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SMART MAXIMUM POWER POINT TRACKING IN PHOTOVOLTAIC MODULE ARRAYS UNDER PARTIAL SHADING

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Abstract. *This study primarily investigated the output characteristics of photovoltaic module arrays (PMAs) including partially shaded modules and proposed a smart particle swarm optimization (PSO)-based maximum power point tracking (MPPT) method. The proposed method can be used to successfully track the global optima of characteristic curves exhibiting multiple peaks. The slope and slope change rate of characteristic curves are included in the proposed method to adjust the weighting of the PSO algorithm and improve the performance of maximum power point trackers. Simulation tests were conducted on PMAs (in various series-parallel configurations) exhibiting two, three, or four peaks in their power-voltage characteristic curves when partial shading occurred. The simulation results confirmed that the proposed MPPT algorithm can successfully track the actual maximum power points when applied to multipeaked output characteristic curves of PMAs. In addition, the tracking performance of the proposed method is superior to that of the conventional PSO algorithm.*
Keywords: Characteristic curves with multiple peaks, Maximum power point tracking (MPPT), Partial shading, Particle swarm optimization (PSO), Photovoltaic module array (PMA)

1. **Introduction.** Sunlight intensity and temperature considerably influence the output power of photovoltaic module arrays (PMAs), causing it to exhibit nonlinear changes. Consequently, maximum power point tracking (MPPT) controllers must be installed to maintain the output power at the maximum output power point. This is a vital research topic in the field of photovoltaic power generation systems. Perturb and observe method [1] is the most commonly adopted method among conventional MPPT techniques. However, in this method, maximum power points (MPPs) cannot be precisely tracked and the power generation efficiency may decline because oscillations occurring around the MPPs may result in increased tracking losses. In addition, this method can be applied to MPPT only in module arrays exhibiting characteristic single-peaked curves. When a characteristic curve exhibits multiple peaks, this method is likely to track local MPPs rather than global MPPs.

In recent years, numerous scholars have proposed smart MPPT techniques that can be applied to PMAs [2-4] to track MPPs precisely and simultaneously improve dynamic and steady tracking performance levels. Nevertheless, such methods are effective only when applied to the MPPT of PMAs with no shaded modules. Output curves, however, typically exhibit multiple peaks when PMA modules are partially shaded. Therefore, developing an algorithm that can precisely track actual MPPs in complex and nonlinear output curves is vital. In [5,6], a particle swarm optimization (PSO)-based MPPT tracker for PMAs was proposed. The tracker can track global MPPs in multipeaked output characteristic curves; however, the tracking robustness is insufficient because the algorithm involves using constant weighting values. This thus results in a low global MPP tracking success rate. In addition, the dynamic response speed is insufficient when the tracker successfully tracks the MPPs.

In the present study, an improved tracking method was developed by capitalizing on the advantages of the PSO algorithm. The proposed algorithm can successfully avoid tracking only the local MPPs in multipeaked PMA characteristic curves and can rapidly and steadily track global MPPs. In this paper, Section 2 described briefly the implementation procedure of conventional PSO algorithm. Then, a modified PSO algorithm illustrated in Section 3 was proposed to track the actual maximum power points when applied to multipeaked output characteristic curves of PMAs. Final, in Section 4, some simulation results are made to demonstrate the effectiveness of the proposed modified PSO algorithm. Conclusions are made in Section 5.

2. Conventional PSO Algorithm.

PSO, an optimization theory developed by Kennedy and Eberhart in 1995 [7], is a collective intelligence-based algorithm and is a branch of evolutionary computing. Inspired by the foraging behavior of birds, Kennedy and Eberhart applied the approach to solving problems related to search and optimization. Specifically, a bird flying in space is considered a particle and all particles moving in space correspond to a fitness value mapped using an objective function. In addition, all particles move at a certain speed, which can be used to determine the direction and distance of their movement. Two types of memory values affect particles moving in space. Each particle's current optimal position is stored in the individual best memory position (P_{best}), and memory exchange occurs between particles. The optimal positions of particles in a group are compared and the results are stored in the group best position (G_{best}). In this process, the direction and speed of particle swarm movement are modified constantly, rapidly converging at the global optimum.

The implementation procedures of the conventional PSO are described in the following paragraphs:

1) Define the number of particles and maximum number of iterations, weights, and learning factors.
2) Initialize particle swarms and randomly define the positions and speeds of all particles.
3) Integrate the initial positions into the objective function to assess the particles' fitness function values.
4) Compare the particles' fitness function values with their individual best memory positions (P_{best}) and update the position with the P_{best}.
5) Compare P_{best} with the group best memory value (G_{best}) and update the values if P_{best} is superior to G_{best}.
6) Update the particle speeds and positions by using the following PSO kernel formulas:

$$V_i^{j+1} = W \times V_i^j + C_1 \times rand1(\bullet) \times \left(P_{besti} - P_i^j\right) + C_2 \times rand2(\bullet) \times \left(G_{best} - P_i^j\right) \quad (1)$$

$$P_i^{j+1} = V_i^{j+1} + P_i^j \quad (2)$$

where V_i^j is the speed of particle i in iteration j; P_i^j is the position of particle i in iteration j; $rand1(\bullet)$ and $rand2(\bullet)$ are random number generators, which generate random real numbers between 0 and 1 to enhance the variability of particle swarms; W is the weighting; C_1 and C_2 are learning factors; P_{besti} is the individual optimum of particle i; and G_{best} is the group optimum.

7) If the termination conditions are satisfied, terminate the tracking; otherwise, repeat Steps 4 to 6. The termination condition is the identification of the global optimum or the satisfaction of the maximum number of iterations.

The tracking efficiency and success rate of the conventional PSO are primarily determined according to the set values of the weighting and learning factors [8]. A considerably high weighting may result in imprecise search outcomes because of the extremely large particle movement increment. However, an extremely low weighting may result in excessively slow particle movement. The search may thus yield local optima in problems with multiple peaks. Therefore, the weighting should be determined according to the objective function.

3. **Proposed Modified PSO Algorithm.** When PMA modules are partially shaded, the fixed weighting W used in the conventional PSO must be adjusted according to the characteristics of various multipeak curves. Otherwise, extremely high or low weighting may result in tracking errors. The conventional PSO MPPT is thus inadequate for PMAs including modules highly exposed to the possibility of shading. Therefore, the current study proposes a modified method.

In the proposed method, the weighting W is modified, as shown in the following paragraphs:

1) Modified weighting formula for linear reductions in W:

$$W = (W_{\max} - W_{\min}) \times (n - j)/n + W_{\min} \tag{3}$$

$W_{\max}$: Maximum weighting
$W_{\min}$: Minimum weighting
n: Maximum number of iterations
j: Current number of iterations

The physical significance of the modified weighting formula is that relatively large increments are used to increase the search speed in the initial particle search because the particle is relatively far from the global optimum. Furthermore, in this method, the search is prevented from being trapped into local optima when an extremely small increment is used. However, W decreases as the number of iterations increases. At this time, the particle approaches the MPP; consequently, the reductions in W may result in smaller particle step increments, enabling the particle to track the MPP more precisely.

2) In addition to achieving linear reductions in W, we integrated the slope error e and slope error variation $\dot{e}$ of the P-V characteristic curves of PMAs to improve the modification, where $e \triangleq \frac{dP_{pv}}{dV_{pv}} - 0$ and $\dot{e} \triangleq e(j+1) - e(j)$. The conditions involved in determining these errors can be divided into five categories (Figure 1). These five conditions can be used to determine the current particle position and adjust the weighting. Table 1 shows the adjusted W values in this study.

Table 1. Weighting adjusted according to the slope errors and slope error variations of characteristic curves

Section of characteristic curve	Range of slope error	$\dot{e} < 0$	$\dot{e} > 0$
1	$0 < e \leq 1$	$W - 0.05$	$W + 0.02$
2	$1 < e \leq 2$	$W - 0.02$	$W + 0.05$
3	$e > 2$	$W + 0.05$	$W + 0.05$
4	$-1 \leq e < 0$	$W + 0.02$	$W - 0.05$
5	$-2 \leq e < -1$	$W - 0.02$	$W + 0.02$
6	$e < -2$	$W + 0.05$	$W + 0.05$

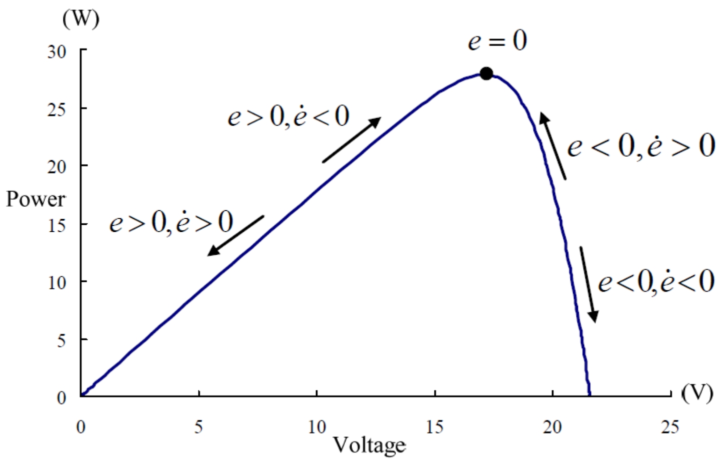


FIGURE 1. Schematic of how to determine the slope error and slope error variation of P-V characteristic curves

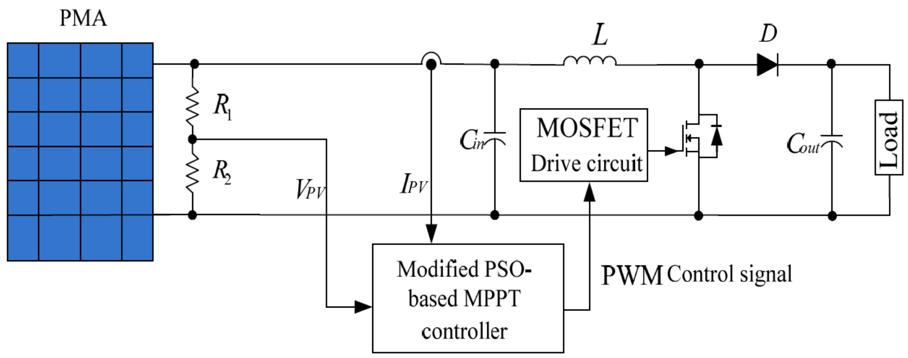


FIGURE 2. Architecture of the MPPT control system designed according to the modified PSO

Figure 2 illustrates the architecture of the MPPT control system that was designed based on the modified PSO, indicating that it comprises two primary subsystems: a boost converter and MPPT controller. In this system, the MPPT controller controls the duty cycle of the boost converter [9], enabling PMAs to achieve maximum output power when the modules are partially shaded. The PWM control signal with the calculated value of the PSO algorithm was transmitted to the boost converter to activate a power semiconductor switch. Subsequently, the output voltage and current values of the PV module array were extracted to calculate the power value and then inputted it to the PSO kernel formula. These steps were repeated until the maximal iteration number was achieved.

4. **Simulation Results.** Solar Pro [10] was employed to simulate the characteristic curves produced by PMAs with various connections and existing under dissimilar shade conditions. Next, Matlab software [11] was used to simulate the MPPT results returned by the conventional and modified PSO algorithms, and the simulations were compared and analyzed. Table 2 lists four cases of PMA testing conditions. Figures 3(a)-3(d) depict the simulated P-V characteristic curves for Cases 1-4.

To compare the effects of the weighting setting procedures in the two methods on the tracking efficiency, we set parameters at fixed values other than the weighting in the simulations. Table 3 shows relevant parameter settings for the two algorithms.

Table 2. PMA testing conditions

Case	Testing conditions
1	2-series: 0% shaded + 70% shaded
2	3-series: 0% shaded + 50% shaded + 70% shaded
3	4-series: 0% shaded + 30% shaded + 50% shaded + 70% shaded
4	2-series, 2-parallel: (25% shaded + 0% shaded) // (55% shaded + 0% shaded)

Note: "+" represents a series connection and "//" represents a parallel connection.

Table 3. Parameter settings used in the conventional and modified PSO tracking methods

Algorithm / Parameters	Conventional PSO	Modified PSO
Weighting W	0.4	$W_{\max} = 0.8$, $W_{\min} = 0.2$; linear decreases and slope error determination
Learning factors C_1 and C_2	Both set to 2	Both set to 2
Number of particles p	4	4
Maximum number of iterations n	100	100

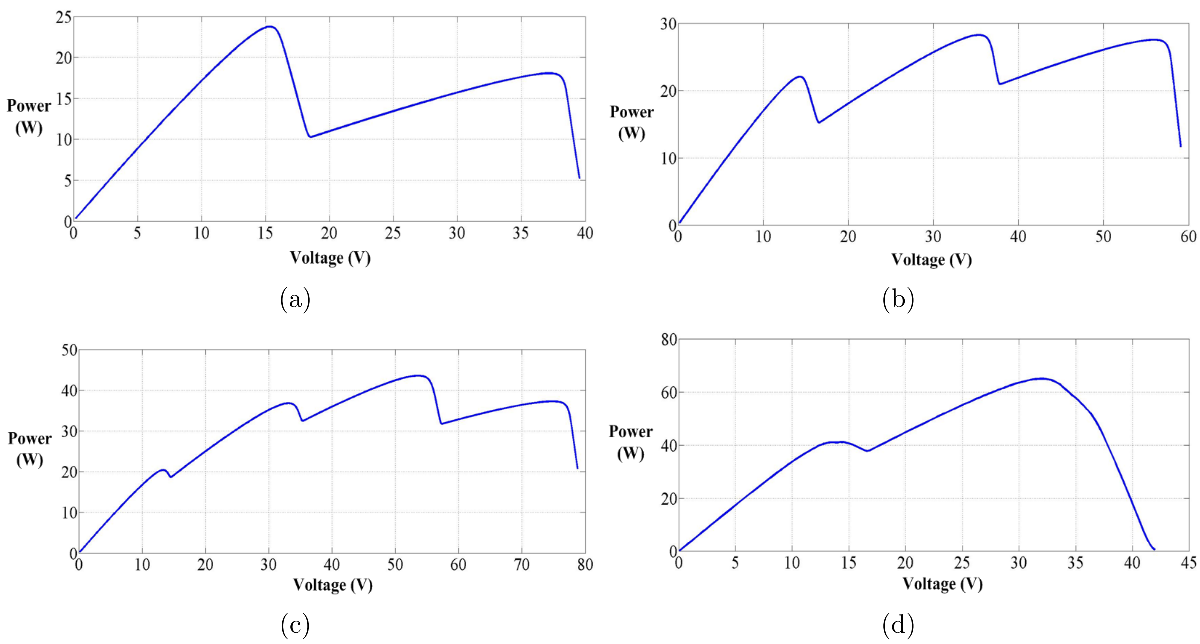


Figure 3. Simulated P-V characteristic curve for: (a) Case 1 (2-series: 0% shaded + 70% shaded); (b) Case 2 (3-series: 0% shaded + 50% shaded + 70% shaded); (c) Case 3 (4-series: 0% shaded + 30% shaded + 50% shaded + 70% shaded); (d) Case 4 [2-series, 2-parallel: (25% shaded + 0% shaded) // (55% shaded + 0% shaded)]

Case 1: (2-series: 0% shaded + 70% shaded)

Figure 3(a) shows the simulated P-V characteristic curve for Case 1. Two peaks were observed in this case, and the actual MPP was positioned on the left. When the conventional PSO method was used in this case, a local MPP was tracked and it was trapped. This thus reduced the tracking speed and success rate considerably. Figure 4(a) illustrates

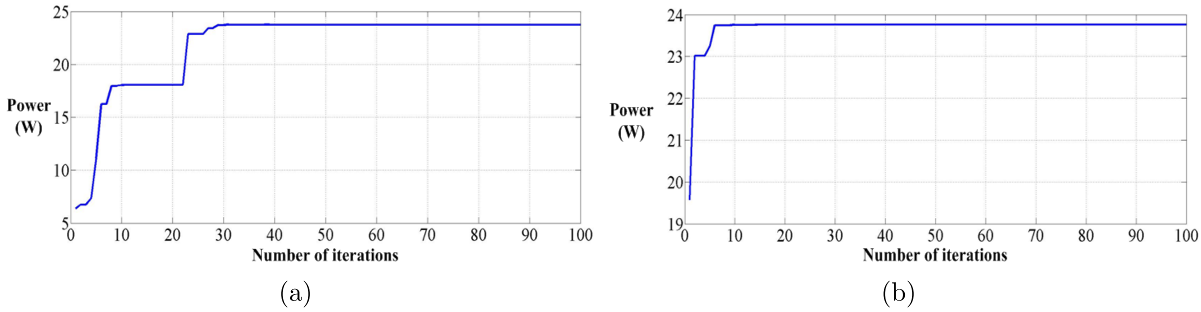


FIGURE 4. Simulated tracking results for Case 1 (2-series: 0% shaded + 70% shaded): (a) results obtained using the conventional PSO; (b) results obtained using the modified PSO

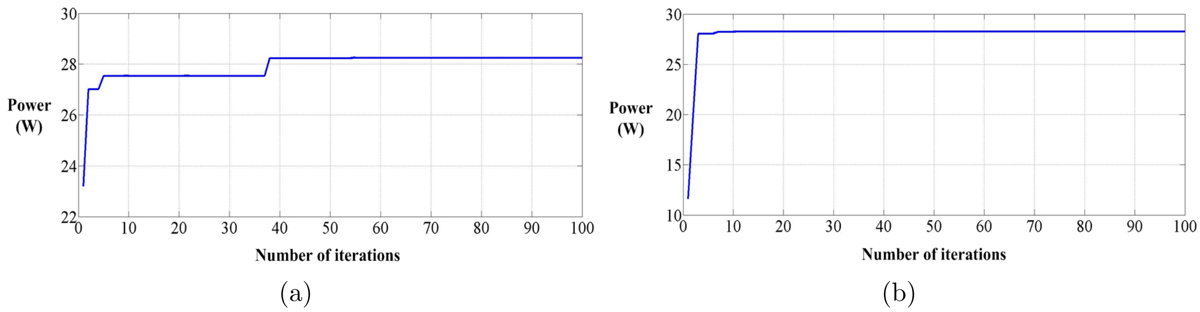


FIGURE 5. Simulated tracking results for Case 2 (3-series: 0% shaded + 50% shaded + 70% shaded): (a) results obtained using the conventional PSO; (b) results obtained using the modified PSO

the tracking process. By contrast, the modified PSO algorithm yielded superior tracking performance, and the tracking speed was not affected by the position of the actual MPPT. Figure 4(b) depicts the tracking process.

Case 2: (3-series: 0% shaded + 50% shaded + 70% shaded)

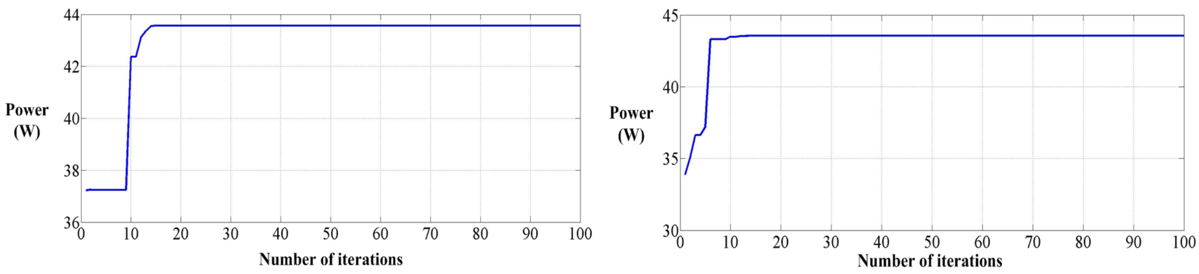
Figure 3(b) shows the simulated P-V characteristic curve for Case 2. Three peaks occurred in this case, and the actual MPP was positioned in the middle. The conventional PSO algorithm required 38 iterations in this case. Figure 5(a) depicts the tracking process. By contrast, the number of iterations necessitated by the modified PSO algorithm was similar to that in the previous case, yielding a considerably faster tracking speed than that of the conventional PSO. Figure 5(b) illustrates the tracking process.

Case 3: (4-series: 0% shaded + 30% shaded + 50% shaded + 70% shaded)

Figure 3(c) illustrates the simulated P-V characteristic curve for Case 3. Four peaks were observed in this case, and the actual MPP was located on the third peak. The conventional PSO algorithm demonstrated satisfactory tracking performance, necessitating 14 iterations. Figure 6(a) shows the tracking process. However, using the modified PSO algorithm prevented the four-peak characteristic output curve from affecting the tracking, registering a 100% success rate and requiring only 10 iterations. Figure 6(b) depicts the tracking process.

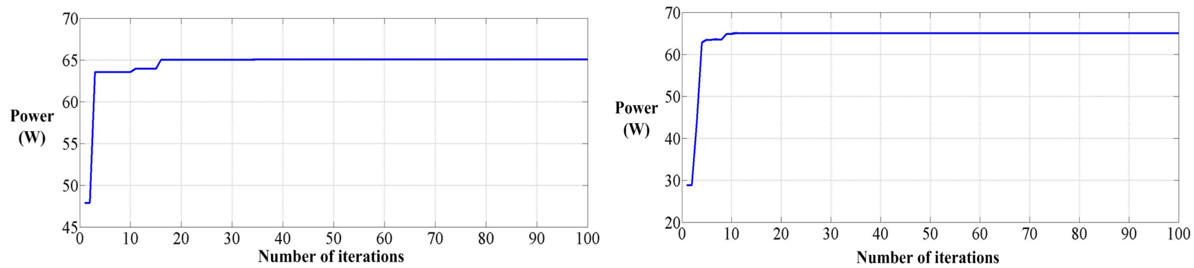
Case 4: [2-series, 2-parallel: (25% shaded + 0% shaded) // (55% shaded + 0% shaded)]

Figure 3(d) shows the P-V characteristic curve for Case 4. In this case, two peaks were observed, and the actual MPP was positioned on the right. The conventional PSO algorithm showed satisfactory tracking performance in this case, and the number of searches trapped in local optima was low. Therefore, the average number of iterations was 16. The tracking process is depicted in Figure 7(a). The modified PSO algorithm exhibited



(a) (b)

Figure 6. Simulated tracking results for Case 3 (4-series: 0% shaded + 30% shaded + 50% shaded + 70% shaded): (a) results obtained using the conventional PSO; (b) results obtained using the modified PSO



(a) (b)

Figure 7. Simulated tracking results for Case 4 [2-series, 2-parallel: (25% shaded + 0% shaded) // (55% shaded + 0% shaded)]: (a) results obtained using the conventional PSO; (b) results obtained using the modified PSO

superior performance to that of the conventional PSO algorithm, with a success rate of 100% and necessitating only 9 iterations. Figure 7(b) illustrates the tracking process.

The simulation results of the four representative cases selected in this study (Figures 4-7) indicate that the modified PSO tracking algorithm is superior to the conventional PSO algorithm in tracking speed and success rate.

5. **Conclusions.** This study proposes a modified PSO algorithm for conducting MPPT in PMAs. PSO is typically used to simulate the bird foraging behavior, ensuring the realization of distributed search and optimal memory sharing. Therefore, particles can be subjected to search operations in a large area, converging at the MPP and avoiding local optima. In addition, the modified PSO algorithm developed in this study emphasizes weighting regulation. Specifically, the weighting decrease linearly, and the slope error and slope error variation of output characteristic curves are used to obtain the particles' positions and the distance between a particle and the MPP. Subsequently, the weighting is adjusted to enhance the robustness of the PSO and increase the success rate and convergence rate of the actual MPPT process. The simulation results confirm that compared with the conventional PSO algorithm, the modified PSO algorithm is more effective in tracking the actual MPPT process under various shade conditions. In the future, some experimental results will be made to demonstrate the effectiveness of the proposed MPPT method based on modified PSO algorithm for practical photovoltaic system.

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