, higher than the P&O algorithm's 85.14%. These results indicate that the CS algorithm is better able to maintain GMPP tracking under dynamic PSC conditions compared to the P&O algorithm.

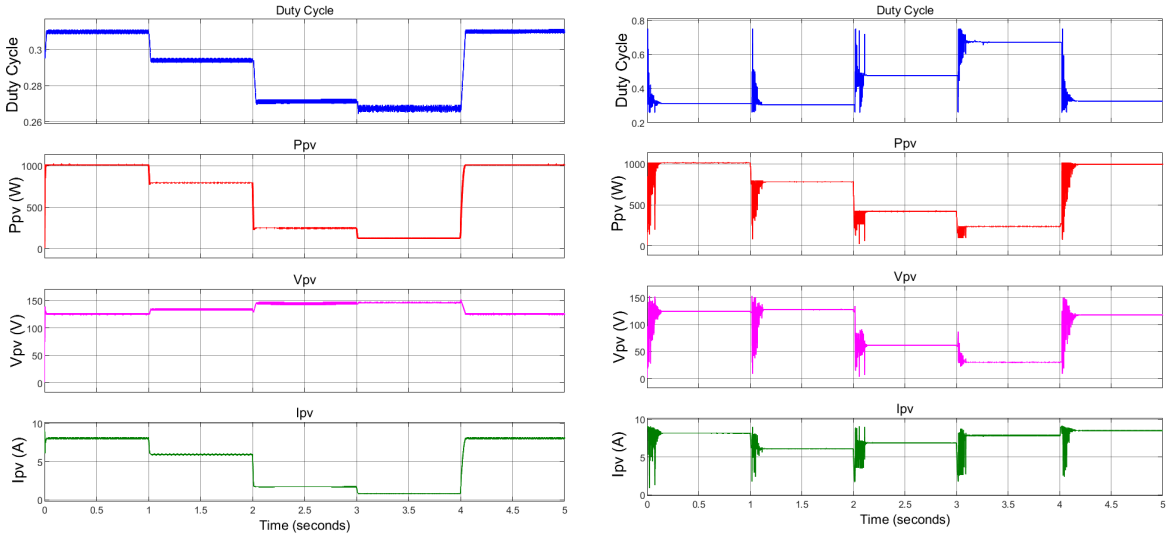


Figure 15. Results of Dynamic Simulation Using (a) P&O and (b) CS Algorithm

G. Overall Performance Comparison

Table 6 summarizes the performance of P&O and CS under all static test conditions, based on the results in Sections D and E. Both methods successfully reached the GMPP under uniform conditions and Case 1, but under severe partial shading (Case 2 and Case 3), P&O became trapped at the LMPP with efficiencies dropping to 57.85% and 52.55%, whereas CS reliably tracked the GMPP with efficiencies exceeding 99.30% and 99.52%, achieving an average overall efficiency of 93.35%, compared with 73.24% for P&O. CS maintained steady-state oscillations of 0.29-0.80% in all cases, while the lower oscillations of P&O in Case 2 and Case 3 (0.47% and 0.17%) occurred only because it was trapped at an LMPP.

Table 6. Summary of MPPT Performance Results

Test Profile	MPPT	P_{mpp} (W)	$P_{Tracked}$ (W)	Tracking Eff. (%)	GMPP Track	Track Time (s)	Osc. (%)	P_{Out} (W)	Converter Eff. (%)	Overall Efficiency (%)
No Shadow	CS	1013.8	1013.33	99.95	Success	0.148	0.39	939.15	92.68	92.64
	P&O		1012.80	99.90	Success	0.028	0.69	941.16	92.93	92.84
Case 1	CS	796.35	795.63	99.91	Success	0.182	0.29	750.77	94.36	94.28
	P&O		795.14	99.85	Success	0.029	0.79	752.03	94.58	94.43
Case 2	CS	426.11	423.14	99.30	Success	0.204	0.73	398.04	94.07	93.41
	P&O		246.51	57.85	Failed	0.041	0.47	235.70	95.62	55.31
Case 3	CS	236.19	235.06	99.52	Success	0.160	0.80	219.87	93.54	93.09
	P&O		124.11	52.55	Failed	0.128	0.17	119.02	95.90	50.39
Average	CS			99.67		0.173			93.66	93.35
	P&O			77.53		0.056			94.76	73.24

Table 7 compares the proposed method with previous studies that also tested uniform irradiance and three partial shading conditions. All values are averages over the four test conditions, taken from Table 6 for the proposed method and calculated from the results tables reported in [12] and [20] for the other methods. The proposed CS achieved an average tracking efficiency of 99.67%, comparable to PSO [12] with 99.68% and higher than CS [20] with 99.22% and GA [20] with 97%. Its average tracking time of 0.173 s is also shorter than all three other results. These results confirm that the proposed CS algorithm provides a strong balance between tracking efficiency and speed under both uniform irradiance and partial shading conditions. However, since the compared studies utilized different system and converter types, this comparison serves as an indication rather than a direct comparison.

Table 7. Comparative Performance of MPPT Methods

MPPT Method	Converter	Load	Average Tracking Efficiency (%)	Average Track Time (s)
The Proposed Method	Buck-boost	Battery	99.67	0.173
CS algorithm in [20]	Boost	Resistor	99.22	0.220
GA algorithm in [20]	Boost	Resistor	97	0.330
PSO algorithm in [12]	Boost	Resistor	99.68	0.700

CONCLUSION

This study developed and evaluated a Cuckoo Search (CS) based maximum power point tracking (MPPT) algorithm using a buck-boost converter for PV battery charging under partial shading conditions (PSC). PSC changes the I-V and P-V characteristics of the PV system by producing multiple local maximum power points and a global maximum power point, reducing the effectiveness of conventional MPPT methods. The Perturb and Observe (P&O) algorithm achieved a tracking efficiency of 99.90% with a tracking time of 0.028 s under uniform irradiance; however, under PSC, its efficiency decreased to 52.55-99.85% and it failed to track the GMPP under complex shading due to LMPP convergence. The proposed CS based MPPT employs Lévy flight and nest-updating mechanisms to optimize the converter duty cycle, with optimal parameters Pa = 0.25, α = 0.4, and β = 1.5. Under uniform irradiance, CS achieved a tracking efficiency of 99.95% with a tracking time of 0.148 s, while under PSC it consistently tracked the GMPP with an efficiency of 99.30-99.91%. CS also maintained low steady-state oscillations of 0.29-0.80% across all test conditions, indicating stable operation after convergence. Although CS required a longer tracking time than P&O, the simulation results indicate that it provides more reliable GMPP tracking under PSC and a higher average overall tracking efficiency of 93.35%, compared with 73.24% for P&O. These findings suggest that CS-based MPPT is a promising approach for PV systems operating under partial shading conditions.

ACKNOWLEDGMENT

The authors would like to express their sincere gratitude to the Department of Electrical Engineering, Faculty of Engineering, Universitas Riau, Indonesia, for providing academic support and research facilities. The authors also appreciate the assistance and valuable contributions of all individuals who supported the successful completion of this research.

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