PV MPPT Control under Partial Shading Conditions with a Particle Replacement Gaussian Particle Swarm Optimization Method

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As a complementary renewable power source, the photovoltaics (PV) has played an increasingly important role in various applications. However, although the PV has been considerably developed in the past decades, the global maximum power point tracking (MPPT) under partial shading conditions still needs to be focused on. In this paper, a novel simulated annealing and particle replacement assisted Gaussian particle swarm optimization algorithm (GPSO) has been proposed. The proposed algorithm has been divided into two stages. In the first stage, the particles are replaced with Gaussian distribution at each iteration to reduce the particle distribution range, and when the distribution range is sufficiently narrow, this stage is completed. In the second stage, the GPSO update was used to track the global maximum power point for the generated particles from the reduced distribution range. The proposed algorithm has been verified with simulation and experiments. Compared with the conventional particle swarm optimization algorithm, the proposed method exhibited considerable improvement for both MPPT time and PV output power stability.

Keywords: Gaussian particle swarm optimization, global maximum power point tracking, partial shading conditions, particle replacement, photovoltaic, simulated annealing

1. Introduction

Due to the increasingly severe energy crisis in recent years, it is urgent to replace the conventional power generation methods such as the fossil-fuel power station\textsuperscript{(1)}. Among all the new energy sources, the PV is one of the most promising methods and has been focused all over the world due to the solar irradiance excellent accessibility and inexhaustibility\textsuperscript{(2)}. With the developments of several decades, the PV has been adopted as an important supplementary role in the power system worldwide\textsuperscript{(3)}.

Based on the PV property, the output power with respect to the voltage possesses only one peak with the uniform solar irradiance. Therefore, to make the most of the solar irradiance, the PV MPPT control should be conducted under working conditions\textsuperscript{(4)}. So far, various local MPPT algorithms have been developed in the past decades, such as the constant voltage tracking (CVT)\textsuperscript{(5)}, Perturb and Observe (P&O)\textsuperscript{(6)}, and incremental conductance (IC)\textsuperscript{(7)} methods. However, under working conditions, the solar irradiance on PV panel will not always uniform and this issue is called as the partial shading. Under the partial shading conditions, the output power of PV cells with lower solar irradiance will be reduced, and then the PV panel output exhibits multiple peaks property\textsuperscript{(8)}. Therefore, in this case, it is necessary to track the GMPP under working conditions.

The conduct the global MPPT control, various intelligent computation methods have been focused, such as the firefly algorithm (FA)\textsuperscript{(9)}, cuckoo search\textsuperscript{(10)}, gray wolf optimization (GWO)\textsuperscript{(11)}, particle swarm optimization (PSO)\textsuperscript{(12)}. Among all the current algorithms, PSO is one of the most widely employed methods due to the reasons the algorithm implementation is not based on objective function gradients and only few parameters are required to be tuned. Furthermore, PSO algorithm possesses unique characteristic memory with the particle movements. Since the PSO algorithm was proposed, it has been employed in numerous applications in various areas. For the application of PV MPPT control, the PSO research developments mainly include the methods of parameter modification and combination with other intelligent algorithms. A deterministic PSO (DPSO) algorithm is proposed to reduce the particle convergence time with deterministic acceleration factors\textsuperscript{(13)}. An elite PSO (EPSO) with mutation is proposed, and when the algorithm is conducted, the particles with higher fitness will be sorted out to generate a new swarm to lead to a faster convergence\textsuperscript{(14)}. The formentioned DPSO and EPSO have effectively reduced the tracking time at the
cost of particle exploratory capability decrease. However, when the PV curve is too complex, the DPSO and EPSO reliability should be focused. Combined PSO with proportional-integral (PI) (15), with P&O (16), with IC (17) algorithms are also proposed. In these algorithms, the PSO is employed to locate the global peak area and the PI/P&O/IC are used to accurately track the global maximum after the global peak is detected. Furthermore, a Fuzzy algorithm based PSO method is proposed to cope with the extreme environmental conditions (18).

In the algorithm, the steady-state oscillation has been reduced even with large fluctuations of irradiance and temperature. A hybridization of DE and PSO method is proposed (19) to reduce the tracking time, and in the algorithm, the DE and PSO are employed in an alternative fashion: the PSO is applied at every odd iteration and the DE is run in every even iteration. Similarly, PSO is also combined with other algorithms, such as the ant colony optimization (20), lagrange interpolation formula (21), genetic (22), sliding mode (23) and chaos (24) algorithms. For these novel PSO algorithms, the particle movement in PSO is still conducted step-by-step, and then the PSO stage will still cost too much time and should be optimized. In order to solve this problem, an overall distribution PSO algorithm is proposed (25). Because the particles at the PSO beginning stages are replaced to reduce the converge steps, the GMPP tracking time has been effectively cut down. However, the PSO particle replacement feasibility analysis is only based on simulation data but not mathematical proof, and the Cauchy distribution employed to generate the new particles is not mathematically related to the PSO overall distribution. Furthermore, the countdown method for global peak detection costs too much time.

Therefore, in this paper, a SA assisted particle replaced GPSO algorithm has been proposed. The proposed algorithm is conducted with two stages. In the first stage, the particles are replaced at each iteration based on the Gaussian distribution with SA assistance to accelerate the convergence. In the second stage, the accurate optimal positioning is conducted with GPSO algorithm. The proposed Gaussian distribution based particle replacement has been verified with mathematical proof, and the employed SA can improve the algorithm global peak search ability. This paper is organized as follows. Section II introduces the PV model and output property under partial shading conditions. Section III describes the standard particle swarm optimization algorithm. Section IV presents the Gaussian particle swarm optimization algorithm. Section V shows the proposed particle replacement method. Section VI describes the global area detection method. Section VII presents the simulation results. Section VIII presents the experiment results. Finally, this paper is concluded in the section IX.

2. PV Property and Equivalent Model

To obtain the required output characteristics, in each PV panel, there are multiple modules connected in series and parallel in Fig. 1(a). When the solar irradiance of some modules such as $M_1$ decreases, the output voltage and current of $M_1$ will be reduced. Therefore, in this case, the branch of $M_1$ will be reversely charged by other branches as a load, and this is called as the hot-spot issue. Considering this issue, the bypass diode is employed to protect the modules from the output difference effect between the series connected branches.

To investigate the PV output property under partial shading conditions, in this paper, the two diode equivalent model in Fig. 1(b) is employed to simulate the PV cell (26). The PV model is shown in Fig. 1(c), in the model there is a diode network composed of $N_p \times N_s$ diodes. Based on the model, the total current $I_{pv}$ output from the PV can be obtained as follows.

$$I_{pv} = IN_p \sum_{i=1}^{2} I_{di}N_p \exp \left( \frac{V_{pv} + \frac{N_s}{N_p} I_{pv}R_s}{\alpha VT_i N_s} \right) \frac{N_p}{N_s} \frac{V_{pv} + \frac{N_s}{N_p} I_{pv}R_s}{N_p \alpha VT_i}$$

In Eq. (1), $I_{pv}$ is the PV cell output current and $V_{pv}$ is the PV cell output voltage; $R_i$ and $R_p$ are the series and parallel resistance, respectively; $\alpha$ is the adjustment coefficient; $V_T$ is the thermal voltage of the diodes; $I_i$ is the light generated current and can be obtained in Eq. (2). The diode saturation currents $I_{di}$ and $I_{do}$ can be obtained in Eq. (3).

$$I = (I_{STC} + K_i (T - T_{STC})) \frac{G}{G_{STC}}$$

In Eq. (2), STC stands for the standard test condition, i.e. temperature $T_{STC}=298$ K and irradiance $G_{STC}=1000$ W/m$^2$; $T$ is the panel temperature; $G$ is the solar irradiance; $K_i$ is the short circuit current coefficient. $I_{PV,STC}$ is the measured PV output current in STC.

$$I_{di} = I_{do} = \frac{I_{SC,STC} + K_i (T - T_{STC})}{\exp \left( \frac{qV_{T} \cdot G_{STC}}{N_s} \right) - 1}$$

In Eq. (3), $I_{SC,STC}$ and $V_{OC,STC}$ are the short circuit current and open circuit voltage in STC, respectively; $K_V$ is the open circuit voltage coefficient.

Based on the PV model, when the modules $M_1$, $M_2$ and $M_3$ solar irradiiances are uniform, the PV output power will possess one peak. When the PV is under partial shading conditions, there will be multiple peaks at the power-voltage characteristics.

In this paper, the global MPPT method is planned to be employed in a high power PV electric vehicle wireless
charger prototype. Because due to the battery volume limit, so far the electric vehicles have been mainly driven in the urban area. However, due to the urban area crowded conditions, the PV panel is highly possible to be partially shaded by the surrounding buildings and trees at day time. Therefore, in this case, the global MPPT control is urgently required under working conditions.

In this paper, a 50 W PV MPPT experiment will be employed to verify the proposed algorithm, and a buck converter in Fig. 1(d) is used to conduct the PV MPPT control. The converter parameters are shown in Table 1.

### 3. PSO Algorithm

PSO is a stochastic optimization algorithm which is conducted on the basis of a swarm of particles with position and velocity updates at each iteration to simulate the social behaviors of animal groups. The PSO particle velocity and position updates can be obtained as follows.

\[
\begin{align*}
    v_i^{(k+1)} &= w v_i^{(k)} + c_1 r_1 (P_i - x_i^{(k)}) + c_2 r_2 (G - x_i^{(k)}) \quad \cdots \quad (4) \\
    x_i^{(k+1)} &= x_i^{(k)} + v_i^{(k+1)} \quad \cdots \quad (5)
\end{align*}
\]

In the velocity update of Eq. (4), \(w\) is the inertia weight which represents the previous momentum of particle. \(c_1\) and \(c_2\) are the personal and global optimal acceleration coefficients, respectively. Those two parameters determine the particle proneness from the personal optimal value \(P_i\) and global optimal value \(G\). \(r_1\) and \(r_2\) are the random values following the uniform distribution of \(U(0, 1)\).

In PSO, the particle velocity and position will be updated according to the position differences between the current working point and personal best as well as global best positions. With the updates, the particles will gradually move toward the global best position. When the algorithm precision or iteration steps meet the preset requirement, the global best position particle data will be determined.

### 4. GPSO Algorithm

#### 4.1 GPSO Velocity and Position Updates

However, in Eqs. (4) and (5), there are three parameters, namely \(w\), \(c_1\) and \(c_2\). They should be preset before the algorithm initialization and the inappropriate values will influence the algorithm performance. To solve this issue, the GPSO algorithm is employed in this paper. Compared with the PSO, GPSO can improve the algorithm convergence ability and reduce the parameters which should be preset before the algorithm initialization\(^{(20)}\).

The GPSO velocity and position updates are shown as follows.

\[
\begin{align*}
    v_i^{(k+1)} &= v_i^{(k)} + g_1 (P_i - x_i^{(k)}) + g_2 (G - x_i^{(k)}) \quad \cdots \quad (6) \\
    x_i^{(k+1)} &= x_i^{(k)} + v_i^{(k+1)} \quad \cdots \quad (7)
\end{align*}
\]

In the velocity update of Eq. (6), \(g_1\) and \(g_2\) follow the Gaussian distribution of \(N(\mu_1, \sigma_1^2)\) and \(N(\mu_2, \sigma_2^2)\), respectively. Therefore, in GPSO algorithm, only \(g_1\) and \(g_2\) need to be pretuned before the algorithm initialization.

#### 4.2 Particle Distribution Property Analysis

In GPSO, the particle distribution is analyzed as follows. Based on Eqs. (6) and (7), suppose the following can be obtained.

\[
\begin{align*}
    a_{1i}^{(k)} &= P_i - x_i^{(k)} \quad \cdots \quad (8) \\
    a_{2i}^{(k)} &= G - x_i^{(k)} \quad \cdots \quad (9) \\
    \beta_i^{(k)} &= v_i^{(k)} \quad \cdots \quad (10) \\
    \gamma_i^{(k)} &= x_i^{(k)} \quad \cdots \quad (11)
\end{align*}
\]

Therefore, Eqs. (6) and (7) can be simplified as follows.

\[
\begin{align*}
    x_i^{(k+1)} &= \gamma_i^{(k)} + \beta_i^{(k)} + a_{1i}^{(k)} g_1 + a_{2i}^{(k)} g_2 \quad \cdots \quad (12)
\end{align*}
\]

Furthermore, suppose the following can be obtained.

\[
\begin{align*}
    Z_i^{(k)} &= x_i^{(k+1)} \quad \cdots \quad (13) \\
    X_i^{(k)} &= N \left( \mu_i^{(k)} + \frac{\beta_i^{(k)} + \gamma_i^{(k)}}{2}, \frac{\sigma_1^2}{2} \right) \quad \cdots \quad (14) \\
    X_i^{(k)} &= N \left( \mu_i^{(k)} + \frac{\beta_i^{(k)} + \gamma_i^{(k)}}{2}, \frac{\sigma_2^2}{2} \right) \quad \cdots \quad (15)
\end{align*}
\]

Therefore, Eq. (16) can be obtained.

\[
Z_i^{(k)} = X_i^{(k)} + X_i^{(k)} \quad \cdots \quad (16)
\]

Therefore, the \(i\)th particle distribution at the \(k\)th iteration \(Z_i^{(k)}\) follows the Gaussian distribution in Eq. (17).

\[
Z_i^{(k)} \sim N \left( \mu_i^{(k)}, \sigma_i^2 \right) \quad \cdots \quad (17)
\]

\[
\begin{align*}
    \mu_i^{(k)} &= a_{1i}^{(k)} \mu_1 + a_{2i}^{(k)} \mu_2 + \beta_i^{(k)} + \gamma_i^{(k)} \quad \cdots \quad (18) \\
    \sigma_i^2 &= a_{1i}^{(k)} \sigma_1^2 + a_{2i}^{(k)} \sigma_2^2 \quad \cdots \quad (19)
\end{align*}
\]

In the equation, \(\sim\) means the random variable \(Z_i^{(k)}\) has the probability distribution \(N(\mu_i^{(k)}, \sigma_i^2)\).

Suppose there are \(n_p\) particles at each iteration, and the distribution of all the particles of \(k\)th iteration \(Z_i^{(k)}\) can be obtained in Eq. (20).

\[
Z^{(k)} = \sum_{i=1}^{n_p} Z_i^{(k)} \sim N \left( \mu_{ite}, \sigma_{ite}^2 \right) \quad \cdots \quad (20)
\]

\[
\begin{align*}
    \mu_{ite} &= \sum_{i=1}^{n_p} (a_{1i}^{(k)} \mu_1 + a_{2i}^{(k)} \mu_2 + \beta_i^{(k)} + \gamma_i^{(k)}) \quad \cdots \quad (21) \\
    \sigma_{ite}^2 &= \sum_{i=1}^{n_p} (a_{1i}^{(k)} \sigma_1^2 + a_{2i}^{(k)} \sigma_2^2) \quad \cdots \quad (22)
\end{align*}
\]

Suppose there are \(n_{ite}\) iterations conducted in GPSO algorithm, and the distribution of all the particles from all the iterations \(Z_{all}\) can be obtained in Eq. (23). Due to the Gaussian distribution property, the overall distribution \(Z_{all}\) of all the particles from all the iterations also follows the Gaussian distribution.

\[
Z_{all} = \sum_{k=1}^{n_{ite}} Z_i^{(k)} = \sum_{k=1}^{n_{ite}} \sum_{i=1}^{n_p} Z_i^{(k)} \sim N \left( \mu_{all}, \sigma_{all}^2 \right) \quad \cdots \quad (23)
\]

\[
\begin{align*}
    \mu_{all} &= \sum_{k=1}^{n_{ite}} \sum_{i=1}^{n_p} (a_{1i}^{(k)} \mu_1 + a_{2i}^{(k)} \mu_2 + \beta_i^{(k)} + \gamma_i^{(k)}) \quad \cdots \quad (24)
\end{align*}
\]
After the GPSO algorithm has conducted a certain iterations, the majority of particles will move to the optimal position. Therefore, the personal and global optimal points can be seen to share the same position.

\[ x_{i}^{(k)} = P_i = G \] \hspace{1cm} (29)

The particle velocity update approaches zero.

\[ \lim_{k=\infty} \alpha_{1}^{(k)} \mu_1 + \alpha_{2}^{(k)} \mu_2 + \beta_1^{(k)} = 0 \] \hspace{1cm} (30)

Furthermore, the variance of particle distribution \( Z_i \) will also approach zero.

\[ \lim_{k=\infty} \alpha_{1}^{2(k)} \sigma_1^2 + \alpha_{2}^{2(k)} \sigma_2^2 = 0 \] \hspace{1cm} (31)

Therefore, the particle distribution \( Z_i \) after enough iterations can be obtained in the following.

\[ Z_i^{(k)} \sim N(\gamma_i^{(k)}, \epsilon^{(k)}) \] \hspace{1cm} (32)

In the equation, \( \epsilon^{(k)} \) is the variance of the \( i^{th} \) particle at the \( k^{th} \) iteration. Furthermore, \( k \) is high enough in Eq. (32).

Based on the analysis, the following property of particles in GPSO can be obtained.

1. The overall distribution \( Z_{all} \) in GPSO follows the Gaussian distribution based on Eqs. (23)–(25).

2. Because both \( Z_{all} \) and \( Z_{all} \) follow the Gaussian distribution, after GPSO is conducted with enough iterations, the majority of particles will move to the optimal position.

3. Because in GPSO, the particle movements are independent based on Eqs. (6) and (7), the optimal position can be tracked by all the particles when PSO finishes. Compared with the particles which are near the optimal position (called as particle group A), it takes more time for the particles which are far from the optimal position (called as group B) to move to the optimal position. Furthermore, because the particles of group B are far from the optimal position, their powers are not related to the global best which is the key factor determining all the particle movements. Then it can be regarded that group B is less valuable than group A. If there are enough particles in group A, the particles of group B can be ignored and discarded. The tracking process can be achieved only based on group A.

\[ \sigma_{all}^2 = \sum_{k=1}^{n_k} \sum_{i=1}^{n_i} (\alpha_{1}^{(k)} \sigma_1^2 + \alpha_{2}^{(k)} \sigma_2^2) \] \hspace{1cm} (25)

5. GPSO Particle Replacement Method

5.1 GPSO Process Analysis

As analyzed above, the GPSO algorithm can track the optimal position with a certain iterations and the process is shown in Fig. 2(a). For example, there are 4 particles employed in the GPSO and to track the optimal position, those 4 particles are uniformly distributed in the particle range at the initial iteration. With the velocity and position updates at each iteration, the optimal position can be tracked by all particles after several iterations. However, because the particle \( Par_1 \) initial position is far away from the optimal position compared with other 3 particles, it takes more time for \( Par_1 \) to track the optimal position. Therefore, even though the other particles have already tracked the optimal position, the GPSO algorithm cannot stop the iteration process until all the particles have tracked the optimal position. In this way, the tracking process will cost much more time especially when there are a great deal of particles employed.

As shown in Fig. 2(b), if the rough position of optimal value can be estimated in advance, the initial particle range can be reduced. In the following, the 4 particles can be uniformly distributed in the narrower range and the tracking process will cost less time. Therefore, if the rough position of the optimal value can be detected the GPSO tracking time can be reduced.

5.2 Particle Replacement

Based on the GPSO overall distribution property, after a certain times of iteration, the majority of particles will move around the optimal position. Furthermore, the optimal position can be tracked only based on the particles which are near the optimal position and the other particles which are far away from the optimal position can be omitted.

In general, the whole optimal position tracking process can be divided into two stages, namely the PR stage and GPSO stage in Fig. 2(c). In the PR stage, the particles at each iteration are generated from the Gaussian distribution with a certain expectation and variance. In this way, the particles which are far away from the optimal position at each iteration can be discarded to reduce the tracking time. With the algorithm iterating, the particle range will be reduced gradually to discard the particles which are far away from the
optimal position. The particle range decrease is approached by reducing the Gaussian distribution variance.

In details, in Fig. 2(c), at the kth iteration, all the particles fitness will be calculated. The highest value \(h^k_{LM}\) of the kth iteration, and the corresponding position \(Par^h_{LM}\) will be recorded, respectively. Furthermore, until the kth iteration, the local maximum \(LM^k\) and the corresponding position \(Par^h_{LM}\) should also be recorded, respectively. Therefore, the following equations can be obtained.

When \(h^k_{LM} \geq LM^{k-1}\):

\[
LM^k = h^k_{LM} \quad \ldots \ldots (30) \\
Par^k_{LM} = Par^h_{LM} \quad \ldots \ldots (31)
\]

When \(h^k_{LM} < LM^{k-1}\):

\[
LM^k = LM^{k-1} \quad \ldots \ldots (32) \\
Par^k_{LM} = Par^{k-1}_{LM} \quad \ldots \ldots (33)
\]

Furthermore, to generate the new particles at the kth iteration, the Gaussian distribution expectation \(\mu^k\) and variance \(\sigma^{2(k)}\) are prepared for the \(k + 1\)th iteration particles.

**a. When \(h^k_{LM} \geq LM^{k-1}\)**

In this case, in Fig. 3(a) and (b), the local maximum \(LM^k\) and the position \(Par^k_{LM}\) should be updated according to Eqs. (30) and (31). Because the \(LM^k\) increases at the kth iteration, it can be concluded that the particles at the kth iteration are moved toward the GMPP and the GMPP may have not been tracked. Therefore, in order not to exclude the GMPP from the particle range, the Gaussian distribution variance cannot be reduced. In this way, the Gaussian expectation and variance updates are obtained as follows.

\[
\mu^k = Par^k_{LM} \quad \ldots \ldots (34) \\
\sigma^{2(k)} = \sigma^{2(k-1)} \quad \ldots \ldots (35)
\]

**b. When \(h^k_{LM} < LM^{k-1}\)**

In this case, the local maximum \(LM^k\) and the position \(Par^k_{LM}\) should be kept same according to Eqs. (32) and (33). Because \(h^k_{LM} < LM^{k-1}\), there is a probability that the current local maximum \(LM^k\) is the GMPP.

If \(LM^k\) is not the GMPP in Fig. 3(c), because \(h^k_{LM} < LM^{k-1}\), the current local maximum \(LM^k\) is the LMP. Therefore, the particles at the \(k + 1\)th iteration should be generated to explore the point whose fitness is higher than \(LM^k\). To search the appropriate point, the Gaussian distribution expectation should stay at \(LM^k\) and the variance should not be reduced not to exclude the GMPP. Therefore, the following equations can be obtained.

\[
\mu^k = Par^k_{LM} \quad \ldots \ldots (36) \\
\sigma^{2(k-1)} = \sigma^{2(k-1)} \quad \ldots \ldots (37)
\]

However, if \(LM^k\) is the GMPP in Fig. 3(d), for the k + 1th iteration, the Gaussian distribution expectation \(\mu^k\) should be kept at \(Par^k_{LM}\). Furthermore, to reduce the particle range to move the particles toward the GMPP, the variance \(\sigma^{2(k)}\) should be reduced. Therefore, the Gaussian expectation and variance updates are obtained as follows.

\[
\mu^k = Par^k_{LM} \quad \ldots \ldots (38) \\
\sigma^{2(k)} = \beta \sigma^{2(k-1)}, \beta \in (0, 1) \quad \ldots \ldots (39)
\]

Based on the above analysis, no matter whether \(h^k_{LM}\) is higher than \(LM^{k-1}\) or not, the Gaussian distribution expectation should be \(LM^k\). Furthermore, the Gaussian distribution variance \(\sigma^{2(k)}\) is related to whether the current local maximum \(LM^k\) is the GMPP. The PR stage flowchart is shown in Fig. 4. Because only when \(LM^k\) is the GMPP can the Gaussian distribution variance be reduced, the GMPP detection is the key factor which determines the algorithm accuracy and processing time.

6. Global Maximum Power Point Detection

6.1 Countdown Method

When the local maximum \(LM^k\) approaches the GMPP, namely \(LM^k = GMPP\), the probability that the highest values \(h^k_{LM}, h^{k+1}_{LM}, \ldots, h^{k+n}_{LM}\) of
next $n$ consecutive iterations are lower than $LM^{(k)}$ is high. On the contrary, when $LM^{(k)} < GMPP$, the probability will be low. Therefore, in the countdown method, when the system highest value $h^{(k)}$, $h^{(k+1)}$, $h^{(k+2)}$, ..., $h^{(k+n)}$ are lower than the current local maximum $LM^{(k)}$ consecutively for more than $c_d$ times, the current local maximum $LM^{(k)}$ is taken as the GMPP and the particle range should be reduced. However, if the times cannot exceed $c_d$, the $LM^{(k)}$ will be seen as the LMPP and the particle range will not be reduced. The flowchart of countdown method is shown in Fig. 6(a).

However, the value $c_d$ should be precisely decided because high $c_d$ can lead to unnecessary long tracking time while low $c_d$ will cause false particle range reduction. In details, in Figs. 5(a) and (b), in the starting iterations of the algorithm, the particle range is wide and all the particles are scattered. When the system highest value $h^{(k)}$ decreases from $A$ to $B$ after $c_d$ times, the current local maximum $LM^{(k)}$ will not be changed. According to the countdown method, the particle range should be reduced, leading to the GMPP is excluded from the particle range and the algorithm will be failed. Therefore, the countdown method can lead to particle range reduction mistake excluding the GMPP in this condition. In the ending iterations in Figs. 5(c) and (d), almost all the particles have moved to the GMPP position. If the highest value $h^{(k)}$ decreases, it means the GMPP position has been missed and there is no need to conduct further iterations until $c_d$ is approached. Therefore, in this case, the countdown method will lead to unnecessary extra tracking time.

6.2 Simulated Annealing Method As analyzed above, when the highest value $h^{(k)}$ at the $k^{th}$ iteration decreases, the particle range reduction probability of the starting and ending iterations is different. In this paper, the SA algorithm is employed to calculate the probability of particle range decrease. The SA algorithm simulates the process of metal annealing in a controlled manner to track the GMPP. For the SA method, the initial temperature $T_{ini}$, final temperature $T_f$ and cooling rate $\alpha_T$ are required. At each iteration, the system temperature $T_k$ will be calculated and based on $T_k$ several perturbations will be added to the system current working point. If the energy of new working point with some perturbation is higher than the current working point energy, the perturbation will be accepted. If the new energy is lower than the current energy, the perturbation will be determined to be accepted or not based on the acceptance probability $P_{sa}$. $P_{sa}$ is related with the current system temperature and fitness difference between two working points. In the paper, the system energy can be replaced with the PV output power, therefore the probability $P_{sa}$ is obtained in the following.

$$P_{sa} = \exp \left( \frac{F^{(k)} - F^{(k-1)}}{T_k} \right)$$ \hspace{1cm} (40)

$$T_k = \alpha_T T_{ini}, \alpha_T \in (0, 1)$$ \hspace{1cm} (41)

In Eq. (40), $F^{(k)}$ and $F^{(k-1)}$ are the PV output power at $k^{th}$ and $k-1^{th}$ iterations, respectively. $T_k$ is the system temperature of the $k^{th}$ iteration.

Furthermore, because in the starting iterations the probability of $LM^{(k)} = GMPP$ is low and in the ending iterations it is high, the GMPP detection probability $P_{GMPP}$ can be obtained as follows.

$$P_{GMPP} = 1 - P_{sa}$$ \hspace{1cm} (42)

Therefore, the SA flowchart is shown in Fig. 6(b). In Fig. 6(b), $P_{rand}$ is the random probability.

Based on the above analysis, in the countdown method, the global maximum power point detection mainly depends on the countdown factor $c_d$. However, for different PV output power curves, different $c_d$ values may be required. In applications, the countdown factor $c_d$ should be carefully determined, and when the solar irradiance changes, the preset $c_d$ may not be still appropriate for the new PV output power. However, on the other hand, in the SA method, the global maximum power point detection is based on the probability analysis. Even though the solar irradiance changes, the probability $P_{GMPP}$ will be calculated according to the new PV output power data based on Eqs. (40)–(42). Therefore, the changed PV property will not influence the global maximum power point detection process, indicating the SA method will be more reliable than the countdown method.

7. Simulation Verification

The proposed methods are verified with Matlab simulation. The employed PV output property is shown in Fig. 7, and the global maximums are shown in Table 2. In order to track the global maximum, the employed PSO, PR-GPSO and SA-PR-GPSO algorithms parameters are set in the following. In the
PSO method, the inertia weight \( \omega \), personal coefficient \( c_1 \) and global coefficient \( c_2 \) are set as 0.4, 0.2 and 2, respectively. In the PR-GPSO method, the particle replacement follows the Gaussian distribution with the initial variance as \( \sigma^2 = 0.1 \) the countdown factor is set as \( c_d = 4 \). (In this paper, \( c_d \) is selected from the set of \( \{2, 3, 4, 5, 6\} \) based on simulation and experiment performances. Based on the case 1, 2 and 3, when \( c_d = 4 \), the shortest tracking time is achieved.) After the particle replacement stage, in the following GPSO stage, the acceleration coefficients are set as \( g_1 \sim N(0.2, 0.1) \) and \( g_2 \sim N(2, 0.1) \). In the SA-PR-GPSO method, the initial temperature \( T_{ini} \) and temperature decrease factor \( \alpha_T \) are set as 10 and 0.1, respectively. The final temperature \( T_f \) is set as the temperature when \( P_{GMPP} > 0.95 \). After the particle replacement stage, the following GPSO stage also shares the same parameters with the PR-GPSO method. In all the methods, 4 particles are employed and the initial duties are set as 0.1, 0.4, 0.7 and 0.9, respectively. The frequency of 3 algorithms is set as 40 Hz. Furthermore, the step upper limit in all the PSO/GPSO stages should be carefully determined. On one hand, the low step limit will lead to small tracking step and then the tracking time would be prolonged. On the other hand, when the high limit is employed, the particles will overshoot the global optimal position in the tracking process and then the tracking time also will be increased. In this paper, in order to determine the step limit, a set of \( [0.01, 0.03, 0.05, 0.08, 0.1] \) has been tested and when the limit is equal to 0.05, the shortest tracking time has been achieved. Therefore, in this paper, the step upper limit is set as 0.05.

Furthermore, in this paper, the algorithm tracking time is defined as the time from 0 to the moment when the PV output power error is limited within 5% of the theory maximum power \( P_{max} \). The MPPT efficiency is defined as follows.

\[
\eta_{MPPT} = \frac{P_{sta}}{P_{max}} \tag{43}
\]

In the equation, \( P_{sta} \) is the tracked power in the steady state; \( P_{max} \) is the theory maximum power. For case 1, 2 and 3, the \( P_{max} \) is 48.98 W, 47.53 W and 49.02 W as shown in Table 2.

The simulation results are shown in Figs. 8, 9, 10 and Table 3. All the methods have achieved the GMPP tracking in all cases. In case 1 of two peaks, the stable states for the PSO, PR-GPSO and SA-PR-GPSO when the global maximum positions are tracked are achieved within 0.38 s, 0.16 s and 0.08 s, respectively. The MPPT efficiency of 3 methods is 99.75%, 99.80% and 99.87%, respectively. Furthermore, the PV output power of PSO method fluctuates much intensely than the PR-GPSO and SA-PR-GPSO methods. The reason for this issue is that the particles in the PSO method are updated step by step, and at the beginning stage of algorithm iteration, the particles are far away from each other as shown in Fig. 8(b). When different particles are calculated the fitness in one iteration, the PV output power will intensely fluctuate. In the PR-GPSO method, because the particles are replaced at the beginning stage as shown in Fig. 8(b), the output power fluctuates much less intensely. However, because the countdown factor \( c_d \) cost too much time at the ending part of the PR stage, the tracking time is not effectively reduced. In the proposed SA-PR-GPSO method, because of the assistance of SA algorithm, both the tracking time and PV output power fluctuation are improved. In Fig. 8(b), the particle duty updates converge faster than the PR-GPSO method. The global maximum can be effectively tracked only after 4 iterations.

In case 2 of 3 peaks, the global maximums are effectively tracked within 0.27 s, 0.24 s and 0.12 s, respectively. The MPPT efficiency of 3 methods is 99.81%, 99.83% and 99.85%, respectively. Furthermore, in case 3, the global maximums are effectively tracked within 0.28 s, 0.24 s and 0.10 s, respectively. The MPPT efficiency of 3 methods is 99.79%, 99.81% and 99.88%, respectively.

Therefore, in case 1, 2 and 3, the proposed SA-PR-GPSO method has presented the shortest tracking time and the least intensity PV output power fluctuation.

### 8. Experiment Verification

The proposed method is verified by experiments with the platform in Fig. 11. The frequency of the PSO, PR-GPSO and SA-PR-GPSO algorithms is set as 13 Hz. Furthermore, the maximum step of particle duty is limited to 0.02 and the converter parameters are shown in Table 1. The PV array simulator Keysight E4350B is employed to simulate the PV output under partial shading conditions in Fig. 7 and Table 2. The employed load is a non-inductive load with the parameter of \( RL = 5 \Omega \) and the whole system controller is TMS320F28335.

The experiment results are shown in Figs. 12, 13, 14 and Table 4. All the methods have achieved the GMPP tracking in all cases. In case 1 of 2 peaks, the stable states for the PSO, PR-GPSO and SA-PR-GPSO when the global maximum positions are tracked are achieved within 2.4 s, 1.8 s and 0.8 s, respectively. The MPPT efficiency of 3 methods is 96.20%, 97.57% and 98.14%, respectively. Similar to the simulation results, the PV output power fluctuates the most intensely for the PSO algorithm, and the reason is the step-by-step particle duty update. Because in the PR-GPSO and SA-PR-GPSO algorithms, the beginning stage is conducted with particle replacement, the PV output power fluctuate much less.

### Table 2. PV property under partial shading conditions

<table>
<thead>
<tr>
<th>Case</th>
<th>( V_{sta}/V )</th>
<th>( I_{sta}/A )</th>
<th>( P_{sta}/W )</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>27.61</td>
<td>1.77</td>
<td>48.98</td>
</tr>
<tr>
<td>2</td>
<td>24.40</td>
<td>1.95</td>
<td>47.53</td>
</tr>
<tr>
<td>3</td>
<td>30.37</td>
<td>1.61</td>
<td>49.02</td>
</tr>
</tbody>
</table>

![Fig. 7](image-url) (a) Case 1 of 2 peaks. (b) Case 2 of 3 peaks. (c) Case 3 of 4 peaks
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Fig. 8. Case 1: simulation tracking results of PSO, PR-GPSO and SA-PR-GPSO (a) Power variation. (b) Duty variation. (c) Voltage variation. (d) Current variation

Fig. 9. Case 2: simulation tracking results of PSO, PR-GPSO and SA-PR-GPSO (a) Power variation. (b) Duty variation. (c) Voltage variation. (d) Current variation

Fig. 10. Case 3: simulation tracking results of PSO, PR-GPSO and SA-PR-GPSO (a) Power variation. (b) Duty variation. (c) Voltage variation. (d) Current variation

Fig. 11. Experiment platform establishment

intensely. Because the countdown factor \( c_b \) cost too much time at the ending part of the PR stage, compared with the PSO method, the PR-GPSO method only reduced 25% tracking time. On the other hand, the proposed SA-PR-GPSO method effectively reduced the tracking time because the employed SA algorithm can detect the GMPP position by probability analysis. From Table 4, the GMPP of 3 methods are tracked at the 32\(^{th}\), 24\(^{th}\) and 11\(^{th}\) iteration respectively, and this demonstrates the feasibility of proposed SA-PR-GPSO algorithm.

In case 2 of 3 peaks, the global maximums are effectively tracked within 2.4 s, 1.7 s and 1.0 s, respectively. The MPPT efficiency of 3 methods is 96.19%, 97.48%, and 98.00%, respectively. Furthermore, in case 3 of 4 peaks, the global maximums are effectively tracked within 2.4 s, 1.4 s and 0.8 s, respectively. The MPPT efficiency of 3 methods is 97.12%, 98.29% and 98.42%, respectively. Therefore, the proposed SA-PR-GPSO method has presented the shortest tracking time and least intensity PV output fluctuation.

Furthermore, in this paper, due to the experiment platform

Table 3. Simulation results of 3 methods

<table>
<thead>
<tr>
<th>Case</th>
<th>Method</th>
<th>( P_{\text{m}}/\text{W} )</th>
<th>MPPT efficiency</th>
<th>Iteration</th>
<th>Tracking time/s</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>PSO</td>
<td>48.86</td>
<td>99.75%</td>
<td>16</td>
<td>0.38</td>
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<tr>
<td></td>
<td>PR-GPSO</td>
<td>48.88</td>
<td>99.80%</td>
<td>7</td>
<td>0.16</td>
</tr>
<tr>
<td></td>
<td>SA-PR-GPSO</td>
<td>49.82</td>
<td>99.87%</td>
<td>4</td>
<td>0.08</td>
</tr>
<tr>
<td>2</td>
<td>PSO</td>
<td>47.44</td>
<td>99.81%</td>
<td>11</td>
<td>0.27</td>
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<tr>
<td></td>
<td>PR-GPSO</td>
<td>47.45</td>
<td>99.83%</td>
<td>10</td>
<td>0.24</td>
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<tr>
<td></td>
<td>SA-PR-GPSO</td>
<td>47.46</td>
<td>99.85%</td>
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<td>0.12</td>
</tr>
<tr>
<td>3</td>
<td>PSO</td>
<td>48.91</td>
<td>99.79%</td>
<td>12</td>
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<td></td>
<td>PR-GPSO</td>
<td>48.92</td>
<td>99.81%</td>
<td>10</td>
<td>0.24</td>
</tr>
<tr>
<td></td>
<td>SA-PR-GPSO</td>
<td>48.96</td>
<td>99.88%</td>
<td>5</td>
<td>0.10</td>
</tr>
</tbody>
</table>

Table 4. Experiment results of 3 methods

<table>
<thead>
<tr>
<th>Case</th>
<th>Method</th>
<th>( P_{\text{m}}/\text{W} )</th>
<th>MPPT efficiency</th>
<th>Iteration</th>
<th>Tracking time/s</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>PSO</td>
<td>47.12</td>
<td>96.20%</td>
<td>32</td>
<td>2.4</td>
</tr>
<tr>
<td></td>
<td>PR-GPSO</td>
<td>47.79</td>
<td>97.57%</td>
<td>24</td>
<td>1.8</td>
</tr>
<tr>
<td></td>
<td>SA-PR-GPSO</td>
<td>48.07</td>
<td>98.14%</td>
<td>11</td>
<td>0.8</td>
</tr>
<tr>
<td>2</td>
<td>PSO</td>
<td>45.72</td>
<td>96.19%</td>
<td>32</td>
<td>2.4</td>
</tr>
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<td></td>
<td>PR-GPSO</td>
<td>46.33</td>
<td>97.48%</td>
<td>23</td>
<td>1.7</td>
</tr>
<tr>
<td></td>
<td>SA-PR-GPSO</td>
<td>46.58</td>
<td>98.00%</td>
<td>13</td>
<td>1.0</td>
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<tr>
<td>3</td>
<td>PSO</td>
<td>47.61</td>
<td>97.12%</td>
<td>32</td>
<td>2.4</td>
</tr>
<tr>
<td></td>
<td>PR-GPSO</td>
<td>48.18</td>
<td>98.29%</td>
<td>19</td>
<td>1.4</td>
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<tr>
<td></td>
<td>SA-PR-GPSO</td>
<td>48.34</td>
<td>98.42%</td>
<td>11</td>
<td>0.8</td>
</tr>
</tbody>
</table>
hardware limitation, the solar irradiance doesn’t change in the experiment verification. However, under working conditions, the solar irradiance often changes in time domain. For the future research prospects, the PV power maximum value can be employed to detect the solar irradiance change. When the MPPT is achieved, the converter duty will be determined. However, after sometime, if the PV output power with the determined duty deviates from the maximum value with a certain degree, it can be regarded that the solar irradiance has changed and in this case, the proposed MPPT algorithm will be reconducted to search for the new maximum power.

9. Conclusion

In this paper, a novel SA-PR-GPSO algorithm has been proposed to track the PV GMPP under partial shading conditions. The particle replacement has been verified with mathematical proof and it can reduce the particle update steps and repress the output power fluctuation. Furthermore, the SA algorithm can determine whether the current working point is at the global peak or not. With the employed PR and SA assistance, the proposed SA-PR-GPSO has exhibited effective improvement in MPPT experiments. Compared with PSO algorithm, with the proposed method, the MPPT time has been reduced from 2.4 s to 0.8 s with 2-peak PV curve, 2.4 s to 1.0 s with 3-peak PV curve and 2.4 s to 0.8 s with 4-peak curve, respectively. The effectively reduced tracking time has verified the proposed SA-PR-GPSO method feasibility.

References


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