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Global Maximum Power Point Tracking of Photovoltaic Module Arrays Based on Improved Cuckoo Search Algorithm

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Abstract: In this paper, an improved cuckoo search-learning-based optimization algorithm (CSLBOA) for the maximum power point tracking (MPPT) of a photovoltaic module array is presented. For any shading discovered on a photovoltaic module array, there will be more than one maximum power point (MPP) observed in the power–voltage (P–V) characteristic curve of the photovoltaic module array. However, only the local maximum power point (LMPP) can be tracked by the traditional maximum power point tracker, but not the global maximum power point (GMPP). Therefore, in this paper, an intelligent maximum power point tracker based on an improved cuckoo search algorithm is presented to address the abovementioned issue. First, Matlab software is used to simulate the P–V characteristic curves of a photovoltaic module array with single-peak, double-peak, triple-peak, and quadruple-peak values while the photovoltaic module arrays are under different shading conditions. Second, the improved cuckoo search algorithm proposed is applied to track the global maximum power point precisely and efficiently. According to the simulation results, it shows that the improved cuckoo search algorithm has a better tracking speed response and steady-state performance than those of traditional ones.

Keywords: cuckoo search-learning-based optimization algorithm (CSLBOA); maximum power point tracking (MPPT); photovoltaic module array; global maximum power point (GMPP)

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1. Introduction

In recent years, the development of renewable energy has played a high profile as it helps reduce the use of fossil fuels, mitigates the greenhouse effect, and reduces air pollution. Among them, the photovoltaic power generation system has the advantages of no fuel consumption, low maintenance cost, and environmental protection, which expands its market share year by year. However, the limitations of the photovoltaic power generation system include low conversion efficiency and the significant effect of the maximum output power point influenced by the environment. In order to overcome these problems, it is necessary to develop MPPT control technologies to enhance efficient energy conversion. Most MPPT control strategies perform well under stable weather conditions. However, when the photovoltaic power generation system is installed in a cloudy area with a rapid irradiance fluctuation due to unstable weather conditions, the MPPT controller may not be capable of handling the mentioned irradiance even if there is enough insolation. This limits the application and development of the photovoltaic power generation system accordingly. In order to solve this problem, it is important to develop new MPPT algorithms with good transient responses. In addition, when the photovoltaic module array is partially shaded, there will be multiple peaks presented in its output P–V characteristic curve, resulting in multiple local maximum power points (LMPPs). Conventional MPPT technology has difficulties in searching the GMPP because searching stops when any peak is reached, degrading the tracking performance of the photovoltaic power generation system. In addition, as shading is common for large photovoltaic power generation systems, it is necessary to develop a new MPPT algorithm that can quickly and accurately find the GMPP even when shading occurs. In order to fully grasp the significant business opportunities of photovoltaic power generation systems and to expand the market of renewable energy-related industries, it is important and urgent to develop a new MPPT method with good transient responses and the ability to search for the best solution in the whole area. Based on this, it is very important to develop an intelligent MPPT algorithm with fast tracking speeds, simple architecture, low cost, high accuracy, and low energy loss for photovoltaic power generation systems under shading conditions.

A photovoltaic power generation system is composed of a photovoltaic module array, a power conditioner, and a transmission and distribution system, wherein the power conditioner is also capable of tracking the maximum power point [1–4]. Due to the output power of a photovoltaic module array varying based on the intensity of insolation and temperature, photovoltaic module arrays shall be controlled by the maximum power point tracker, to ensure the maximum power delivered by photovoltaic module arrays regardless of insolation or temperature.

Based on different conditions of insolation and ambient temperature on the photovoltaic module array, there will be corresponding power–voltage (P–V) characteristic curves generated accordingly. Currently, there are many traditional maximum power point tracking methods [5–7] applied in power conditioners, in which perturbation and observation (P and O) [6] and power feedback [7] are most widely used. The perturbation and observation method is characterized by a simple structure, fewer required parameters, and a low circuit cost. It will change the output power by continuously applying a fixed perturbation and determines the perturbation direction by comparing the output power before and after the change until the maximum power point is tracked. Unfortunately, power is lost easily during such a tracking process, so there will be a trade-off between tracking speed and the step size. On the other hand, the power feedback method makes logic decisions based on the variations in output power and voltage of photovoltaic module arrays, and it determines whether the photovoltaic module arrays are working at the maximum power point by calculating the ratio of the output power to the output voltage. When the slope of power-to-voltage is not equal to zero, it will adjust the output voltage by either increasing or decreasing until the zero slope is obtained. The power feedback method can improve the oscillation issue around the maximum power point and reduce the power loss observed in the perturbation and observation method; however, considering its drawbacks, it is impossible to make a precise measurement on the sensing elements in the real circuit, so it is unlikely to operate at the zero slope.

When the photovoltaic module array is shaded or failed, there will be more than one maximum power point (MPP) observed in the power–voltage characteristic curve of the photovoltaic module array. However, only the local maximum power point (LMPP) can be tracked by the traditional maximum power point tracker, but not the global maximum power point (GMPP) [8,9].

In recent years, many scholars have proposed various intelligent maximum power point tracking methods [10–17] in response to such multi-peak values caused by some shaded modules in the photovoltaic module array [18]. The most popular algorithms include ant colony optimization (ACO) [11], artificial bee colony algorithms (ABC) [12], and particle swarm optimization (PSO) [13,14]. Ant colony optimization [11] is characterized by fewer parameters and a simple structure, but its searching speed is slow. As a probabilistic algorithm for optimizing routes, it imitates the foraging habits of ants, leaving pheromones along the routes to guide those ants behind. Because more pheromones will remain in shorter foraging routes, those ants behind can determine their foraging routes based on the pheromone concentration, therefore saving time spent in random search. On the other hand, the artificial bee colony algorithm [12] works by the separation of duties in a bee colony, wherein worker bees, responsible for finding food sources, transmit information of food size and direction through dancing to increase the yield of food, while onlooker bees collect all information to guide the worker bees to choose the best collection routes. Although fewer parameters are required and the convergent speed is faster in the artificial bee colony algorithms, the tracking speed and stability are both affected by the number of scout bees, leading to a longer tracking response time. For particle swarm optimization [13,14] originating from research on the predation behavior of birds, it is based on the information sharing among individuals in the swarm, making the movement of the entire swarm evolve from disorder to order during the solution space to obtain the optimal solution. The PSO algorithm proposed in reference [13,14] does not use a complex calculation process and expensive hardware equipment, but treats the partial shading of the photovoltaic module as a mathematical problem and finds the optimal solution through the mutual traction and improvement between particles, thereby achieving the search for the global maximum power points. Compared with other evolutionary algorithms, the PSO method only needs few evolutionary swarms, but it is easy to obtain regional solutions instead of accurate search results. In the firefly search algorithm proposed by Sundareswaran, when the behavior where the firefly with weak light follows the behavior of the firefly with strong light is simulated in searching for the GMPPs, it considers the voltage point of each sample as the light emitted by the firefly, thereby updating the voltage operating point continuously until the MPP is found [15]. However, when the photovoltaic module array is partially shaded, the traditional firefly search algorithm will be trapped in the LMMP during tracking and fail to track the GMMP. In addition, some scholars have proposed MPPT technology based on artificial neural networks. For example, Gowid et al. used open-circuit voltage, short-circuit current, irradiance, and fill factor as input parameters for artificial neural networks (ANNs), and voltage and current at the MPP as output parameters [16]. Although this method can track quickly with great accuracy, it requires an additional irradiance meter and cannot provide the correct fill factor. On the other hand, Lin et al. used the voltage, current, and temperature at the current operating point as the input of the ANN, and used the voltage of the MPP as the output [17]. Although it can effectively reduce the number of input parameters, it is still difficult to apply to the actual photovoltaic power generation system due to complicated equations caused by too many hidden layers.

Based on the above reasons, an improved cuckoo search algorithm [19] for tracking the maximum power point of a photovoltaic module array with some modules shaded or failed is presented. It has the advantages of few parameters, simple structure, and easy-to-understand principle, as well as a shorter tracking time by automatically adjusting its step factor. In this paper, an improved cuckoo search algorithm is evolved from traditional ones, wherein its maximum power point tracker has a better tracking speed response and steady-state performance even when the characteristic curve of the photovoltaic module arrays presents multi-peak values due to the shading or failure of some modules. The research results of this paper can be further used to estimate the power generation loss of the photovoltaic module array under different shading conditions in the future and its long-term power generation and evaluate the sustainable economic efficiency photovoltaic power generation system under shade [20].

This paper is divided into five sections. The first section is an introduction to the composition of photovoltaic power generation systems and a briefing on the existing conventional MPPT method and intelligent MPPT method, as well as their advantages and disadvantages. The second section describes the shading characteristics of the photovoltaic module array and the P–V output characteristics curve when some modules are shaded. In the third section, we first introduce the operating principle of the traditional cuckoo algorithm and its iteration formula, and then explain the improvement strategy of the improved cuckoo algorithm proposed in this paper for the iteration formula. In the fourth section, Matlab software is used to simulate the MPPT of the photovoltaic module array under different shading conditions based on the traditional cuckoo algorithm and the improved cuckoo algorithm. The simulation results are used to compare the tracking speed response and stability performance of the proposed improved cuckoo algorithm and the traditional cuckoo algorithm. Finally, the study's conclusions are presented in the fifth section, and future research directions are discussed.

2. Failure and Shading Characteristics of Photovoltaic Module Arrays

When some modules in the photovoltaic module array are shaded, the output power–voltage curve will change nonlinearly, resulting in multi-peak values. As the output voltage and current of the module array decrease, the total output power of the module array will decrease accordingly. Therefore, in order to study the P–V and I–V output characteristics of the photovoltaic module array with some modules in the series and parallel arrays shaded, the photovoltaic modules produced by Sunworld Co. LTD [21] were used in this study, set under different shading conditions and configured as arrays with different series-parallel configurations for testing. Their electrical specifications are shown in Table 1 [21]. In this paper, Matlab software [22] was used to simulate the P–V and I–V characteristic curves of monolithic photovoltaic modules under standard test conditions (STCs) (i.e., air mass 1.5, insolation intensity 1000 W/m^2, and the temperature of photovoltaic module 25 °C) without shading or with different shading ratios. The simulation result is shown in Figure 1.

Table 1. Data specifications of electrical parameters of photovoltaic modules produced by Sunworld [21].

Parameters	Specifications
Rated maximum output power (P_{mp})	20 W
Current at maximum output power point (I_{mp})	1.1 A
Voltage at maximum output power point (V_{mp})	18.18 V
Short-circuit current (I_{sc})	1.15 A
Open-circuit voltage (V_{oc})	22.32 V
Length and width of module	395 mm × 345 mm

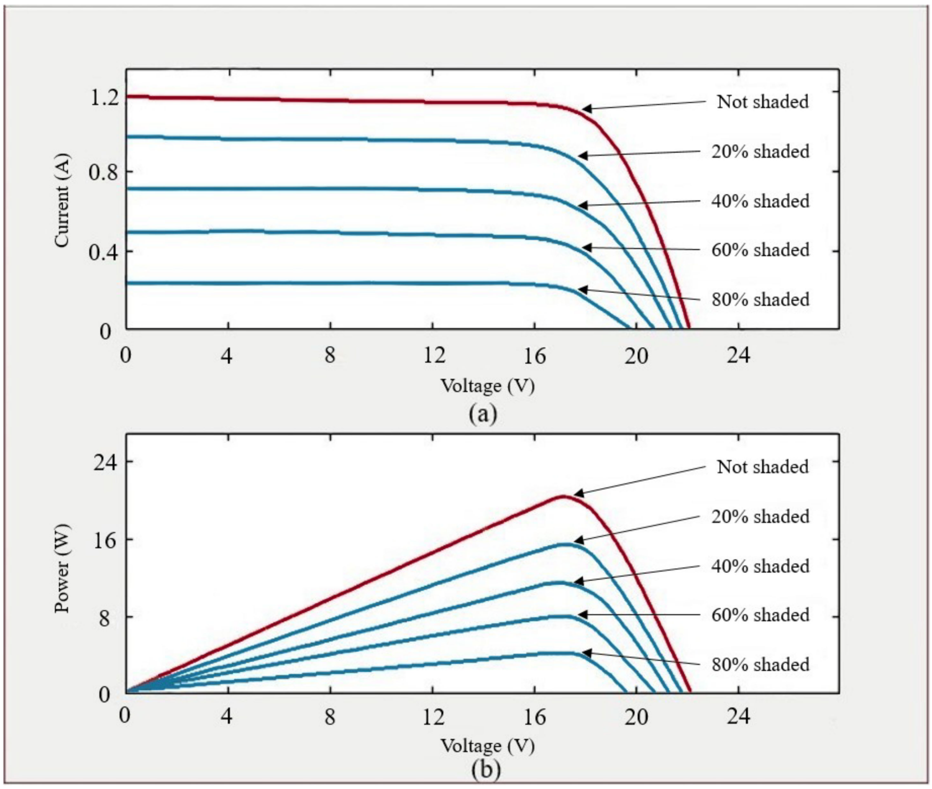

Figure 1. (**a**) I–V and (**b**) P–V characteristic curves of monolithic photovoltaic module under different shading ratios [22].

In this paper, the improved cuckoo search algorithm is applied for the maximum power point tracking of photovoltaic module arrays. First, take traditional cuckoo search algorithm as an example for explanation, and those parameters applied are shown in Table 2.

Table 2. Settings of parameters applied in the traditional cuckoo algorithm.

Parameters	Specifications
Number of nests (n)	25
Discovered probability (P_a)	0.25
Number of iterations (T)	50
Step factor (β)	1.5

Please refer to the steps of the traditional cuckoo algorithm as follows [23,24]:

Step 1. Set the number of nests to n, the discovered probability to P_a, the number of iterations to T, and the step factor to β.

Step 2. Generate new solutions of the number of bird nests n by applying Equation (1) of the Le'vy flight random-walk formula, and obtain the best and worst new solutions, x_{best}^{t+1} and x_{worst}^{t+1}, respectively, among all numbers of bird nests n by comparison.

$$x_i^{t+1} = x_i^t + \alpha \oplus le'vy(\lambda), i = 1, 2, \ldots, n \tag{1}$$

where x_i^t and x_i^{t+1} represent the position of the ith bird nest in the tth and t + 1th iterations, respectively; α represents the step size; $\oplus$ is the entry-wise multiplication; n is the number of bird nests; $le'vy(\lambda)$ is the route of Le'vy random search. Apply the Mantegna algorithm to help the Le'vy distribution generate more stable random numbers; therefore, the iteration of Equation (1) can be modified to Equation (2).

$$x_i^{t+1} = x_i^t + stepsize \oplus randn(\bullet), i = 1, 2, \ldots, n \tag{2}$$

where $randn(\bullet)$ is a random function fulfilled with a Gaussian distribution; $stepsize = \alpha \bullet S \oplus \left(x_i^t - x_{best}^t\right)$, α is usually set to 0.01, x_{best}^t is the best position of the bird nest obtained by the tth iteration, and S is calculated by modifying these two Gaussian distribution variables u and v in Equation (3).

$$S = \frac{u}{\mid v \mid^{1/\beta}} \tag{3}$$

where

$$u \sim N(0, \sigma_u^2),\ v \sim N(0, \sigma_v^2) \tag{4}$$

Set $\sigma_v = 1$ and $\beta = 1.5$ in Equations (3) and (4), and σ_u can be calculated from Equation (5).

$$\sigma_u = \left\{ \frac{\Gamma(1+\beta) \bullet sin(\pi\beta/2)}{\Gamma[(1+\beta)/2] \bullet \beta \bullet 2^{((\beta-1)/2)}} \right\}^{1/\beta} \tag{5}$$

where $\Gamma(\bullet)$ is an integral Gamma function.

Then, replace the best new solution x_{best}^{t+1} obtained in Step 2 by x_{best}^t, and also replace the worst new solution x_{worst}^{t+1} by x_{worst}^t.

Step 3. As in the host's ideas and principles of the bird nest to remove those cuckoo eggs it discovered, obtain a random number r that fulfills the uniform distribution of $[0, 1]$ and compare it with the discovered probability $P_a \in [0, 1]$; if $r < P_a$, the host of the bird nest discovers those cuckoo eggs and then skips this step and goes to

Step 4 directly; on the contrary, if $r > P_a$, apply Equation (6) to generate iterations for obtaining new solutions.

$$x_i^{t+1} = x_i^t + r\left(x_{best}^t - x_{worst}^t\right), i = 1, 2, \ldots, n \tag{6}$$

where x_{best}^t and x_{worst}^t represent the best and worst values of the random solutions in the tth iteration, respectively. Obtain and compare the new solutions generated by Equation (6), and replace the best new solution and the worst new solution among all numbers of bird nests n, x_{best}^{t+1} and x_{worst}^{t+1} by x_{best}^t and x_{worst}^t, respectively.

Step 4. Stop to generate iterations until the targeted number of iterations is reached; otherwise, skip to Step 2.

2.1. Improved Cuckoo Algorithm Proposed

The improved cuckoo search algorithm proposed in this paper is an improvement based on the traditional ones, where the upper and lower limits of the step factor are first set and the step factor is allowed to vary according to the change in the number of iterations and the slope of the P–V characteristic curve. When the slope of the P–V curve is smaller, the step factor becomes smaller accordingly. In addition, the maximum power point is updated after each iteration until the global maximum power point is discovered, allowing it to track the global maximum power point more precisely and efficiently and to improve the tracking performance of the maximum power point tracker, and the step factor is adjusted, as stated in Equation (7). The settings of relevant parameters applied in this paper are shown in Table 3, and the adjusted value of β obtained by Equation (7), which is adjusted based on the slope of the P–V characteristic curve, is shown in Table 4.

$$\beta = \beta_{max} - \left\{ (\beta_{max} - \beta_{min}) \times \left(\frac{t}{T}\right)^2 \right\} \tag{7}$$

where β represents the step factor, β_{max} and β_{min} are the upper and lower limits of the step factor, respectively, t represents the current number of iterations, and T is the maximum number of iterations.

Table 3. Settings of parameters applied in the improved cuckoo algorithm.

Parameter Name	Settings of Parameters
Number of nests (n)	25
Discovered probability (P_a)	0.25
Number of iterations (T)	50
Step factor (β)	1.5
Upper limit of step factor (β_{max})	1.52
Lower limit of step factor (β_{min})	1.42

Table 4. The step change factor based on the slope of P–V curve for improved cuckoo algorithm.

$m = \frac{P_{(t+1)} - P_{(t)}}{V_{(t+1)} - V_{(t)}}$	$\Delta P = P_{(t+1)} - P_{(t)}$ $\Delta P > 0$
$m > 2$	$\beta + 0.02$
$2 \geq m \geq 1.5$	$\beta + 0.01$
$1.5 \geq m \geq 1$	$\beta - 0.04$
$1 \geq m \geq 0.5$	$\beta - 0.06$
$0.5 \geq m \geq 0$	$\beta - 0.08$
$m = 0$	β

Table 4. *Cont.*

$0 \leq m \leq -0.5$	$\beta - 0.08$
$-0.5 \leq m \leq -1$	$\beta - 0.06$
$-1 \leq m \leq -1.5$	$\beta - 0.04$
$-1.5 \leq m \leq -2$	$\beta + 0.01$
$m < -2$	$\beta + 0.02$

2.2. Maximum Power Point Tracker Based on the Improved Cuckoo Algorithm Proposed

Figure 2 shows a flowchart of the maximum power point tracking of photovoltaic module arrays based on the improved cuckoo algorithm proposed in this paper, and Figure 3 shows the structure of the maximum power point tracking controller proposed.

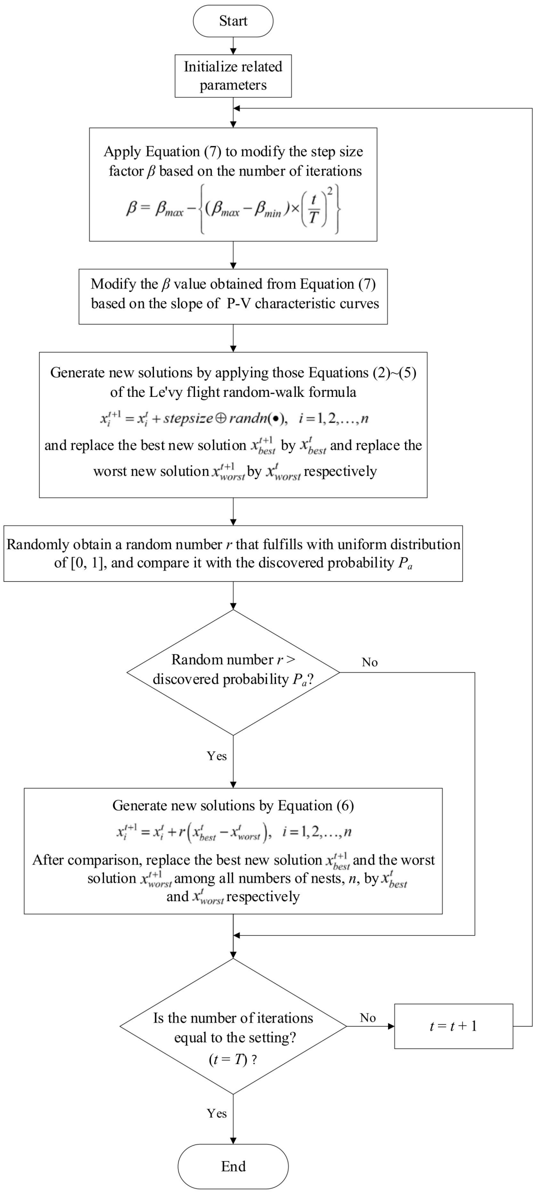

Figure 2. Flowchart of the maximum power point tracking based on the improved cuckoo algorithm.

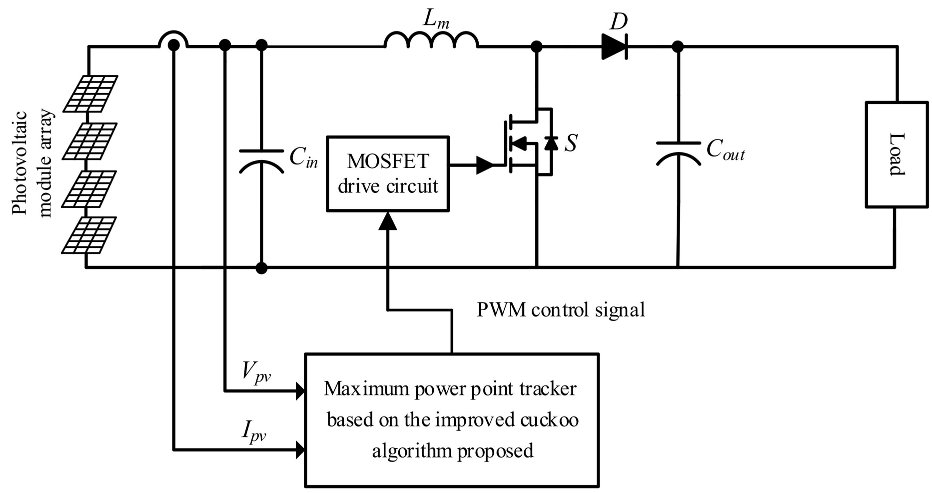

Figure 3. The structure of the maximum power point tracking controller based on the improved cuckoo algorithm.

A boost converter was used for maximum power point tracking in this paper, and the parameter settings of its circuit components are listed in Table 5 [25].

Table 5. Specifications of the main components in the boost converter [25].

Items	Specifications
Energy storage inductance (L_m)	415 uH, withstand current 10 A
Filter capacitor (C_{in})	330 uF, withstand voltage 450 V
Filter capacitor (C_{out})	330 uF, withstand voltage 450 V
Fast diode (D) IQBD60E60A1	V_{RRM} withstand voltage 600 V, I_{FAV} withstand current 60 A
Power semiconductor (S) MOSFET IRFP460	V_{DSS} withstand voltage 500 V, I_D withstand current 20 A

3. Simulation Results

In this paper, Matlab software was used to carry out the improved cuckoo search algorithm and modeling of photovoltaic modules produced by Sunworld. In addition, maximum power point tracking was simulated under six different operation conditions of photovoltaic module arrays, in which single-peak and multi-peak values generated due to those connection configurations and shading ratios, as stated in Table 6. As the voltages of the maximum power point of the photovoltaic module array under different insolation were about 0.8~1.0 times the voltage of maximum power point V_{mp} under the standard test condition (STC), the initial voltage tracked in this paper was set to 0.8 V_{mp}.

Table 6. Six cases with different parallel series configurations and shading ratios selected.

Case	Series-Parallel Configuration and Shading Ratio	The Number of Peaks in the P–V Curve
1	4 series and 1 parallel: Shaded 0% + Shaded 0% + Shaded 0% + Shaded 0%	Single-peak
2	4 series and 1 parallel: Shaded 0% + Shaded 0% + Shaded 0% + Shaded 50%	Double-peak
3	4 series and 1 parallel: Shaded 0% + Shaded 0% + Shaded 20% + Shaded 50%	Triple-peak
4	4 series and 1 parallel: Shaded 0% + Shaded 20% + Shaded 40% + Shaded 50%	Quadruple-peak
5	2 series and 2 parallels: (Shaded 30% + Shaded 0%)//(Shaded 50% + Shaded 0%)	Double-peak
6	2 series and 2 parallels: (Shaded 50% + Shaded 0%)//(Shaded 50% + Shaded 0%)	Double-peak

Note: The symbol "+" stands for series connection, while the symbol "//" stands for parallel connection.

3.1. Case 1: 4 Series and 1 Parallel (Not Shaded)

Figure 4 shows the P–V characteristic curve of the photovoltaic module array produced by Sunworld with 4 series and 1 parallel connection and not shaded. When the photovoltaic module array worked normally without shading, its maximum output power was about 80 W. Figure 5 shows the simulation result of maximum power point tracking based on the traditional and improved cuckoo algorithm. According to Figure 5, it showed that both methods could track the maximum power point, but the improved cuckoo algorithm had a better tracking speed response and steady-state performance than those of the traditional one.

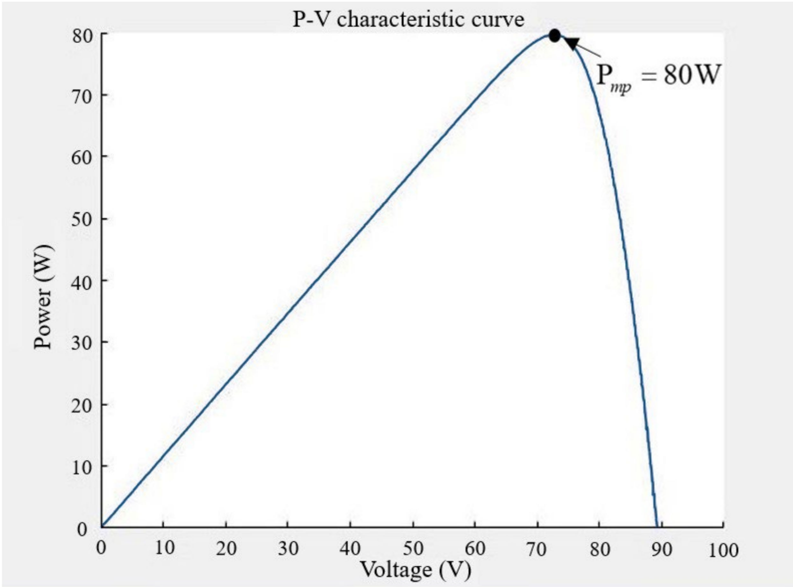

Figure 4. P–V characteristic curve simulation for Case 1.

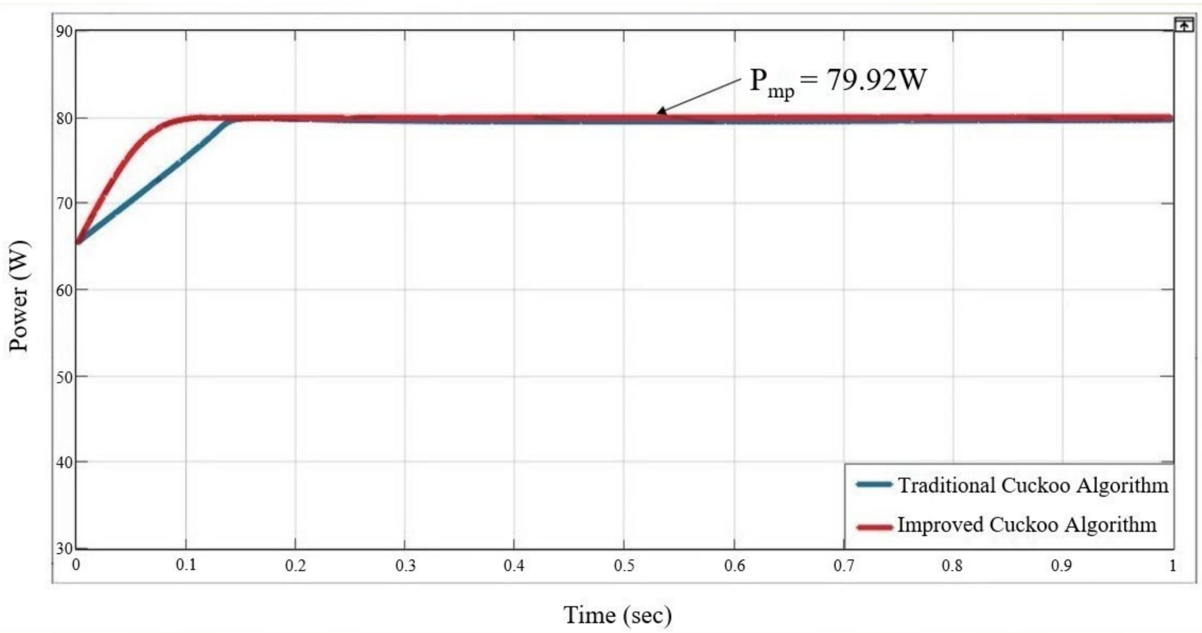

Figure 5. Simulation result of maximum power point tracking of traditional and improved cuckoo algorithm in Case 1.

3.2. Case 2: 4 Series and 1 Parallel (Shaded 0% + Shaded 0% + Shaded 0% + Shaded 50%)

Figure 6 shows the P–V characteristic curve of the photovoltaic module array produced by Sunworld with 4 series and 1 parallel connection, where one photovoltaic module was 50% shaded. It presented double-peak values and its real maximum power point was 60.82 W at the left peak. Figure 7 shows the simulation result of maximum power point tracking based on the traditional and improved cuckoo algorithm. According to Figure 7, it showed that both methods could track the global maximum power point, but the improved cuckoo algorithm had a better tracking speed response and steady-state performance than those of the traditional one even under multi-peak values.

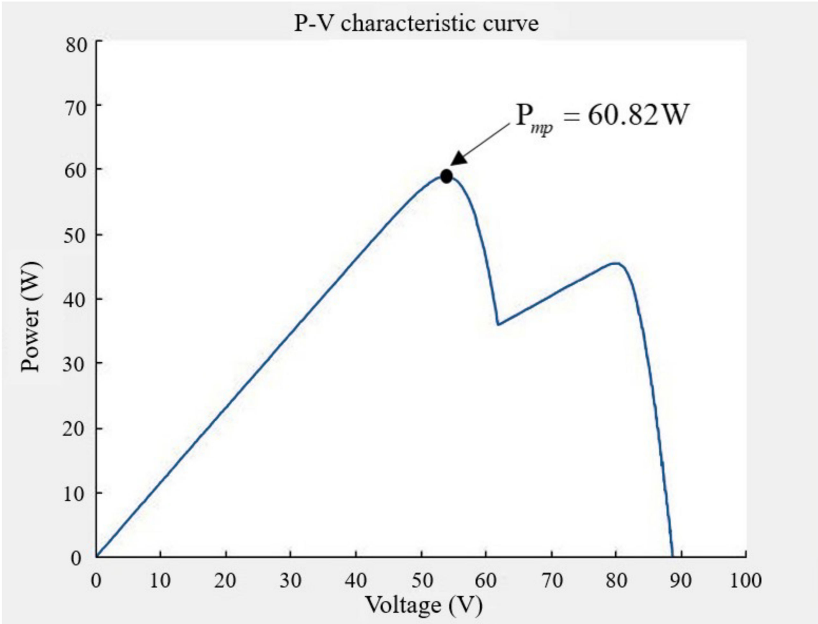

Figure 6. P–V characteristic curve simulation for Case 2.

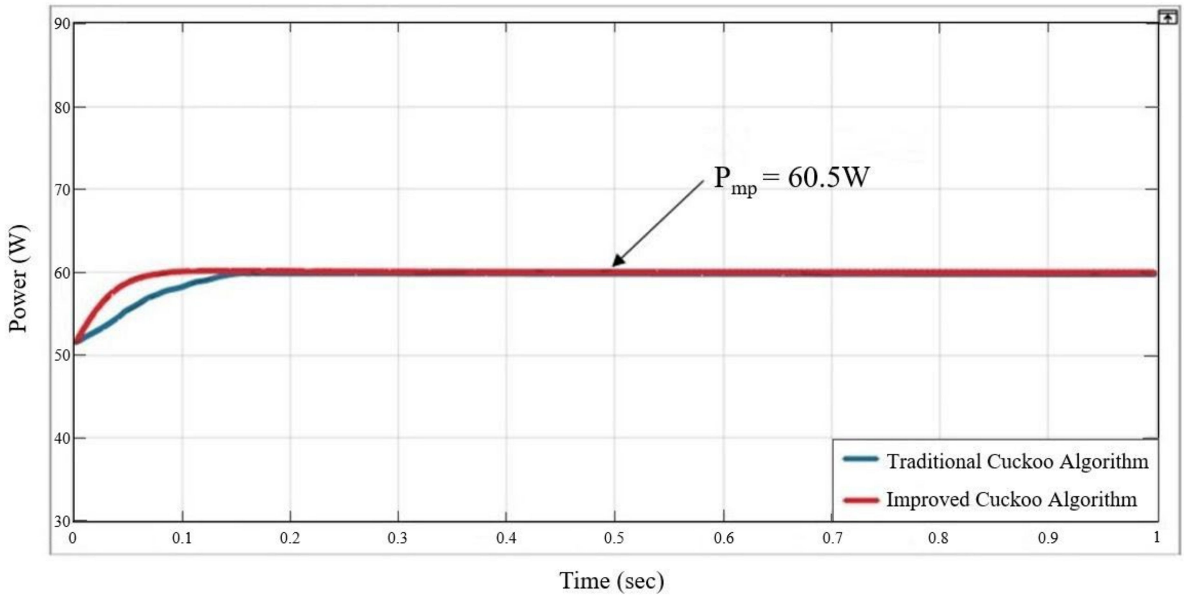

Figure 7. Simulation result of maximum power point tracking of traditional and improved cuckoo algorithm in Case 2.

3.3. Case 3: 4 Series and 1 Parallel (Shaded 0% + Shaded 0% + Shaded 20% + Shaded 50%)

Figure 8 shows the P–V characteristic curve simulation for Case 3, where two modules in the photovoltaic module array are shaded with ratios 20% and 50%, resulting in three-peak values in the characteristic curve. Its real maximum power point was 52.61 W at the middle peak. Figure 9 shows the simulation result of maximum power point tracking based on the traditional and improved cuckoo algorithm. According to Figure 9, it showed that both methods could track the global maximum power point, but neither the tracking speed response nor steady-state performance of the traditional cuckoo algorithm was better than those of the improved one proposed in this paper.

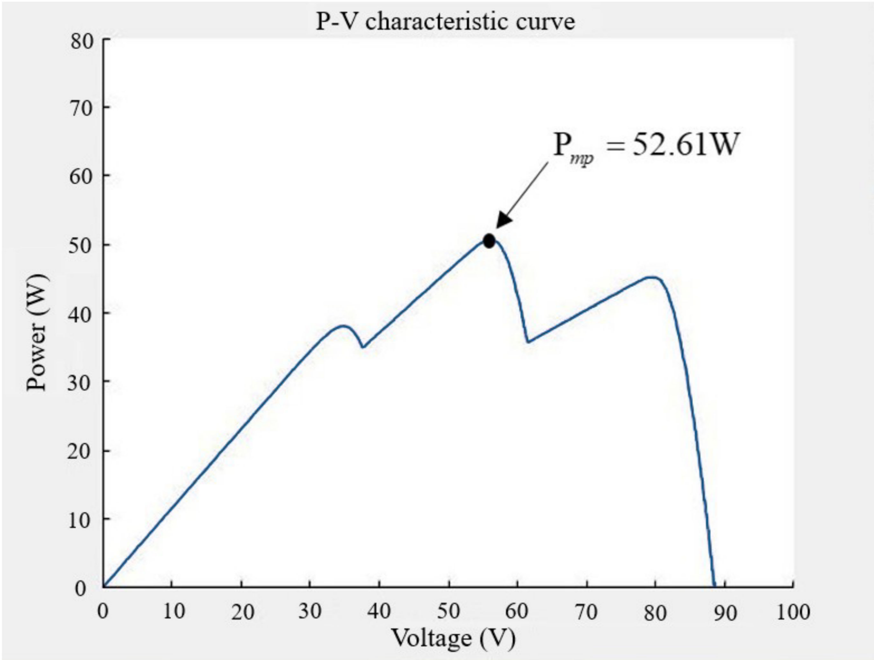

Figure 8. P–V characteristic curve simulation for Case 3.

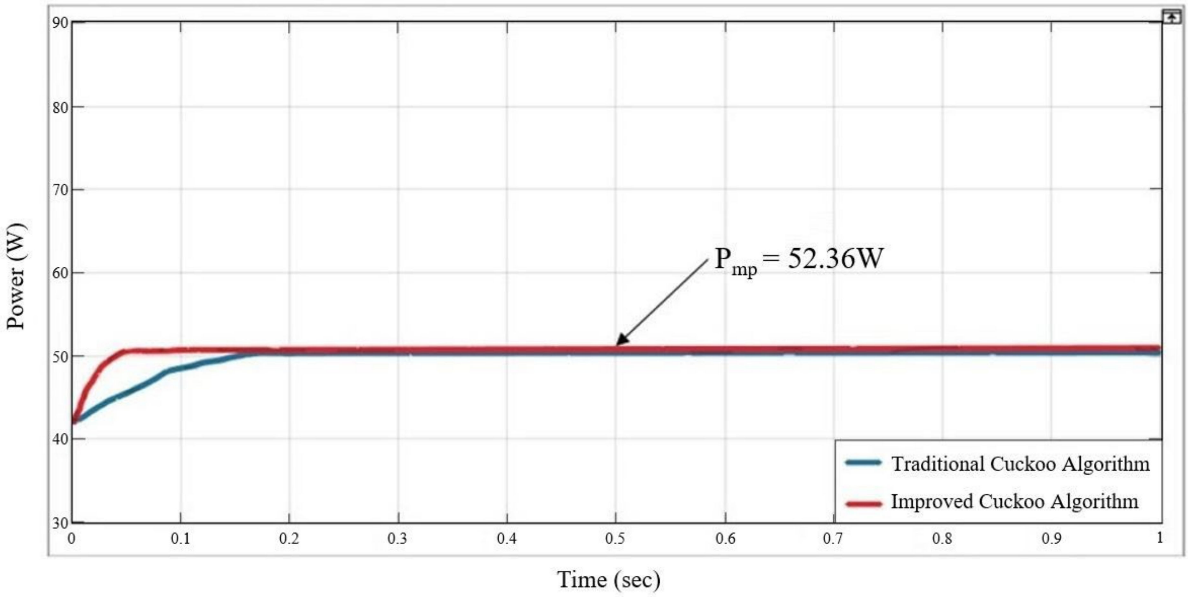

Figure 9. Simulation result of maximum power point tracking of traditional and improved cuckoo algorithm in Case 3.

3.4. Case 4: 4 Series and 1 Parallel (Shaded 0% + Shaded 20% + Shaded 40% + Shaded 50%)

Figure 10 shows the P–V characteristic curve simulation for 4 series and 1 parallel connection, where three modules in the photovoltaic module array were shaded with ratios 20%, 40%, and 50%, resulting in quadruple-peak values in the characteristic curve. Its real maximum power point was 46.28 W at the fourth peak. Figure 11 shows the simulation result of maximum power point tracking based on the traditional and improved cuckoo algorithm. According to Figure 11, it showed that the improved cuckoo algorithm proposed in this paper could track the global maximum power point and had a better tracking speed response and steady-state performance than those of the traditional one under quadruple-peak values.

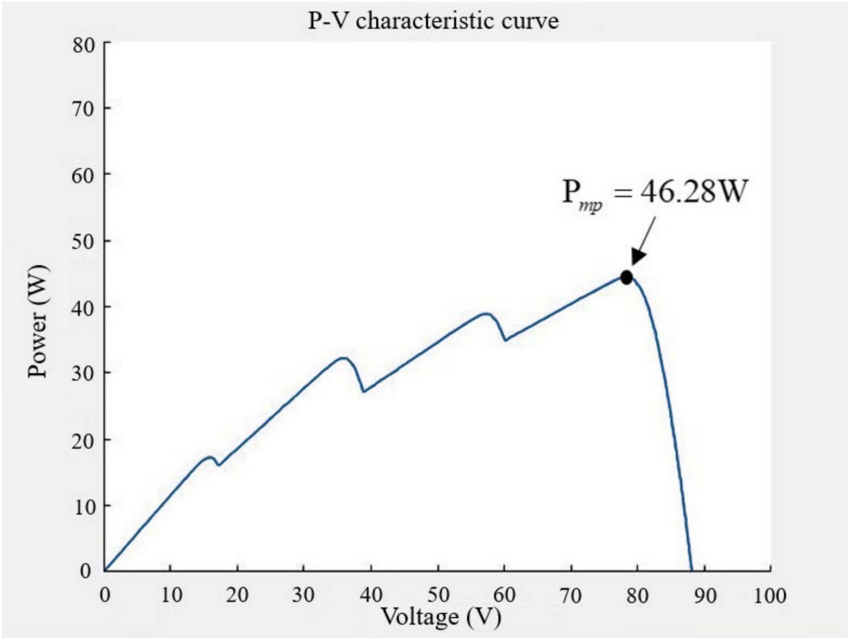

Figure 10. P–V characteristic curve simulation for Case 4.

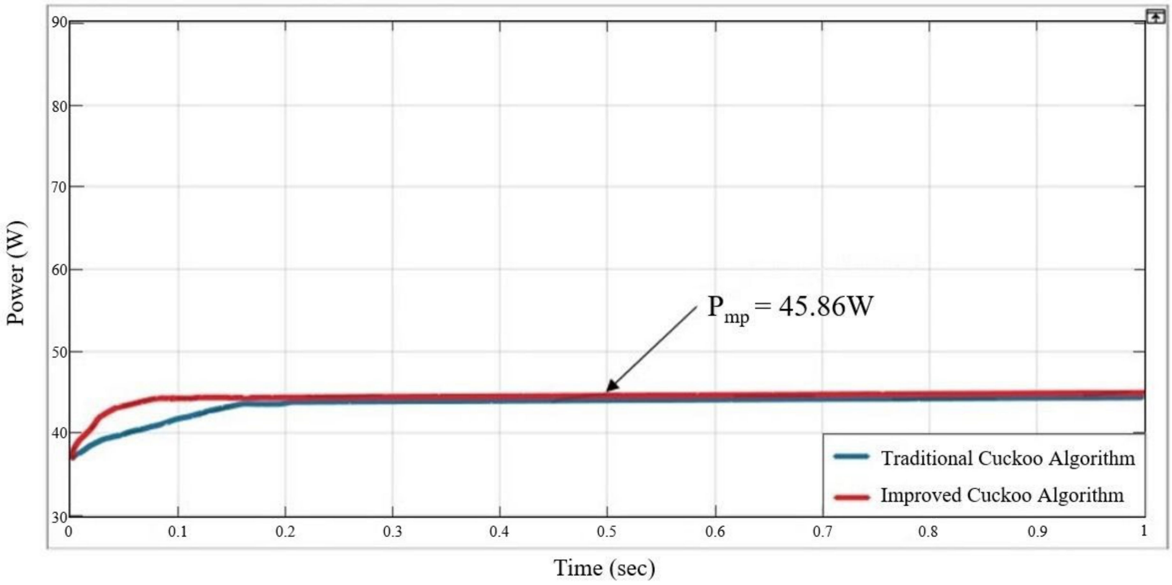

Figure 11. Simulation result of maximum power point tracking of traditional and improved cuckoo algorithm in Case 4.

3.5. Case 5: 2 Series and 2 Parallels ((Shaded 30% + Shaded 0%)//(Shaded 50% + Shaded 0%))

In order to verify that the maximum power point tracking method of the improved cuckoo algorithm was suitable for photovoltaic module arrays with different series-parallel configurations and shading ratios, 4 photovoltaic modules were re-configured to the 2 series and 2 parallels configuration for testing. Figure 12 shows the P–V characteristic curve simulation for 2 series and 2 parallels connection, where two modules in the photovoltaic module array were shaded with ratios 30% and 50%, resulting in double-peak values in the P–V characteristic curve. Its real maximum power point was 51.78 W at the right peak. Figure 13 shows the simulation result of maximum power point tracking based on the traditional and improved cuckoo algorithm. According to Figure 13, it showed that the tracking speed response and steady-state performance of the improved cuckoo algorithm were both better than those of the traditional one.

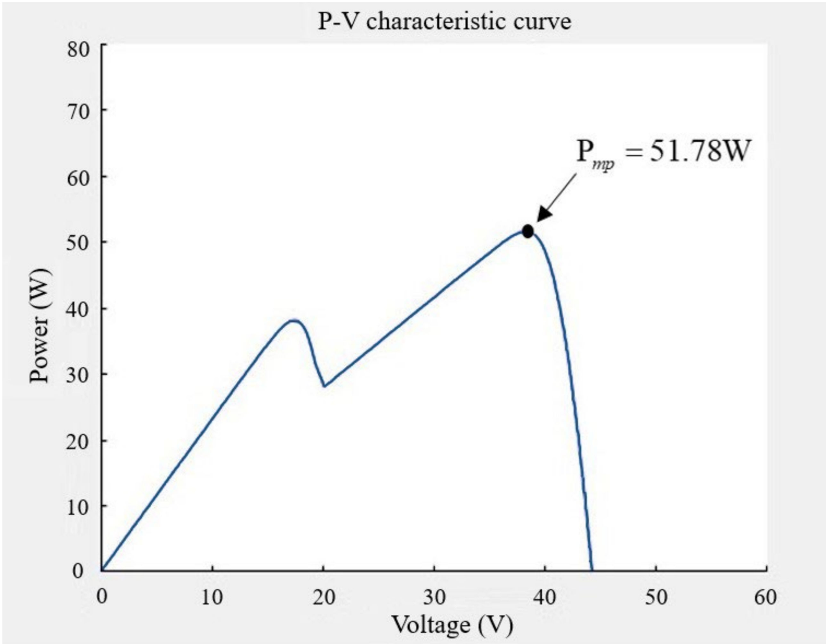

Figure 12. P–V characteristic curve simulation for Case 5.

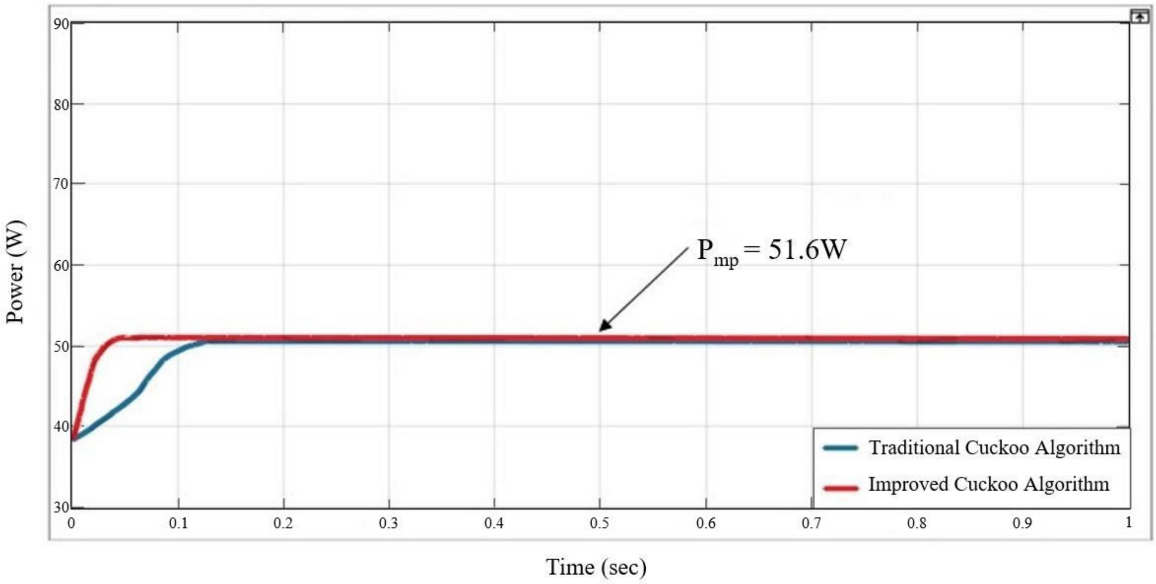

Figure 13. Simulation result of maximum power point tracking of traditional and improved cuckoo algorithm in Case 5.

3.6. Case 6: 2 Series and 2 Parallels ((Shaded 50% + Shaded 0%)//(Shaded 50% + Shaded 0%))

Figure 14 shows the P–V characteristic curve simulation for Case 6, where two photovoltaic modules were both shaded with ratios of 50%, also resulting in double-peak values in the P–V characteristic curve. Its real maximum power point was 43.81 W at the right peak. Figure 15 shows the simulation result of maximum power point tracking based on the traditional and improved cuckoo algorithm. According to Figure 15, it showed that the tracking speed response and steady-state performance of the improved cuckoo algorithm proposed were both better than those of the traditional one.

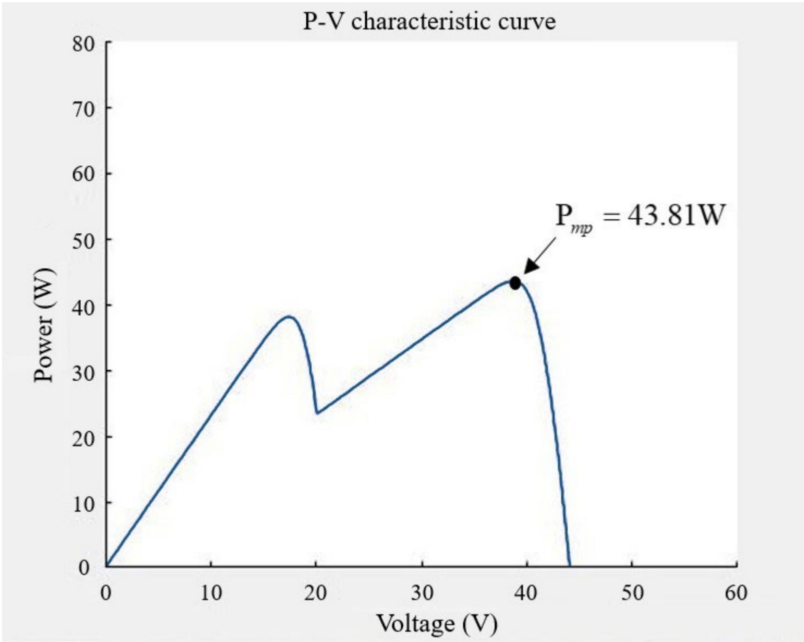

Figure 14. P–V characteristic curve simulation for Case 6.

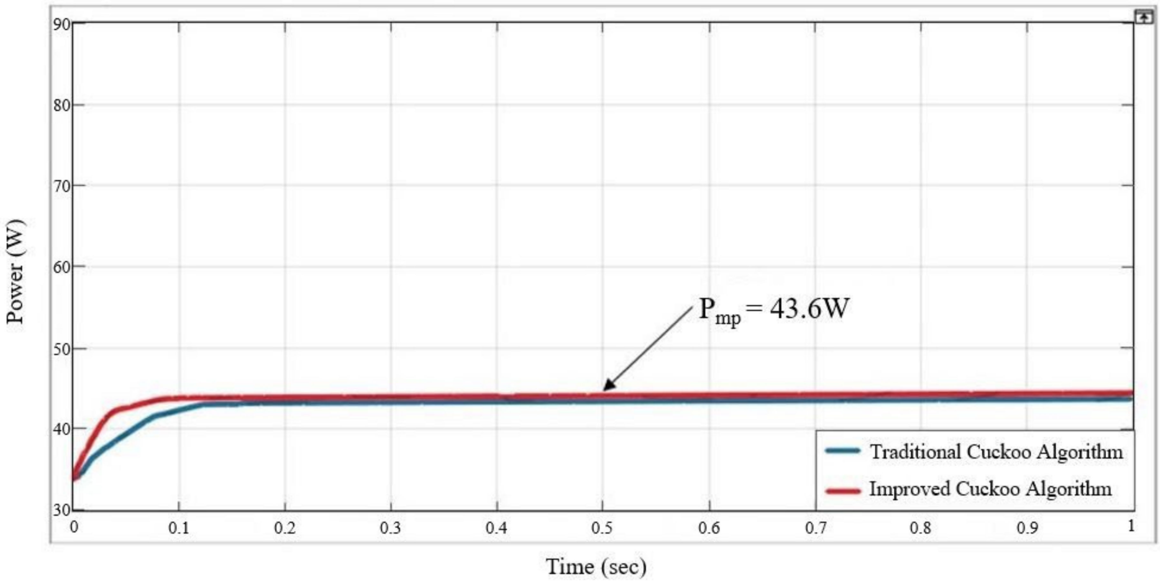

Figure 15. Simulation result of maximum power point tracking of traditional and improved cuckoo algorithm in Case 6.

The test cases used in the simulation in this paper refer to many test cases of intelligent MPPT methods proposed before, such as the particle swarm optimization algorithm (PSO) [26], firefly algorithm (FA) [27], and conventional CSLBA, where photovoltaic module arrays are shaded under a different number of modules and shading ratios, so there is a single peak to four peaks shown in the P–V output characteristic curves, to verify that the proposed intelligent MPPT method can track the maximum power point. Table 7 gives the performance in terms of the average tracking time and the average maximum power for 10 trials among the proposed CSLBOA, conventional CSLBA, the PSO method proposed in [26], and the FA method proposed in [27]. Although the capacity of the photovoltaic module array tested in [26,27] is different from that in this paper, from the test results of the PSO [26], the FA [27] and the conventional CSLBA show that these three methods can all also track the GMPPs under different shading conditions. However, either of their speed responses is far inferior to the improved cuckoo algorithm proposed in this paper.

Table 7. Comparison of simulation tests results for the six selected cases.

Case	Number of Peak(s) of the P–V Curve	Method Proposed in Reference [26]		Method Proposed in Reference [27]		Conventional CSLBA		CSLBOA Proposed in This Study	
		Average Tracking Time	Average Maximum Power	Average Tracking Time	Average Maximum Power	Average Tracking Time	Average Maximum Power	Average Tracking Time	Average Maximum Power
1	1	1.80 s	239 W	None *	None *	0.19 s	79.23 W	0.12 s	79.92 W
2	2	None *	None *	2.25 s	20.7 W	0.17 s	59.92 W	0.10 s	60.50 W
3	3	1.40 s	114 W	2.50 s	16.8 W	0.15 s	51.97 W	0.07 s	52.36 W
4	4	2.61 s	116 W	2.61 s	12.6 W	0.21 s	45.41 W	0.16 s	45.86 W
5	2	None *	None *	None *	None *	0.12 s	51.23 W	0.08 s	51.60 W
6	2	None *	None *	None *	None *	0.14 s	43.14 W	0.10 s	43.60 W

Note: The symbol "None *" indicates that this reference does not provide the test results of this case.

4. Conclusions and Future Research

4.1. Conclusions

In this paper, the improved cuckoo search algorithm applied for the maximum power point tracking of a photovoltaic module array was presented. In order to enhance the tracking efficiency and performance, the traditional cuckoo algorithm was improved, so that the step factor of the cuckoo algorithm could be adjusted according to the slope of the P–V characteristic curve of photovoltaic module arrays and the number of iterations, resulting in precise and efficient global maximum power point tracking whilst the photovoltaic module arrays shaded partially and multi-peak values generated in output characteristic curves. According to the simulation results, it showed that the improved cuckoo algorithm proposed could track the global maximum power point faster under those conditions with different connection configurations and shading ratios of photovoltaic module arrays. It also showed that the improved cuckoo algorithm proposed could track the real maximum power point more precisely and efficiently than those of traditional ones, thereby improving the power generation efficiency of the photovoltaic power generation system. In addition, the improved cuckoo algorithm proposed in this paper can be applied to a photovoltaic module array with any capacity and under different shading conditions for MPPT without changing the parameters in the algorithm, so it has robustness and adaptability.

4.2. Future Reaearch

The proposed algorithms can track all GMPPs of the photovoltaic module array under different shading conditions according to the simulation results. Future research can apply the improved cuckoo algorithm to the actual photovoltaic module array for MPPT and compare the tracking speed and steady-state response with the traditional cuckoo algorithm to verify the simulation results. At the same time, it can be compared with other intelligent algorithms based on the measured MPPT performance, and the measured results can be used to estimate the long-term power generation loss of the photovoltaic module array under different shading conditions, thereby evaluating the sustainable economic benefits of the photovoltaic module array.

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