Maximum Power Point Tracking of Photovoltaic Array based on Multi-hierarchy Second-order Oscillation Particle Swarm Optimization Algorithm

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Abstract: The optimal working condition of photovoltaic (PV) array will change for the illumination distribution. The power-voltage (P-V) curve will has several maximum power points (MPP) when the photovoltaic array working under partially shaded condition (PSC). Researchers has applied the particle swarm optimization (PSO) algorithm in maximum power point tracking (MPPT) when PV array working under PSCs. However, in PSO cause the intelligent agents' moving speed is constant, the convergence speed could not meet the need when the PV array working condition change rapidly; and for the social learning factor of PSO is constant and equal for every agent, if there are more agents fall into local optimum point, these agents cannot jump out from local optimum point cause every agent just could gather together rather than searching for the point has better value. In order to improve these problems of PSO, this paper proposed multi-hierarchy second-order oscillation particle swarm optimization (MHSOPSO) algorithm which combine the second-order evolution equation and analytic hierarchy process (AHP) principle to improve the convergence speed and look beyond the local optimum ability. The model is built in MATLAB and simulated by PSO, second-order oscillation particle swarm optimization(SOPSO) and the proposed MHSOPSO under different working conditions. The result shows that the MHSOPSO could control the PV array working at a higher power under different PSCs in shorter time, in different working conditions, MHSOPSO is able to achieve Global Maximum Power Point (GMPPT) control within 0.5s.

Key–Words: partial shadow; photovoltaic array; second-order oscillation evolutionary equation; AHP; PSO

1 Introduction

Photovoltaic (PV) have been widely used around the world for low environmental pollution and high efficiency. However, the PV arrays are often installed outdoors, so partially shaded condition (PSC) will happen caused by clouds, trees, and dust, which could adversely affect the power-voltage (P-U) curve of PV arrays. [1]. Under such working conditions, efficient Maximum Power Point Tracking (MPPT) algorithm is required to control the operating point of the PV array locate in the maximum power point (MPP), so as to effectively improve the efficiency of the PV array and avoid large power loss due to tracking failure [2]. The traditional MPPT algorithm, like constant voltage tracking (CVT) [3], perturbation and observation (P&O) [4] and incremental conductance (INC) [5], could achieve MPPT accurately under unique illumination working condition. However, when the P-U curve has multiple peaks, the working point of PV arrays will be in the local maximum power point (LMPP) [6], which because of the limitations of traditional algorithms will lead to energy loss. For the drawbacks of traditional algorithm, swarm intelligence algorithms could solve this problem effectively. [7].

Some researchers have applied Particle Swarm Algorithms (PSO) to the MPPT control process of PV arrays to achieve global maximum power point tracking (GMPPT) [8], but because the PSO algorithm requires longer time for the system to converge, it is not suitable for use in scenarios with frequent changes in illumination distribution [9]. And cause the social learning factor of PSO algorithm is constant, the MPPT process is easy to converge to the local maximum power point (LMPP) rather than the global maximum power point (GMPP) [10]. In order to solve the above problems, some researchers proposed many methods to improve the PSO algorithm by fuzzy logic [11], adaptive algorithm [12] and so on [13]. And some paper have combine the PSO algorithm with other soft computing algorithm, like Genetic Algorithm (GA) [14], Artificial Neural Network (ANN) [15].

Although there have been some approaches to improve PSO, they are more about improving the individual factors of the PSO algorithm rather than from the perspective of system convergence. In the MPPT control process, the whole MPPT control process can be divided into pre-algorithm and post-algorithm based on the number of iterations or the distance between agents. In the pre-algorithm, the agents are far away from each other and we want each agent to scan a larger area at a faster rate [16]. While in the post-stage of the algorithm, the agents speed needs to decrease rapidly so that it can accurately converge at the GMPP point without oscillating for a long time [17].

Another problem that exists during the operation of the PSO algorithm is caused by the constant social learning factor [18]. When most of the agents are clustered together because they are not evenly distributed during initialization, even if there are a few agents located at points with higher fitness values, the whole algorithm will follow the principle of "majority rule" and move closer to the group of agents with lower fitness values [19].

In order to solve the problems mentioned above, this paper adopts Second-order Oscillation Particle Swarm Optimization (SOPSO) algorithm to divide the whole MPPT control process into two stages, pre-stage and post-stage [20]. The principle of the second-order oscillation damping coefficient in the automatic control principle is used to establish the second-order oscillation evolution equation, which is combined with the PSO algorithm, thus allowing the algorithm to have a large step size in the pre-stage and scan a larger area in a short time. In the post-stage of the algorithm, a small step size is used to convergence to the best agent, so that the agents can be precisely gathered at the GMPP. After that, the Multi-hierarchy Second-order Oscillation Particle Swarm Optimization (MHSOPSO) algorithm is proposed based on the Analytic Hierarchy Process (AHP) theory [21] [22]. All the agents are assigned social learning factors according to their fitness values. For the agents with high fitness value, the corresponding social learning factor is larger. By this improvement, it can effectively ensure that each agent can converge to the agent with the highest fitness value at a faster rate throughout the process, and at the same time, it also creates chance for the algorithm to jump out from LMPP.

2 PV array output P-U curve

The PV array output characteristics will change as the external illumination intensity changes. In this paper, four PV modules are connected in series, and the electrical parameters of each PV module are:

Open circuit voltage $U_{OC} = 22.5V$
Short circuit current $I_{SC} = 7.5A$
Voltage of MPP $U_{MPP} = 17.5V$
Current of MPP $I_{MPP} = 6.9A$.

The P-U characteristic curve of the PV array under standard operating conditions (25°C, 1000lx) is shown in Figure 1.

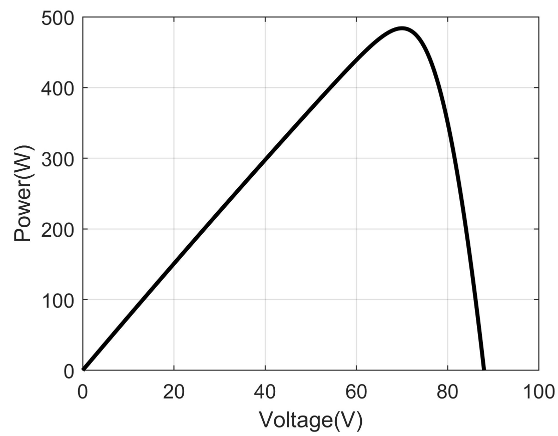

Figure 1. PV array output characteristics curve under unique illumination conditions

3 Application of Multi-hierarchy Second-Order Oscillation Particle Swarm Algorithm in MPPT Control

3.1 Particle swarm optimization algorithm

Particle Swarm Optimization (PSO) is a mature multi-agent optimization algorithm which has been widely used in different fields [23]. Suppose there are n agents searching for the optimal solution in a D-dimensional space, and the velocity and position update formulas for each agents are equations (1) and (2), respectively.

$$v_{id}^{k+1} = \omega v_{id}^{k} + c_1 r_1 (p_{id}^{k} - x_{id}^{k}) + c_2 r_2 (p_{gd}^{k} - x_{gd}^{k}) \tag{1}$$

$$x_{id}^{k+1} = x_{id}^{k} + v_{id}^{k+1} \tag{2}$$

where ω is the inertia weight factor, r_1 and r_2 are random numbers between (0,1), c_1 and c_2 are the self-learning factor and the social learning factor, respectively; k is the current iteration; i is the particle order;

v_{id} is the current velocity of particle i in d-dimension, x_{id} is the current position of particle i in d-dimension, p_{id} is the individual optimal value of the particle in d-dimension, and p_{gd} is the optimal value of all particles in d-diemnsion.

However, since the all parameters in the PSO algorithm are constant values, this will lead to a slow convergence of the algorithm [24]. The proof is as follows.

Let $\phi_1 = c_1 r_1$ and $\phi_2 = c_2 r_2$, equation (1) and equation (2)can be written as equation (3) and equation (4) respectively.

$$v_{id}^{k+1} = \omega v_{id}^k + \phi_1(p_{id}^k - x_{id}^k) + \phi_2(p_{gd}^k - x_{gd}^k) \quad (3)$$

$$x_{id}^{k+1} = x_{id}^k + v_{id}^{k+1} \quad (4)$$

The velocity v update equation is equation (5) where a is the acceleration coefficient. a could be calculate by equation (6).

$$v_{id}^{k+1} = v_{id}^k + a \quad (5)$$

$$a = \phi_1(p_i - x_i(k)) + \phi_2(p_g - x_i(k)) = x_i(k)'' \quad (6)$$

The equation (6) is the second-order differential equation. modify this equation by Laplace transform to get equation (7) which shows the searching position at k_{th} iteration.

$$x_i(k) = C_1 \cos(\sqrt{\phi_1 + \phi_2 k}) + C_2 \sin(\sqrt{\phi_1 + \phi_2 k}) \quad (7)$$

The Laplace transform of equation (7) is deformed to equation (8)

$$s x_i(s) + \phi_1 x_i(s) = \phi_1 p_i(s) \quad (8)$$

Transform equation (8) to equation (9)

$$\frac{x_i(s)}{p_i(s)} = \frac{\phi_1}{s + \phi_1} \quad (9)$$

The equation (9) shows that $\phi_1(p_i - x_i(k))$ is equivalent to an inertial link with p_i as the input and $x_i(k)$ as the output. Similarly, $\phi_2(p_g - x_i(k))$ is equivalent to an inertial link with p_g as the input and $x_i(k)$ as the output. The evolution equation of PSO algorithm could been considered as two inertial links in parallel. Since the input of the inertial link will tend to the input, if the p_i and p_g are constant, the $x_i(t)$ will satisfy equation (10) when the system is stable

$$x_i(k) \to \frac{\phi_1 p_i + \phi_2 p_g}{\phi_1 + \phi_2} \quad (10)$$

The equation (7) shows that the $x_i(t)$ will fluctuate in a constant region but it could not convergence during oscillation process, which means convergence speed $x_i(t)$ is slow and tends to oscillate around the peak point.

For example, set the $C_1 = 1$ and $C_2 = 1$, $\sqrt{\varphi_1 + \varphi_2} = 1$, the function of position is shown in equation (8) and the corresponding figure is shown in figure 2. In this figure, the $x_i(t)$ fluctuates between $-\sqrt{2}$ and $\sqrt{2}$ when the k change from negative infinity to infinity. For this drawback of PSO algorithm, the second-order oscillation factor could improve PSO algorithm to avoid this problem [25].

$$x_i(k) = \cos(k) + \sin(k) \quad (11)$$

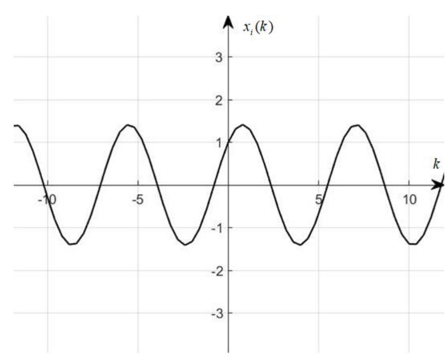

Figure 2. PSO algorithm position function

From the above analysis, it can be concluded that learning by agents with higher adaptation values makes the PSO algorithm have global search capability, but due to the fixed parameters in the algorithm, it cannot be changed adaptively with the operation phase of the algorithm, which leads to a slow convergence of the algorithm and is prone to premature aging.

3.2 Second-order oscillation particle swarm optimization algorithm

The core idea of the second-order oscillation particle swarm algorithm (SOPSO) is to introduce the characteristics of the second-order oscillatory evolution equation in both over-damped and under-damped cases into the self-learning factor and the social learning factor [26].

In order to solve the problem and be able to ensure that the algorithm has different search capabilities and convergence speed at different stages, the SOPSO algorithm is therefore established.The speed and position update equations of the SOPSO algorithm are equation (12) and equation (13), respectively.

$$\begin{aligned} v_{id}^{k+1} = \omega v_{id}^{k} + \phi_1(p_{id}^{k} - (1+\xi_1)x_{id}^{k} - \xi_1 x_{id}^{k-1}) \\ +\phi_2(p_{gd}^{k} - (1+\xi_2)x_{gd}^{k} + \xi_2 x_{gd}^{k-1}) \end{aligned} \tag{12}$$

$$x_{id}^{k+1} = x_{id}^{k} + v_{id}^{k+1} \tag{13}$$

In these two equations, if just consider the second part of the velocity update equation, which means:

$$v_i^{'}(k+1) = \phi_1(p_i - (\xi_1+1)x_i(k) + \xi_1 x_i(k-1)) \tag{14}$$

Then:

$$\begin{aligned} x_i(k+1) - x_i(k) - (x_i(k) - x_i(k-1)) = \\ \phi_1(p_i - (\xi_1+1)x_i(k-1)) - (x_i(k) - x_i(k-1)) \end{aligned} \tag{15}$$

Taking the Laplace transform for this equation (15) to get equation (16)

$$\frac{x_i(s)}{p_i(s)} = \frac{\phi_1}{s^2 + (\phi_1\xi_1+1)s + \phi_1} \tag{16}$$

The roots of this second-order transform function are:

$$R_{1,2} = \frac{-(\phi_1\xi_1+1) \pm \sqrt{(\phi_1\xi_1+1)^2 - 4\phi_1}}{2} \tag{17}$$

if $(\phi_1\xi_1+1)^2 \geq 4\phi_1$, the algorithm converge gradually, system working at over-damped state, $\xi_1 > \frac{2\sqrt{\phi_1}-1}{\phi_1}$.

if $(\phi_1\xi_1+1)^2 < 4\phi_1$, the algorithm converge oscillatory, system working at under-damped state, $\xi_1 < \frac{2\sqrt{\phi_1}-1}{\phi_1}$.

Similarly, when $\xi_2 \geq \frac{2\sqrt{\phi_2}-1}{\phi_2}$, the algorithm converge gradually; when $\xi_2 < \frac{2\sqrt{\phi_2}-1}{\phi_2}$, the algorithm convergence oscillatory. Gradual convergence and oscillatory convergence are shown in Figure 3 and Figure 4, respectively [27] [28].

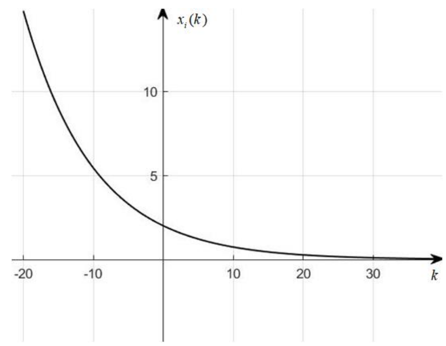

Figure 3. Gradual convergence

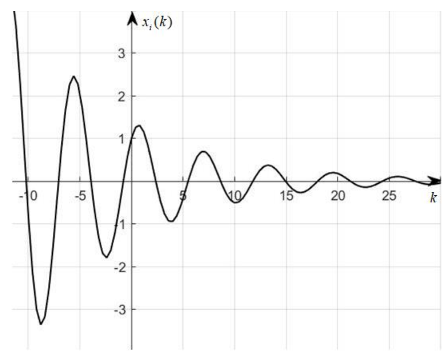

Figure 4. Oscillatory convergence

In the whole global search process, the algorithm takes oscillatory convergence in the pre-stage to ensure the algorithm can have strong search capability; the algorithm takes gradual convergence in the post-stage to enable the algorithm to have high development capability and convergence precision.

3.3 Multi-hierarchy second-order oscillation particle swarm optimization algorithm

Although the SOPSO can adjust the convergence speed and exploration accuracy at different stages, in the mutual learning process between agents, each agent occupies the same social weight, which will lead to the agents with higher fitness value will also be affected by the agents with lower fitness value, which may lead to the reverse learning process between agents, so that the system finally converges to the local optimal point. At the same time, the SOPSO has poor diversity, and there is no targeted acceleration strategy for distant agents. By Analytic Hierarchy Process (AHP) [29], the agents are divided into different hierarchies and weight sizes are determined by the hierarchy differentiation factor ω_{AHP} of the corresponding agents to establish Multi-hierarchy Second-order Oscillation Particle swarm optimization (MHSOPSO).

In order to calculate ω_{AHP} and distinguish the hierarchy in which different agents are located, first, the judgment matrix A is constructed by equation (18)

$$A = \begin{bmatrix} {}^{P_1}/_{P_1} \dots {}^{P_n}/_{P_1} \\ \vdots \\ {}^{P_1}/_{P_n} \dots {}^{P_n}/_{P_n} \end{bmatrix} \tag{18}$$

where P_n is the fitness value of the $n_t h$ agent. After that, the hierarchy factor ω_{AHP} is solved by geometric averaging.

$$\omega_{AHP} = \frac{\left(\prod_{j=1}^{n} {}^{P_j}/_{P_i}\right)^2}{\sum_{i=1}^{n} \left(\prod_{j=1}^{n} {}^{P_j}/_{P_i}\right)^{\frac{1}{n}}}, i = 1, 2 \dots n \tag{19}$$

In order to verify the acceptability of the judgment matrix, the Consistency Index (CI) needs to be calculated by equation (20)

$$CI = \frac{\lambda_{\max} - n}{n - 1} \tag{20}$$

where, λ_{max} is the maximum eigenvalue of matrix A. Finally, the Consistency Ratio (CR) needs to be calculated as:

$$CR = \frac{CI}{RI} \tag{21}$$

where RI is the average random consistency indicator, which can be taken according to Table 1.

Table 1. Table of average random consistency index values

n	1	2	3	4	5	6
RI	0	0	0.52	0.89	1.12	1.24

When CR<0.10, the consistency of matrix A is considered acceptable. At this time, the ω_{AHP} can be calculated by equation (22):

$$\omega_{AHP} = {}^{\omega_{\max}}/_{\omega_i} \tag{22}$$

where ω_{max} is the maximum hierarchy factor value among all agents and ω_i is the corresponding hierarchy factor of the i_{th} particle.

When CR>0.10, the hierarchy factor ω_{AHP} can be assigned directly by equation (23):

$$\omega_{AHP} = 1 \tag{23}$$

The MHSOPSO algorithm velocity and position update formulas are equations (24) and (25) respectively.

$$\begin{aligned} v_{id}^{k+1} = \omega v_{id}^{k} + \phi_1 (p_{id}^{k} - (1+\xi_1) x_{id}^{k} - \xi_1 x_{id}^{k-1}) + \\ \omega_{AHP} \phi_2 (p_{gd}^{k} - (1+\xi_2) x_{gd}^{k} + \xi_2 x_{gd}^{k-1}) \end{aligned} \tag{24}$$

$$x_{id}^{k+1} = x_{id}^{k} + v_{id}^{k+1} \tag{25}$$

3.4 MPPT control based on MHSOPSO

In the process of MPPT control of PV array through MHSOPSO algorithm, the controller output duty cycle is the particle location, and each agent corresponds to the PV array output power value as the objective function. When the system enters the steady state, in order to avoid small light changes leading to overcalculation, the algorithm restart condition is set as shown in equation (26). If the sudden illumination change is considered when the difference between the previous and subsequent power sampling is greater than 5% of PV output power:

$$\frac{\left|P_{(k)} - P_{(k-1)}\right|}{P_{(k)}} > 5\% \tag{26}$$

The MHSOPSO algorithm flow is:

(1) Initialize the position, velocity, and fitness value of each agent in MHSOPSO algorithm.

(2) Calculate the adaptation value corresponding to each agent, which is the corresponding power value at each duty cycle.

(3) If the iteration <3, then take

$$\xi_1 < \tfrac{2\sqrt{\phi_1}-1}{\phi_1}, \xi_2 < \tfrac{2\sqrt{\phi_2}-1}{\phi_2}$$

The current number of iterations >3 is taken as:

$$\xi_1 > \tfrac{2\sqrt{\phi_1}-1}{\phi_1}, \xi_2 > \tfrac{2\sqrt{\phi_2}-1}{\phi_2}$$

(4) Constructing a judgment matrix A based on the fitness values of all agents, and solving the hierarchy factor ω_{AHP} by equations (18) to (23).

(5) Based on equations (24) and (25), update the agent velocities and positions.

(6) Compare the optimal fitness value reached by the agent with the fitness value corresponding to the current position, and if the historical optimal fitness value is greater than the current fitness value, learn from the historical optimal fitness value; otherwise, update the maximum fitness value of the particle.

(7) Comparing the maximum fitness value of each individual to obtain the population maximum fitness value.

(8) Judge whether the PV array power value satisfies equation (18), if it does, go back to step (1), if it does not, go back to step (2).

According to the principle of MHSOPSO algorithm, the flow chart of MPPT control algorithm under different working conditions is shown in Figure 5.

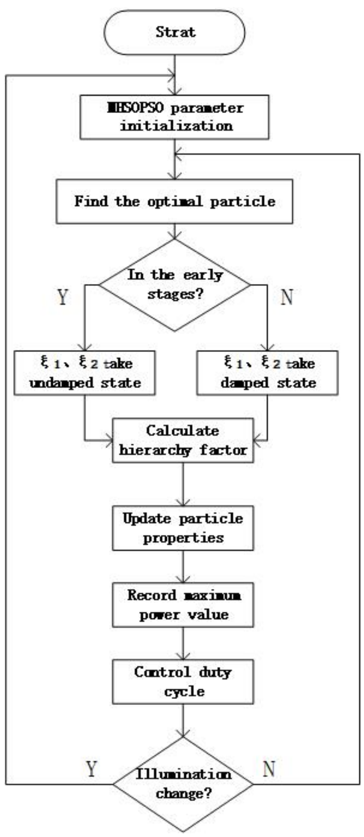

Figure 5. The flowchart of MHSOPSO for MPPT

4 Simulation analysis

The structure diagram of the PV array MPPT control system is shown in Figure 6. In order to avoid hot spot effect and protect the PV modules, a bypass diode will be connected in parallel at each PV module output port. PWM block is pulse width modulator, its switching frequency is 10^4 Hz. In the BOOST circuit, the filter capacitor C_1 is 59e-6F, the booster inductor L is 2e-3H, and the DC bus capacitor C_2 is 90e-6F. The initial positions of the six agents are uniformly distributed in the interval [0.1 0.9], where the positions of the agents correspond to the duty cycle of the switching tubes in the BOOST circuit, and the adaptation value of the agents is the power value corresponding to each agent. The controller sampling time $T = 0.015$s. To verify the superiority of the MHSOPSO algorithm, the control effects of the PSO, SOPSO and MHSOPSO algorithms are compared under three working conditions.

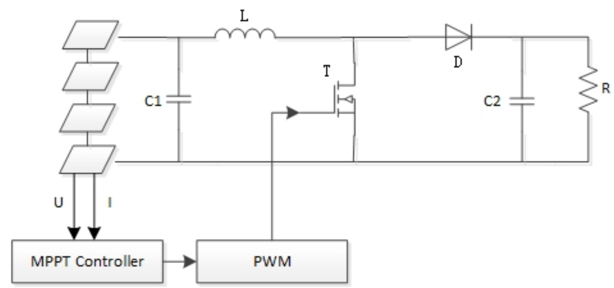

Figure 6. Structure of PV array MPPT control system

4.1 MPPT control under standard operating conditions

When the PV array works under standard working conditions, U_{MPP} = 70V, P_{MPP} = 480W, and the MPPT of PV array is realized by PSO , SOPSO and MHSOPSO. the comparison graph of output power curve obtained by three algorithms is shown in Figure 7, the control of PV array by standard PSO algorithm It takes 1.80s to achieve MPPT at the operating point, which is slower to converge and oscillation more during the tracking process; SOPSO algorithm takes 1.15s to achieve MPPT control, and the system can enter steady state after 0.45s under MHSOPSO control, and the power fluctuation is smaller during the response.

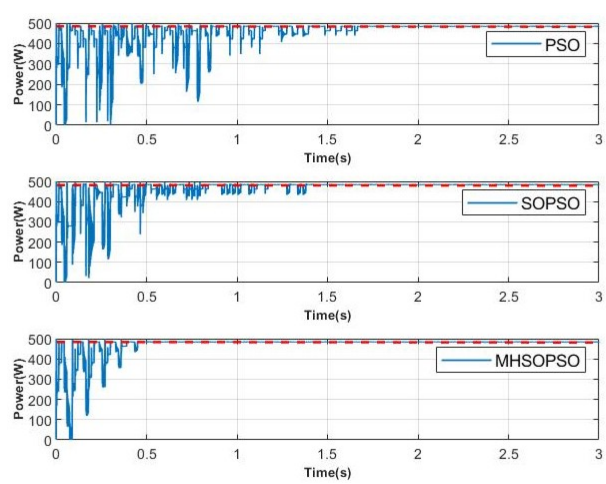

Figure 7. Comparison of PSO, SOPSO and MHSOPSO output power curves under unique illumination condition

4.2 MPPT control under partial shading

The PV modules are linked in parallel with a bypass diode, thus the PV array's P-U output characteristic curve will have multiple peaks when the PV array is subjected to the external environment and partial shading condition (PSC). In this simulation, two PSCs are set. In PSC1, the illumination intensity of the four PV modules are [1000 1000 600 600]lx, P_{MPP}=310W under this working condition; in PSC2, the four PV modules are subjected to illumination intensity of [1000 800 600 400] lx, P_{MPP}=235W in PSC2. The PV array P-U characteristic curves under two shading modes are shown in Figure 8, where all LMPP are marked with black circles and GMPP are marked with black dots.

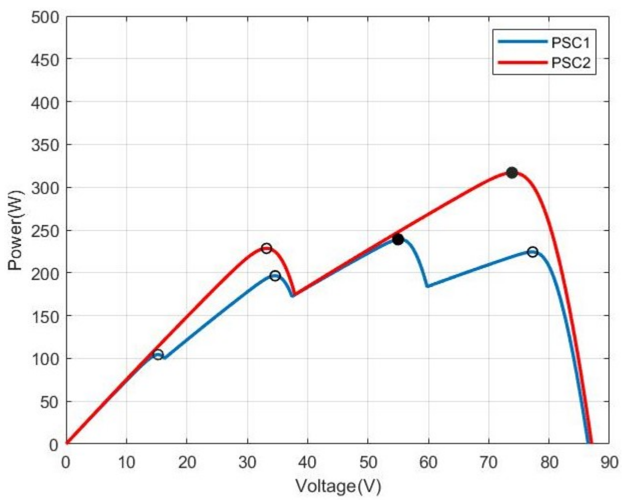

Figure 8. PV array output characteristic curves under two partial shading environments

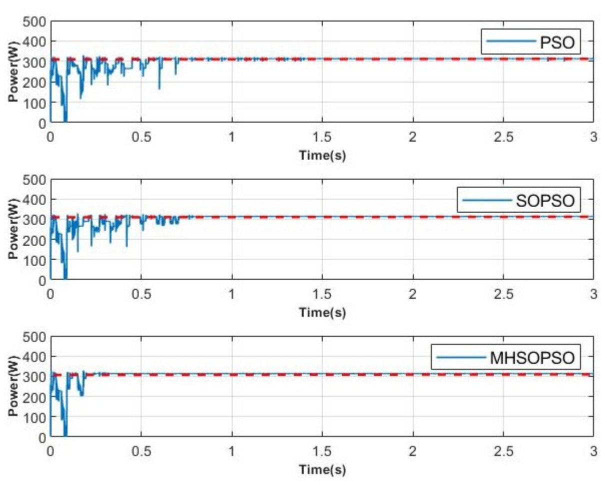

Figure 9. Comparison of PSO, SOPSO, and MHSOPSO output power curves at PSC1

The simulation results performed by PSO, SOPSO and MHSOPSO in two PSCs are shown in Fig.9 and Fig.10, respectively. According to the simulation results of the three algorithms under PSCs, it can be seen that SOPSO has faster search speed in the early stage and more accurate tracking ability in the later stage compared with the traditional PSO algorithm, while MHSOPSO can make the particles farthest from the beat particles learn quickly toward the optimal value, converge faster, and have certain ability to jump out of the local optimum. Under the two PSCs, the PSO algorithm takes 1.40s and 1.56s to track to the maximum power point, respectively, and the SOSPO algorithm achieves MPPT after 0.78s and 0.99s, while under the control of MHSOPSO, the PV array operating point can converge at the MPP in 0.32s and 0.42s, respectively, with faster tracking speed.

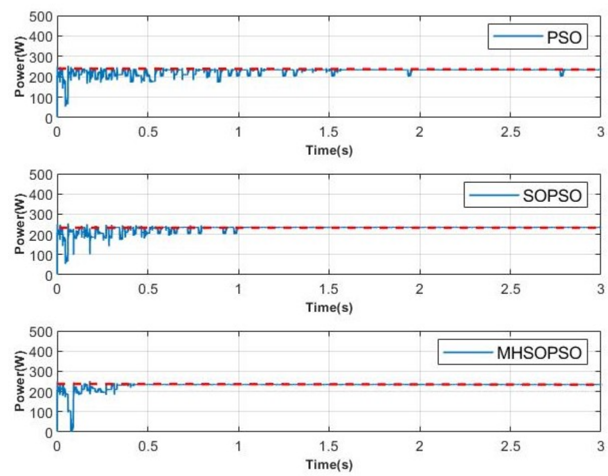

Figure 10. Comparison of PSO, SOPSO and MHSOPSO output power curves at PSC2

4.3 MPPT control under dynamic process

After the system is stabilized, if the degree of PV array output power variation satisfies equation (26), the particle position is initialized in the resolution domain and the maximum power point is retraced. Figure 11 shows the power waveforms of the MPPT control by PSO, SOPSO, and MHSOPSO algorithms during the abrupt change of the operating environment of the PV array from the standard working condition to PSC1 at 3s and to PSC2 at 6s, respectively. Under standard working conditions, the PSO algorithm stabilizes the system in 1.798 seconds, the SOPSO algorithm stabilizes the system in 1.15 seconds, and the MHSOPSO algorithm enters the steady state after 0.45 seconds. With the first sudden change of illumination, the PSO algorithm required 1.56 seconds to reach MPPT, SOPSO algorithm took 1.06 seconds, and MHSOPSO took 0.34 seconds to stabilize; with the second change of illumination, the PSO algorithm took 1.99 seconds to reach MPPT, SOPSO algorithm took 1.13 seconds to reach MPPT, while MHSOPSO could reach MPPT within 0.39 seconds after the change in illumination.

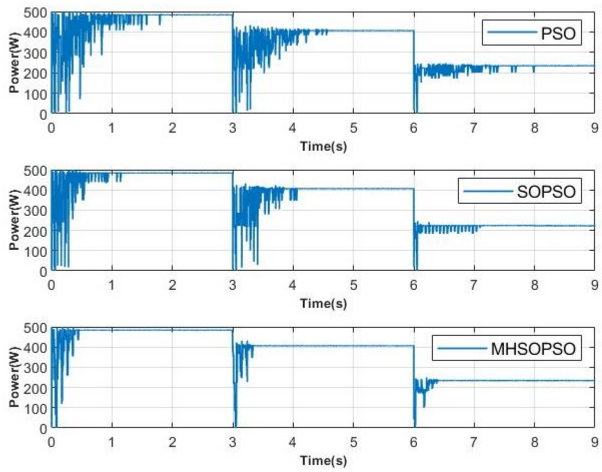

Figure 11. Comparison of PSO, SOPSO and MHSOPSO output power curves under dynamic process

5 Conclusion

The paper analyze the PSO algorithm from the Laplace domain perspective, equate the algorithm to two inertial links in parallel, and obtain the expression for the position when the coefficients are constant, thus demonstrating the disadvantages of the algorithm such as easy prematureness in the global search process, falling into local optimum and slow convergence. After that, the SOPSO algorithm is improved by using different damping coefficients to control the motion speed of each agent in the algorithm according to the pre-stage and post-stage algorithm. In order to decrease the possibility to fall into LMPP in the algorithm and also to further speed up the algorithm operation, the MHSOPSO algorithm is obtained by combining with AHP theory. The above algorithm is applied to the PV MPPT control process and tested under different working conditions. The results show that the MHSOPSO algorithm has the advantages of wide exploration range and fast convergence compared with the other two algorithms, and can be used in the environment with frequent changes of light distribution.

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