A Novel Particle Jump Particle Swarm Optimization Method for PV MPPT Control under Partial Shading Conditions

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With the sharp increase in the global energy demands, photovoltaics (PV) have been developed significantly in recent years. However, when the PV work under partial shading conditions, the global maximum power point tracking control should be executed. In this paper, a novel particle swarm optimization (PSO) algorithm with the particle jump improvement is proposed to track the global maximum (GM) of PV output power under partial shading conditions. In the proposed method, each particle is allocated within respective intervals at initial iteration such that the particle only explores the corresponding interval to determine the potential GM. When the corresponding interval has been traversed without determining the GM, the interval will be discarded and the particle will jump to the interval where the current tracked GM is present. Therefore, each interval of the converter duty range will be traversed by only one particle and the total algorithm tracking time will be reduced. The proposed algorithm is verified with a simulation and an experiment. Based on the experimental results, the tracking times of the proposed method are 0.8 s, 0.8 s, and 1.2 s when the PV output power possesses 2, 3, and 4 peaks under partial shading conditions, respectively.

Keywords: particle swarm optimization, global maximum power point tracking, particle jump, photovoltaic, simulated annealing

1. Introduction

In recent years, all of the population, technology and economy have achieved great advancements all over the world, and the energy consumption has also approached a sharp increase[11–13]. Considering this issue, the research on renewable energy resource has attracted the worldwide attention and some significant developments have been established in various areas[14]. Among all the renewable energy resources which are focused, due to the high accessibility and inexhaustibility of solar energy, the PV has been regarded as one of the most promising candidates for the future energy sources[15]. The PV has been employed in various areas, such as the power grid, electric vehicle as well as space exploration, and it has brought about a great deal of improvements to the corresponding applications[16].

In order to make the most of the solar irradiance, the PV maximum power point tracking (MPPT) should be conducted under working conditions[17]. Due to the PV property, when the solar irradiance on the PV panel is uniform, the PV output power with respect to the voltage only possesses one peak. On the other hand, when the solar irradiance is not uniform, namely the PV panel is under partial shading conditions, there will be multiple peaks at the power-voltage curve[18]. Therefore, considering the solar irradiance, the PV MPPT algorithms also can be divided into two categories, namely the local maximum tracking algorithm and global maximum tracking algorithm.

When the solar irradiance is uniform, because the PV output power only possesses one peak, the local maximum tracking algorithms, such as the Perturb&Observe (P&O), Incremental Conductance (InCon) and Constant Voltage (CV) methods, can be employed[19]. For these methods, the computation cost and hardware requirement are low, and they are simple to be conducted. However, under working conditions, because of the shadows of clouds, buildings or trees, the solar irradiance on the PV panel is not possible to be kept uniform all the time. Therefore, in this case, the global MPPT algorithms should be employed to search the GM among the multiple local maximums (LMs)[20]. So far, there have been various GM tracking algorithms developed in the PV area, such as the Particle Swarm Optimization (PSO)[11–13], Flower Pollination Algorithm (FPA)[14,15], Differential Evolution (DE)[16,17], Genetic Algorithm (GA)[18,19], Firefly Algorithm (FA)[20,21] and Grey Wolf Optimizer (GWO)[22,23].

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An improved DE algorithm with the whale optimization is also achieved high stability due to the iteration optimization. Proposed (24), and due to the successive particle mutations the proposed algorithms.

A novel enhanced leader PSO algorithm has been proposed (25), and all the introduced papers face the same issue: the partial shading conditions. The proposed algorithm consists of two parts: particle jump and PSO stages. At the first stage, the particle jump process can achieve the rough GM positioning and at the second stage, PSO can conduct the fast convergence to the global peak. The paper is organized as follows: section 2 analyzes the PV output property; section 3 introduces the PSO algorithm; section 4 proposes the particle jump method; section 5 expresses the particle jump detection method; section 6 and 7 conduct the simulation and experiment; section 8 presents the conclusion.

2. PV Model and Output Property Analysis

In order to enhance the PV output power, there are a great deal of PV cells connected in series and parallel in a PV panel. In this paper, the one-diode PV cell model in Fig. 1(a) is employed to analyze the PV output current (100 W/m²). Based on the model, the output current of a PV cell can be obtained as follows.

\[ I = I_S - I_0 \left( \exp \left( \frac{V + R_s \cdot I}{n \cdot V_t} \right) - 1 \right) - \frac{V + R_s \cdot I}{R_{sh}} \cdots \cdots \cdots (1) \]

In the equation, \( V \) and \( I \) are the PV cell output voltage and current, respectively; \( I_S \) is the light generated current; \( V_t \) is thejunction thermal voltage; \( I_0 \) is the leakage or reverse saturation current; \( n \) is the diode quality factor; \( R_s \) is the series resistance; \( R_{sh} \) is the shunt resistance. Furthermore, the light generated current \( I_S \) can be obtained as follows.

\[ I_S = \frac{S}{S_{ref}} \left[ I_{S_{ref}} + \alpha_{sc} (T - T_{ref}) \right] \cdots \cdots \cdots \cdots (2) \]

In the equation, \( S_{ref} \) stands for the reference conditions; \( S \) and \( S_{ref} \) are the solar irradiance intensity and reference (1000 W/m²), respectively; \( T \) and \( T_{ref} \) are the panel temperature and reference (25°C), respectively; \( I_{S_{ref}} \) is the PV cell output current under the reference standards of \( S_{ref} \) and \( T_{ref} \); \( \alpha_{sc} \) is the absolute temperature coefficient of short circuit current.

In addition, the diode reverse saturation current \( I_0 \) can be obtained as follows.
In the equation, $I_{0,ref}$ is the diode reverse saturation current under reference condition; $k_b$ is the Boltzmann constant of $k_b = 1.3806503 \times 10^{-23} J/K$; $E_g$ and $E_{g,ref}$ are the bandgap energy of the silicon and reference, respectively.

Because the output of one PV cell is really weak, in applications the PV cells are always connected in series and parallel to yield the PV module model in Fig. 1(b). In the PV module model, $V_m$ and $I_m$ are the PV module output voltage and current, respectively. Then the PV modules are further connected in network to generate the PV panel in Fig. 1(c). Based on the PV panel model, $V_{pe}$ and $I_{pe}$ are the PV panel output voltage and current, respectively. Because the PV modules are connected in series, in this paper, it can be concluded that the PV panel voltage, current and power are $V_{pe} = 4V_m$, $I_{pe} = I_m$ and $P_{pe} = V_{pe}I_{pe}$, respectively. Based on the above model analysis, when the solar irradiance on the PV panel is not uniform under partial shading conditions, the PV output power will possess multiple peaks. In order to make the most use of solar energy, the global maximum of PV output power should be tracked. In this paper, the PV output properties in Fig. 1(d), (e), (f) and Table 1 are employed to verify the proposed global MPPT tracking algorithm.

Based on the PV property, when the system equivalent resistance looking from the PV is equal to be the optimal value the PV maximum power can be tracked. In this paper, in order to transform the system equivalent resistance, the converter in Fig. 1(g) is employed. The converter switching frequency is 20 kHz, and the inductor $L$ and capacitor $C$ and load $R_L$ are 1 mH, 1000 μF and 5 Ω, respectively.

### 3. Particle Swarm Optimization Algorithm

The PSO algorithm is a method which employs an amount of particles simulating the social behaviors of animal groups to explore the global optimal position. Under working conditions, the particle movement in PSO algorithm is achieved by the particle velocity and position updates. The corresponding velocity and position update equations are shown as follows.

$$ v_i^{(k+1)} = w v_i^{(k)} + c_1 r_1 (P_{Mi} - x_i^{(k)}) + c_2 r_2 (G_M - x_i^{(k)}) \quad \cdots \quad (4) $$

$$ x_i^{(k+1)} = x_i^{(k)} + v_i^{(k)} \quad \cdots \quad (5) $$

In the velocity update of Eq. (4): $w$ is the inertia weight which determines how much the particle current state is influenced by the last state; $P_{Mi}$ is the personal maximum (PM) position of the $i^{th}$ particle; $G_M$ is the GM position; $c_1$ and $c_2$ are the scaling factors which determine how much the particle tendentiousness is between $P_{Mi}$ and $G_M$. Higher $c_1$ means the particle movement is more influenced by the PM and then the real GM position is more possible to be tracked, but the tracking time will be prolonged. Higher $c_2$ means the particle movement is more influenced by the current GM position.

| Case | $V_{ref}$/V | $I_{ref}$/A | $P_{ref}$/W |
|------|-------------|-------------|-------------|
| 1    | 27.61       | 1.77        | 48.98       |
| 2    | 24.40       | 1.95        | 47.53       |
| 3    | 30.37       | 1.61        | 49.02       |

The algorithm convergence time will be reduced but the probability of tracking the real GM position also decreases; $r_1$ and $r_2$ are the random values following the uniform distribution $U(0, 1)$. In the position update of Eq. (5), with the current velocity update, the particle position can be updated.

In each iteration, all the particles will be employed as the converter duty to obtain the corresponding fitness, namely the PV power. In the algorithm conducting process, the PM positions and GM position are updated based on all the particle positions and fitness. Furthermore, with the guidance of the personal and GM positions, all the particles will gradually move toward the GM position. After the PSO algorithm iterates enough times, the GM can be effectively tracked.

### 4. Particle Jump Method Proposal

Because of the capability of tracking the GM, the PSO algorithm has been employed into various areas. However, as shown in Eq. (5), the particle position in the PSO algorithm is updated step by step under working conditions. On one hand, because all the particle positions are updated gradually with velocity increments, the GM position is highly possible to be tracked with appropriate parameters of $w$, $c_1$ and $c_2$. On the other hand, in general, the velocity increment is always limited within an appropriate range to reduce the algorithm fluctuation, and then the PSO algorithm will take too much time to achieve the convergence of all the employed particles.

#### 4.1 Invalid Interval Traversal Analysis in PSO Algorithm

Due to the PV property, under partial shading conditions, the PV output power with respect to voltage is a two-dimension curve, and the particle position is the converter duty varying in the range of (0, 1), as shown in Fig. 2(a). There are 4 particles of $a$, $b$, $c$ and $d$ are employed and the GM is at the position of particle $c$.

In the MPPT process, both particle $a$ and $b$ move to the right side to the global maximum power point and suppose the distance is traversed by particle $a$ and $b$ in succession as shown in Fig. 2(b). However, there are two points should be mentioned: (1) because the initial positions and velocities of particle $a$ and $b$ are different, the possibility that particle $a$ and $b$ traverse the duty range $d_{ab}$ with the same position and velocity at each iteration is low enough; (2) the distance $d_{ab}$ is traversed twice by the particle $a$ and $b$, and the former
traversal is valid while the latter one is invalid. Therefore, it can be concluded that if the particle $b$ can jump over the duty range $d_{ab}$, the tracking time of particle $b$ from the initial position to the global optimal position $c$ can be reduced. Therefore, in this way, the total tracking time of PSO algorithm can be effectively reduced.

### 4.2 Particle Jump Process Analysis

The proposed particle jump method is analyzed in this section, and to simplify the analysis, 4 particles are employed in the PSO algorithm. Furthermore, in order to conduct the particle jump method, the following should be hypothesized: Compared with the LMs, the possibility that the real GM is in the neighborhood area of the current tracked GM is higher. In order to avoid the overlapping of the traversed duty ranges of each particle, the converter duty range is divided into 4 intervals as shown in Fig. 3(a). Then, the particle jump process in Fig. 3 is analyzed in the following.

**Step 1:** In the algorithm initialization, the 4 particles are placed at the center position of respective intervals. Furthermore, each particle possesses a corresponding Gaussian distribution. In the initialization, the expectations of Gaussian distributions are set as the particle positions and the variances are the same, namely: $\mu_a = a, \mu_b = b, \mu_c = c, \mu_d = d$ and $\sigma_a^2 = \sigma_b^2 = \sigma_c^2 = \sigma_d^2$.

**Step 2:** At the 1st iteration, the PV output powers of the 4 particles are calculated as shown in Fig. 3(b). Among all the powers, the LMs and GM are determined. For example, at this iteration, the power $P_c$, of particle $c$ in the interval 3 is both the GM and the LM$_3$. Furthermore, the powers of $P_a$, $P_b$ and $P_d$ of particle $a$, $b$ and $d$ are the LMs of interval 1, 2 and 4, respectively.

**Step 3:** In order to search for the potential duties whose power can exceed the current GM, the particles in the interval 1, 2 and 4 for the next iteration should be regenerated in wider ranges. In this paper, because the particle positions are determined by the corresponding Gaussian distributions, the wider range search is conducted by increasing the corresponding distribution variance as shown in Fig. 3(c). For example, because the particle $c$ power $P_c$ is the current GM, the variance of $N_c(\mu_c, \sigma_c^2)$ is not increased while the other variances are increased. Furthermore, the expectations of the 4 Gaussian distributions are set as the LMs.

**Step 4:** With the updated LMs and GM, the particles for the next iteration are regenerated with the corresponding Gaussian distributions as shown in Fig. 3(d). Because $\sigma_a^2$, $\sigma_b^2$ and $\sigma_d^2$ are increased, the new particles $a$, $b$ and $d$ can explore more widely in the corresponding intervals.

**Step 5:** With the new particles at this iteration, all the particle powers are also calculated. Comparing the current powers with the previous data, the LMs and GM should be updated as shown in Fig. 3(e).

**Step 6:** The variances of the Gaussian distributions whose particle powers are not the GM should be increased, and the expectations should also be updated with the LMs as shown in Fig. 3(f). For example, because the particle power $P_a$, $P_b$ and $P_d$ are not the GM, the variances $\sigma_a^2$, $\sigma_b^2$ and $\sigma_d^2$ will be further increased to obtain more scattered particles for the next iteration. Furthermore, the expectations $\mu_a$, $\mu_b$ and $\mu_d$ are updated with the LM$_1$, LM$_2$ and LM$_4$, respectively. After this step, the algorithm will move to the step 4 to repeat the potential particle searching process.

**Step 7:** With the repeated iterations from step 4 to 6, the variances of the Gaussian distributions whose particle powers are not the GM will be continuously increased, and there will be an iteration at which the variance is high enough. When the variance is high enough, it can be seen that this interval

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Fig. 3. Particle jump stage (a) Step 1. (b) Step 2. (c) Step 3. (d) Step 4. (e) Step 5. (f) Step 6. (g) Step 7. (h) Step 8. (i) Step 9

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has been completely traversed and there is no potential particle in the current interval whose power can be higher than the GM. Therefore, this interval should be discarded and the particle of this interval should be moved to other intervals. Because the real GM is the most likely to appear in the interval where the current tracked GM is, the particle whose interval is discarded should jump to the current GM interval.

For example, in Fig. 3(g), the particle $a$ jumps into the interval 3 and the interval 1 is discarded.

Furthermore, the new position of particle $a$ in the interval 3 also should be analyzed. In this paper, the new position of the jumping particle $a$ is generated with the Gaussian distribution of GM. In other word, $\mu_a$ is generated according to $N_c(\mu_a, \sigma_c^2)$. Furthermore, the Gaussian distribution variance $\sigma_a^2$ is equal to that of GM Gaussian distribution, namely $\sigma_a^2 = \sigma_c^2$.

Step 8 and 9: In step 7, the particle $a$ jumps into the interval 3, and the interval 1 is discarded. Repeat the above steps for enough iterations, and then the rest particles $b$ and $d$ will also jump into the interval where the GM is, namely the interval 3 in this paper.

With the steps 1-9, all the employed particles are moved to the interval where the current tracked GM is, and the particle jump stage will be ended. In the following, the PSO stage will be conducted to track the real GM. Therefore, based on the above analysis, the particle jump stage is used to estimate the rough position of the GM and rapidly reduce the particle distribution range. After the particle jump stage, all the particles will move to the same interval and in order to track the accurate position of GM, the PSO stage starts. Compared with the conventional PSO algorithm, the proposed 2-stage PSO method can effectively reduce the tracking time.

5. Particle Jump Detection Analysis

As analyzed above, when the particle Gaussian distribution variance is high enough, the corresponding interval should be discarded and the particle should jump into the current GM interval. However, the standard to determine whether the variance is high enough is difficult to be decided. Therefore, in this section, there are two methods are discussed, namely the variance increase method and simulated annealing method.

5.1 Variance Increase Method Because when the variance is high enough the particle should jump, a preset standard $\sigma_{in}^2$ can be employed to determine whether the current variance is high enough or not. The variance decrease method is shown in Fig. 4(a). In details, at each iteration, the current Gaussian distribution variance of each particle is compared with the preset standard, when the variance exceeds the standard, the corresponding particle will jump into the interval where the current global GM is.

For the variance decrease method, the simple complementation is one of the most effective advantages, but the disadvantage is also obvious. The variance standard $\sigma_{in}^2$ should be carefully determined, because: on one hand, a too high standard will cause long traversal time before the particles jump and then the total tracking time will be prolonged; on the other hand, a low standard indicates that the traversal process is not sufficient and then the potential duties will be missed.

5.2 Simulated Annealing Method Simulated annealing (SA) algorithm is a Monte-Carlo based stochastic optimal point tracking method, and it is based on the temperature decrease of melt iron annealing process. SA algorithm can endow the optimal point tracking process with a probability which gradually decreases to zero. Based on the Metropolis principle, the system will break away from the local optimal positions to achieve the global optimal point tracking.

To conduct the SA algorithm, the following parameters are required: the initial temperature $T_{ini}$, final temperature $T_f$ and cooling rate $\alpha_T$. After the algorithm initialization, under working conditions, the system fitness will be calculated. If the current fitness is higher than the tracked current GM, the system state will be updated with the current working point and the system temperature $T_{cu}$ will be reduced for the next algorithm iteration. If the current fitness is lower than the current GM, the probability $P$ that the system would accept the current state will be calculated. If the probability is higher than the standard $P_{rand}$, the current state will be accepted and if it is lower than $P_{rand}$, the state will be omitted. In this way, the system can break away from some local optimal positions and finally achieve the global optimal tracking.

In this paper, the SA algorithm is employed to decide whether the particle jumps from the current interval into the one where the current GM is. As analyzed above, the particle regeneration for the next iteration is based on the Gaussian distribution of each particle. In the proposed SA method, each particle is arranged a SA module in Fig. 4(b), and in the
SA module, the PV output power $P_{pv}$ is employed as the system energy. Therefore, the probability function of each SA module can be obtained as follows.

$$P_{i,\text{jump}} = e^{\Delta E/T_{i,\text{iter}}}, \quad \Delta E = P_{i,\text{max}} - P_{i,\text{iter}}, \quad T_{i,\text{iter}} = \alpha_i^{\text{iter}} T_{i,\text{ini}}$$

In the equations, $AE$ is the system energy difference; $T_{i,\text{iter}}$ is the temperature of the $i^{th}$ iteration; $\alpha$ stands for the particle $a, b, c$ and $d$; $P_{i,\text{iter}}$ is the PV output power of particle $i$; $P_{i,\text{max}}$ is the maximum PV power; $P_{i,\text{jump}}$ is the probability of that the $i^{th}$ particle can find the potential $GM$.

Under working conditions, the regenerated particle will be regarded as a disturbance to the corresponding SA state and the probability $P_{i,\text{jump}}$ of each particle can be obtained. In this paper, the particle jump probability $P_{i,\text{jump}}$ is defined as follows.

$$P_{i,\text{jump}} = 1 - P_{i,\text{iter}}$$

The proposed SA method flowchart is shown in Fig. 4(c). Therefore, with algorithm iteration conducting, for the $i^{th}$ particle, if the PV output power $P_{i,\text{iter}}$ is lower than the current $GM$, the particle jump probability $P_{i,\text{jump}}$ will keep exponentially increase. In this way, when $P_{i,\text{iter}} < P_{i,\text{max}}$, in the beginning stage, the particle $i$ may not jump, but if it happens in the ending stage, the particle $i$ may jump.

Furthermore, when the PV output power $P_{i,\text{iter}} < GM$, the particle jump probability $P_{i,\text{jump}}$ are low and high at the beginning and ending stages, respectively. Therefore, with the SA method, the particle jump can be determined with variant probability analysis.

### 6. Simulation Verification

In this paper, in order to verify the proposed algorithm, the 2-peak, 3-peak and 4-peak PV output properties as shown in Fig. 1 are employed in both the simulation and experiment verifications. In this section, the proposed algorithm is verified with Matlab simulation. In all the algorithms, there are 4 particles employed and the initial duties are set as 0.2, 0.4, 0.6 and 0.8, respectively, and furthermore, the particle duty update upper limit is 0.02. The employed PSO, PJ-PSO and SA-PJ-PSO algorithms parameters are set in the following. In the PSO method, the inertia weight $w$ is set as 0.4, and the acceleration coefficients $c_1$ and $c_2$ are set as $c_1 = 0.2$ and $c_2 = 2$, respectively; In the PJ-PSO method, the 4 particle position Gaussian distribution expectations are the particle initial duties, respectively: $\mu_a = 0.2, \mu_b = 0.4, \mu_c = 0.6$ and $\mu_d = 0.8$. The initial variances are set as: $\sigma_{a}^{2}, \sigma_{b}^{2}, \sigma_{c}^{2}, \sigma_{d}^{2} = 0.1$. Furthermore, in the variance decrease method, the variance standard $\sigma_{n,\text{iter}}$ for particle jump is 0.35 and the increment is 0.02 when the particle power is lower than the $GM$. In the SA-PJ-PSO method, the parameters are set with the same as the PJ-PSO algorithm except the SA algorithm module. The system initial temperature $T_{ini}$ and cooling factor $\alpha_T$ are set to be 100 and 0.2, respectively. The final temperature $T_{f}$ is set as the temperature when $P_{i,\text{iter}} > 0.95$. In addition, the frequency of the PSO, PJ-PSO and SA-PJ-PSO is set as 40 Hz.

In order to assess the feasibility of proposed method, the tracking performance can be analyzed mainly in tracking...
time and accuracy aspects. When the PV output power fluctuation is limited within 5%, the MPPT control is regarded to have been achieved. The time from the moment when the algorithm starts and to the moment when the MPPT is achieved is defined as the algorithm tracking time. Furthermore, the ratio between the power $P_{sta}$ in the stable state and theory maximum power $P_{max}$ is taken as the tracking efficiency $\eta_{tra}$.

The simulation results are shown in Fig. 5 and Table 2, and based on the results, the MPPT control has been achieved in all the cases. When the PV output power possesses 2 peaks with respect to voltage, the MPPT control is achieved within 0.42 s, 0.24 s and 0.12 s in the methods of PSO, PJ-PSO and SA-PJ-PSO, respectively. Furthermore, the MPPT efficiency $\eta_{tra}$ is 99.78%, 99.82% and 99.83%, respectively. Furthermore, the PV output power of PSO method varies intensely in the tracking process, and this is because the particle position in the PSO algorithm is updated gradually iteration by iteration. On the other hand, the power variation of the proposed SA-PJ-PSO algorithm is much less intense due to the fast convergence of particles with the assistance of particle jump and simulated annealing. In the MPPT simulation of 3 peaks, the tracking time of 3 methods is 0.34 s, 0.22 s and 0.18 s, respectively. Furthermore, the tracking efficiency $\eta_{tra}$ is 99.79%, 99.83% and 99.85%, respectively. In the MPPT simulation of 4 peaks, the tracking time of 3 methods is 0.42 s, 0.22 s and 0.18 s, respectively. Furthermore, the tracking efficiency $\eta_{tra}$ is 99.73%, 99.76% and 99.82%, respectively.

Therefore, in case 1, 2 and 3, the proposed SA-PJ-PSO method has achieved both the shortest MPPT time and the least PV output power fluctuation in the tracking process.

### 7. Experiment Verification

The experiment platform is established in Fig. 6. The PSO, PJ-PSO and SA-PJ-PSO algorithms are conducted at 13 Hz and the upper limit of particle position update step is 0.02. The PV output property under partial shading conditions in Fig. 1 is achieved with the Keysight E4350B.

The experiment results are shown in Fig. 7 and Table 3. Same to the simulation, the MPPT control has been achieved in all the cases. In case 1 of two peaks, the stable states for the PSO, PJ-PSO and SA-PJ-PSO when the $GM$ positions are

### Table 2. Simulation results of 3 methods

| Case | Method | $P_{sta}$/W | $\eta_{tra}$ | Iteration | Time/s |
|------|--------|-------------|--------------|-----------|--------|
| 1    | PSO    | 48.87       | 99.78%       | 17        | 0.42   |
|      | PJ-PSO | 48.89       | 99.82%       | 10        | 0.24   |
|      | SA-PJ-PSO | 48.90   | 99.83%       | 5         | 0.12   |
| 2    | PSO    | 47.43       | 99.79%       | 14        | 0.34   |
|      | PJ-PSO | 47.45       | 99.83%       | 9         | 0.22   |
|      | SA-PJ-PSO | 47.46   | 99.85%       | 8         | 0.18   |
| 3    | PSO    | 48.89       | 99.75%       | 17        | 0.42   |
|      | PJ-PSO | 48.90       | 99.76%       | 9         | 0.22   |
|      | SA-PJ-PSO | 48.93   | 99.82%       | 8         | 0.18   |

![Fig. 6. Experiment platform](image_url)

![Fig. 7. Experiment results of PSO, PJ-PSO and SA-PJ-PSO algorithms](image_url)
Table 3. Experiment results of 3 methods

| Case | Method       | $P_{ref}/W$ | $\eta_{tra}$ | Iteration | Time/s |
|------|--------------|-------------|--------------|-----------|--------|
| 1    | PSO          | 47.62       | 97.22%       | 27        | 2.0    |
|      | PJ-PSO       | 47.81       | 97.61%       | 19        | 1.4    |
| 2    | SA-PJ-PSO    | 48.03       | 98.06%       | 11        | 0.8    |
|      | PJ-PSO       | 48.71       | 97.95%       | 15        | 1.4    |
|      | SA-PJ-PSO    | 46.71       | 98.27%       | 11        | 0.8    |
| 3    | PSO          | 47.04       | 95.98%       | 32        | 2.4    |
|      | PJ-PSO       | 47.69       | 97.59%       | 24        | 1.8    |
|      | SA-PJ-PSO    | 48.13       | 98.18%       | 16        | 1.2    |

tracked are achieved within 2.0 s, 1.4 s and 0.8 s, respectively. Furthermore, the MPPT efficiency $\eta_{tra}$ is 97.22%, 97.61% and 98.06%, respectively. Not only exhibits much better tracking performance than the PSO algorithm, the proposed SA-PJ-PSO algorithm has also possessed advantages over the PJ-PSO algorithm in the MPPT time. Because in the SA-PJ-PSO algorithm, the particle jump is decided based on the probability analysis in SA modules, the too lower or higher variance standard $\sigma_{up}$ in PJ-PSO method can be avoided. In the MPPT experiment of 3 peaks, the tracking time of 3 methods is 2.5 s, 1.4 s and 0.8 s, respectively. Furthermore, the tracking efficiency $\eta_{tra}$ is 97.01%, 97.92% and 98.27%, respectively. In the MPPT experiment of 4 peaks, the tracking time of 3 methods is 2.4 s, 1.8 s and 1.2 s, respectively. Furthermore, the tracking efficiency $\eta_{tra}$ is 95.96%, 97.29% and 98.18%, respectively.

Therefore, same to the simulation results, in case 1, 2 and 3, the proposed SA-PJ-PSO method has presented the shortest tracking time and the least intensity PV output power fluctuation in the tracking process.

8. Conclusion

In this paper, a novel SA-PJ-PSO algorithm has been proposed to track the PV output power $GM$ under partial shading conditions. In order to prevent the particle range which has already been explored to be traversed again, the particle jump method is employed to move the particles over this range to the interval where the current tracked $GM$ is. Furthermore, the SA algorithm is employed to determine whether the particle should jump from the corresponding interval or not. Compared with the conventional methods, the proposed SA-PJ-PSO algorithm has achieved faster and more stable MPPT performance. Based on the experiment results, when the PV output property possesses 2, 3 and 4 peaks, the tracking time is 0.8 s, 0.8 s and 1.2 s, respectively, verifying the proposed algorithm feasibility.

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