Random Reselection Particle Swarm Optimization for Optimal Design of Solar Photovoltaic Modules

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Abstract: Renewable energy is becoming more popular due to environmental concerns about the previous energy source. Accurate solar photovoltaic system model parameters substantially impact the efficiency of solar energy conversion to electricity. In this matter, swarm and evolutionary optimization algorithms have been widely utilized in dealing with practical problems due to their more straightforward concepts, efficacy, flexibility, and easy-to-implement procedural frameworks. However, the nonlinearity and complexity of the photovoltaic parameter identification caused swarm and evolutionary optimizers to exhibit Immaturity in the obtained solutions. To deal with such concerns on immature convergence and imbalanced searching trends, in this paper, we proposed the PSOCS algorithm based on the core components of particle swarm optimization (PSO) and the strategy of random reselection of parasitic nests that appeared in the cuckoo search. The parameters of the single-diode model and the double-diode model are identified based on several experiments. Based on the comprehensive comparisons, results indicate that the developed PSOCS algorithm has higher convergence accuracy and better stability than the original PSO, the original cuckoo search, and other studied algorithms. The findings indicate that we suggest the PSOCS algorithm as an enhanced and efficient approach for dealing with parameter extraction of solar photovoltaic modules. We think this simple variant of PSO can be employed as a tool for the optimal designing of photovoltaic systems.

Keyword: Solar photovoltaic system; Particle swarm optimization; Cuckoo search; Single-diode model; Double-diode model

1. Introduction

In recent years, the frequent occurrence of extreme weather indicates that the Earth's environment is
in a continuous deterioration process, and we need the coupling of multi-energy sources [1, 2]. Energy supply and demand need pollution-free and cost-efficient planning to have an efficient energy system for society [3]. As the sources of pollution continue to be understood, and based on different sources of energy [4, 5], it has been discovered that humans’ overuse of fossil energy is a significant cause of this situation. Solar energy conversion into electricity through photovoltaic cell systems (PV) has become one of the necessary means to solve pollution and energy problems [6, 7]. Since the properties of PV deeply affect the efficiency of the conversion of solar energy into electricity, the development of accurate mathematical models became a hot topic [8-10]. The single, double model, and double diode model (SDM and DDM) are most widely used to characterize the current-voltage characteristics of PV [11, 12]. Both models contain parameters that the mathematical operations cannot determine, and the determination of parameters has an important influence on the model.

In order to solve the problem of parameter identification in PV, many researchers have proposed various approaches from different perspectives. Eswarakanthan et al. [13] used a least-squares optimization algorithm based on a modified Newton model to extract five parameters of a single diode. Chan et al. [14] pointed out that the 5-point method to extract single-diode lumped-circuit models is more reliable and accurate than the curve-fitting method. Ortiz-Conde et al. [15] discussed the implicit transcendental equation for handling photovoltaic models using the Lambert W function. Finally, Appelbaum et al. [16] studied the performance of the gradient descent method to extract single diode parameters.

Recently, many meta-heuristic algorithms have been proposed; such as particle swarm optimizer (PSO), colony predation algorithm (CPA) [17], slime mould algorithm (SMA)1 [18], Harris hawks optimization2 (HHO) [19], hunger games search3 (HGS) [20], and Runge Kutta optimizer4 (RUN) [21]. These algorithms have found their application in many real-life problems such as feature selection [22-26], bankruptcy prediction in [27-29] or works in [30-32], and scheduling problems [33, 34]. However, these domains not limited, and these branches of methods also can be utilized for image segmentation [35, 36], PID optimization control [37-39], gate resource allocation [40, 41], the hard maximum satisfiability problem [42, 43], and fault diagnosis of rolling bearings [44, 45]. Data science also witnessed a series of problems that we need to handle using hybrid or improved optimizers. Such feature spaces are not straightforward like benchmark problems that often are used for efficacy analysis of methods. Researchers verified such approaches in dealing with medical data classification [46-49], parameter optimization [50-53], wind speed prediction [54], engineering design problems in [55-58] or works in [59, 60], detection of foreign fiber in cotton [61, 62], and prediction problems in educational field [63-67]. The successful application of optimization algorithms or their harmonized variants in other fields provides another way of thinking to solve the problem of parameter identification in PV [68], such as genetic algorithm (GA) [69], harmony search (HS) [70], simulated annealing (SA) [71], differential evolution (DE) [72-74], bacterial foraging algorithm (BFA) [75], shuffled frog leaping algorithm (SFLA) [76-78], sine cosine algorithm (SCA) [11], salp swarm algorithm (SSA) [79, 80], HHO [12, 81-83], moth flame optimization (MFO) [84], ant lion optimizer (ALO) [85, 86], gradient-based optimizer [87], SMA [88], spherical evolution algorithm [89], and whale optimization algorithm [90].

The particle swarm optimization (PSO) [91] and the cuckoo search (CS) [92] have a confirmed performance in extracting the parameters of the PV, but the shortcomings of both algorithms are gradually

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1 https://aliasgharheidari.com/SMA.html
2 https://aliasgharheidari.com/HHO.html
3 https://aliasgharheidari.com/HGS.html
4 https://aliasgharheidari.com/RUN.html
exposed as the study progresses. As a result, many researchers have proposed effective improvement strategies to address the shortcomings of both algorithms to deal with the PV. Huang et al. [93] improved the algorithm’s global search performance by introducing chaotic search in response to the standard PSO’s tendency to exhibit precocious and stagnant shortcomings. Jordehi et al. [94] achieved a balance between exploration and exploitation inclinations by modifying the individual acceleration coefficient and the social acceleration coefficient in the PSO algorithm. Mao et al. [95] instead use the grouping approach of the SFLA algorithm to improve the global search capability of the basic PSO algorithm. Merchoui et al. [96] proposed a new adaptive mutation mechanism to solve premature convergence of the PSO algorithm. Rezaee Jordehi [97] suggested a five-staged successive mutation mechanism to tackle premature convergence of the PSO algorithm. Lin et al. [98] also tried to implement the concept of a niche in the PSO algorithm in parallel architecture for parameter identification. Kang et al. [99] designed three strategically different strategies to improve the optimization capabilities of the CS algorithm, including a quasi-oppositional-based learning mechanism, a dynamic adaptive step strategy, and a dynamic adjustment strategy for fractional probability. Chen et al. [100] fused biogeography-based optimization into the CS algorithm to overcome the problem of slow convergence. Long et al. [101] combined the gray wolf optimization algorithm with the CS algorithm to extract the parameters of the PV model.

The study found that the PSO algorithm was competent in exploitation, while the CS algorithm was better at exploitation [102, 103]. To the best of our knowledge, the idea of combining the PSO algorithm with the CS algorithm with our setting has not been applied to the problem of extracting parameters of PV, and it worth investigating. We also agree with the critical views on the initial design of CS [104]. Therefore, this paper proposes taking advantage of the components of the CS algorithm to enhance the optimization capability of the PSO algorithm to extract the parameters of PV. The scientific novelties of this paper are summarized as follow:

a) An enhanced particle swarm optimization with a random reselection mechanism, PSOCS, is created to extract PV parameters.

b) The random reselection mechanism that appeared in the CS algorithm is adopted to enhance the exploration performance of the PSO algorithm.

c) Compared with the original PSO algorithm, CS algorithm, and some other algorithms, the PSOCS algorithm exhibits high accuracy for extracting SDM, DDM, and PV module parameters.

d) Under the external conditions of temperature and irradiance, the PSOCS algorithm shows strong stability.

The structure of this paper is designed as follows. The second section describes the problem of parameter identification of PV and presents mathematical equations. The third section introduces the PSO algorithm and the CS algorithm and proposes the combined ideas. The results of the experiment are analyzed in Section 4. Finally, section 5 summarizes the full text.

2. PV system model and mathematical expression

Mathematical models of PV mainly describe the nonlinear relationship between current and voltage. In this article, the most widely used SDM and DDM are used to characterize the current-voltage characteristics of PV.

2.1. Single-diode mathematical model (SDM)

The equivalent circuit structure of the SDM is depicted in Fig.1, and the specific meaning of each variable is listed in Table 1. The output current is calculated as Eq. (1) [11]:

\begin{equation}
I_{pv} = I_{sc} - I_{0} \left( \exp \left( \frac{V_{pv} + I_{pv} R_{sh}}{n V_{t}} \right) - 1 \right)
\end{equation}
According to Shockley's equation, Eq. (1) is unfolded into a nonlinear relationship between current and voltage Eq. (2) [11], and Table 2 contains the variable definitions:

\[
I_L = I_{ph} - I_d - I_{sh} = I_{ph} - I_{sd1} \cdot \left( \exp \left( \frac{q(V_L + R_S I_L)}{n_k T} \right) - 1 \right) - \frac{V_L + R_S I_L}{R_{sh}} \quad (2)
\]

From Eq. (2) it is known that the SDM contains five unknown variables: \((I_{ph}, I_{sd1}, R_S, R_{sh}, n)\).

**2.2. Double-diode mathematical model (DDM)**

We need to design the objective and involved variable consistently to reach high-quality mathematical modeling [105]. The DDM uses two diodes in parallel with the current source based on an SDM to reduce the effect of recombination current loss on the model accuracy, as shown in Fig. 2. In addition, the nonlinear relationship between specific currents and voltages is shown in Eq. (3) [11]:

\[
I_L = I_{ph} - I_{d1} - I_{d2} - I_{sh} = I_{ph} - I_{sd1} \cdot \left( \exp \left( \frac{q(V_L + R_S I_L)}{n_1 k T} \right) - 1 \right) - I_{sd2} \cdot \left( \exp \left( \frac{q(V_L + R_S I_L)}{n_2 k T} \right) - 1 \right) \quad (3)
\]
where, \( I_{d1} \) and \( I_{d2} \) represent diode currents, \( I_{sd1} \) and \( I_{sd2} \) represent diffusion and saturation currents, respectively, \( n_1 \) and \( n_2 \) represent ideal factors for both diodes, and the other variables are defined as in the SDM. The DDM contains seven unknown variables: \((I_{ph}, I_{sd1}, I_{sd2}, R_{sh}, R_S, n_1, n_2)\).

2.3. Mathematical modeling of PV module

The equivalent circuit of the PV module is based on the series and parallel connection of multiple solar cells, as in Fig.3. The unknown parameters of the PV module are also 5: \((I_{ph}, I_{sd}, R_S, R_{sh}, n)\). The output current \(I_L/N_P\) is calculated as in Eq. (4) [11]:

\[
I_L/N_P = I_{ph} - I_{sd} \cdot \left[ \exp \left( \frac{q(V_L/N_S + R_S I_L/N_P)}{n k T} \right) - 1 \right] - \frac{V_L/N_S + R_S I_L/N_P}{R_{sh}}
\]

where, \( N_S \) represents the number of solar cells in series and \( N_P \) denotes the number of solar cells in parallel.

2.4. Function construction

The purpose of extracting the optimal parameters is to make the error between the data estimated by the model and the measured data converge to the ideal value. Therefore, the root mean square error (RMSE) is used as the objective function of the meta-heuristic algorithm optimization, as shown in Eq. (5).

\[
RMSE(X) = \sqrt{\frac{1}{N} \sum_{k=1}^{N} F(V_L, I_L, X)^2}
\]

where the \( N \) denotes the number of estimated data.

For the objective function of the SDM, \( F(V_L, I_L, X) \) is expressed as Eq. (6):

\[
\begin{align*}
1 \left[ \frac{V_L + R_S I_L}{R_{sh}} \right] \\
\end{align*}
\]
\[
\begin{align*}
F_{\text{DDM}}(V_L, I_L, X) &= I_{ph} - I_{sd} \cdot \left[ \exp\left( \frac{q(V_L + R_S - I_L)}{n_2 k T} \right) - 1 \right] - \frac{V_L + R_S - I_L}{R_{sh}} - I_L \\
X &= (I_{ph}, I_{sd}, R_S, R_{sh}, n_2) \quad (6)
\end{align*}
\]

For the objective function of the DDM, \( F(V_L, I_L, X) \) is expressed as Eq. (7):

\[
\begin{align*}
F_{\text{DDM}}(V_L, I_L, X) &= I_{ph} - I_{sd1} \cdot \left[ \exp\left( \frac{q(V_L + R_S - I_L)}{n_2 k T} \right) - 1 \right] - I_{sd2} \cdot \left[ \exp\left( \frac{q(V_L + R_S - I_L)}{n_2 k T} \right) - 1 \right] - \frac{V_L + R_S - I_L}{R_{sh}} \\
X &= (I_{ph}, I_{sd1}, I_{sd2}, R_S, R_{sh}, n_1, n_2) \quad (7)
\end{align*}
\]

3. Proposed method

The stability of an optimizer is influenced by the right balance between the cores of the stochastic methods. The first core works as an exploratory engine, while the other core works as an exploitative engine. A delicate sense of balance is a complex challenge for an optimizer such as PSO, theoretically and practically, due to the various random patterns within each step of the searching phases and the related history. Hence, if the search is inclined toward the exploration, the method has good coverage, but it will lose sufficient accuracy and focus on the high-quality solutions (in the extreme case, it cannot converge). Also, if the exploitation is unbalanced higher than exploration, the method fails to have enough coverage for visiting various regions and detecting the initial solutions. Therefore, a meta-heuristic with a relatively right balance between exploitation and exploration can better solve the parameter identification problems.

Furthermore, the structure of the PSO algorithm [106] has an advantage in exploitation, while the components of the CS algorithm [107] have a more prominent ability in exploration. Therefore, this paper develops a new algorithm based on the core phases of the PSO and CS algorithms. In this section, an overview of the PSO algorithm and the CS algorithm will be presented first, and then, the new algorithm will be proposed.

3.1. Overview of the PSO

The PSO algorithm [106] is a meta-heuristic based on group collaboration developed by simulating the foraging behavior of a flock of birds in nature. The PSO algorithm abstracts a flock of birds into a group of particles at speed to find the optimal solution to the optimization problem. The PSO algorithm randomly generates a certain number of particles initially within the search space and iterates the search at a certain speed relying on information about the current optimal particle \((p_{\text{best}})\) and the current global particle \((g_{\text{best}})\). The mathematical equation for updating the particle is shown in Eq. (8), Eq. (9) [91]:

\[
v_{i,j}^{t+1} = \omega \times v_{i,j}^t + c_1 \times r_1 \times (p_{\text{best},i} - \text{position}_{i,j}^t) + c_2 \times r_2 \times (g_{\text{best}} - \text{position}_{i,j}^t) \quad (8)
\]

\[
\text{position}_{i,j}^{t+1} = \text{position}_{i,j}^t + v_{i,j}^{t+1} \quad (9)
\]

where, \( v_{i,j}^t \) and \( \text{position}_{i,j}^t \) denote the velocity and the agent position in \( i \)-th particles and \( j \)-th dimension at the \( t \)-th iteration, respectively. \( c_1, c_2 \) represent the individual and social factors, respectively. The \( w \) means inertia weight. \( r_1, r_2 \) are uniformly distributed random numbers in the range of \([0, 1]\).

3.2. Overview of the CS

The parasitic breeding behavior of cuckoos inspires the design of the CS algorithm [107]. Cuckoos use a levy flight strategy to search for and lay eggs on parasitic nests and randomly reselect nests with a certain chance of being found. The nests represent the candidate scenario, and the cuckoo eggs represent the new random solution. The great potential has been observed in hybrizing with other method [108]. The equation for generating new candidate solutions based on the levy flight search strategy is shown in Eq. (10) [92]:

\[
\begin{align*}
{I}_{ph} &= \left( I_{ph} \right)_t + \left( I_{ph} \right)_a + \left( I_{ph} \right)_s \\
{I}_{sd} &= \left( I_{sd} \right)_t + \left( I_{sd} \right)_a + \left( I_{sd} \right)_s
\end{align*}
\]
\[ X_{i,j}^{\text{new}} = X_{i,j}^{\text{current}} + \alpha \times (X_{i,j}^{\text{current}} - X_{\text{global}_j}) \oplus \text{Levy}(\beta) = X_{i,j}^{\text{current}} + \alpha \times (X_{i,j}^{\text{current}} - X_{\text{global}_j}) \times \]

\[ \frac{u}{\beta} \]

where, \( X_{i,j} \) denotes the agent position in \( j \)-th candidate solution and \( j \)-th dimension, \( \alpha \) represents the flight step size, \( X_{\text{global}_j} \) stands for the global solution in \( j \)-th dimension, the \( \oplus \) represents entry-wise multiplications.

The specific definitions of \( u \) and \( v \) are shown in Eq. (11) - (14):

\[ u \sim \mathcal{N}(0, \sigma_u^2) \]  
\[ v \sim \mathcal{N}(0, \sigma_v^2) \]  
\[ \sigma_u = \left[ \frac{\sin(\frac{\beta \pi}{2})}{\Gamma(1+\beta)} \right]^{\frac{1}{\beta}} \]  
\[ \sigma_v = 1 \]

where, \( \mathcal{N} \) denotes the normal distribution, \( \beta \) means the levy flight exponent, \( \Gamma(\cdot) \) represents the Gamma function.

Eq. (15) indicates that new candidate solutions that are found with probability \( (P_a) \) are regenerated randomly.

\[ X_{\text{new}_{i,j}} = \left\{ \begin{array}{ll} X_{i,j}^{\text{current}} + \text{rand} \times (X_{m1,j} - X_{m2,j}) & \text{if } K > P_a \\ X_{i,j}^{\text{current}} & \text{else} \end{array} \right. \]  

where, \( K \) and \( \text{rand} \) are uniformly distributed random numbers in the range of \([0, 1]\), \( m1 \) and \( m2 \) are randomly selected candidate solutions.

### 3.3. The conception of the PSOCS algorithm

The structure of the iterative particle search based on the information of the current optimal particle \( (p_{\text{best}}) \) and the current global particle \( (g_{\text{best}}) \) at a specific rate guarantees the exploitation capability of the PSO algorithm. In the CS algorithm, the idea of the cuckoo reselecting parasitic nests with a certain chance of being found randomly gives the algorithm a scheme to jump out of the local best solution. Thus, the PSOCS algorithm is proposed by combining the particle search structure with the idea that cuckoos randomly reselect their parasitic nests, known as random reselection mechanisms, as in Fig.4. The complete PSOCS algorithm is outlined in Algorithm 1.

The main steps of the PSOCS algorithm are as follows:

**Step 1:** Generate an initial population at random within the search range, and save the current optimal particle \( (p_{\text{best}}) \).

**Step 2:** Keep the information of the current global particle \( (g_{\text{best}}) \) in the population.

**Step 3:** Calculate the inertia weight \( w \), and update all particles using the PSO algorithm.

**Step 4:** Update the current optimal particle \( (p_{\text{best}}) \).

**Step 5:** Randomly generate \( K \), and select new particles using the random reselection mechanisms of the CS algorithm.

**Step 6:** Update the current optimal particle \( (p_{\text{best}}) \).

**Step 7:** Update the position of the current global particle \( (g_{\text{best}}) \).

**Step 8:** Determine if the conditions for reaching an iterative search stop are met. If satisfied, output the final result; otherwise, repeat steps 3-7.
Algorithm 1: Pseudo-code of PSOCS algorithm

Initialization: Maximum number of iterations \( T \), population size \( \text{sizepop} \), dimension \( \text{dim} \), upperbound \( \text{ub} \), lowerbound \( \text{lb} \), fitness, \( c_1, c_2, \omega_{\text{max}}, \omega_{\text{min}}, v, r_1, r_2 \)

1. For \( i = 1: \text{sizepop} \)
2. \( X_{i, \text{dim}} = \text{lb} + (\text{ub} - \text{lb}) \times \text{rand}(1, \text{dim}); \)
3. \( f_{\text{new}} = \text{Function}(X_{i, \text{dim}}); \)
4. if \( f_{\text{new}} \leq \text{fitness}(i) \)
5. \( \text{fitness}(i) = f_{\text{new}}; \)
6. \( p_{\text{best}, i, \text{dim}} = X_{i, \text{dim}}; \)
7. Endif
8. Endfor
9. \( [f_{\text{min}}, f_{\text{minindex}}] = \text{min}(\text{fitness}); \)
10. \( g_{\text{best}} = X_{f_{\text{minindex}}, \text{dim}}; \)
11. while \( t < T \)
12. \( \omega = \omega_{\text{max}} - t \times \frac{\omega_{\text{max}} - \omega_{\text{min}}}{T}; \)
13. For \( i = 1: \text{sizepop} \)
14. \( v_{i, \text{dim}} = \omega \times v_{i, \text{dim}} + c_1 \times r_1 \times (p_{\text{best}, i, \text{dim}} - X_{i, \text{dim}}) + c_2 \times r_2 (g_{\text{best}} - X_{i, \text{dim}}); \)
15. \( X_{i, \text{dim}} = X_{i, \text{dim}} + v_{i, \text{dim}}; \)
16. \( f_{\text{new}} = \text{Function}(X_{i, \text{dim}}); \)
17. if \( f_{\text{new}} \leq \text{fitness}(i) \)
18. \( \text{fitness}(i) = f_{\text{new}}; \)
19. \( p_{\text{best}, i, \text{dim}} = X_{i, \text{dim}}; \)
20. Endif
21. Endfor
22. \( K = \text{rand}(\text{sizepop}, \text{dim}) > p_a \)
23. \( \text{stepsize} = \text{rand} \times (X_{\text{randompermutaion}, \text{dim}} - X_{\text{randompermuatation}, \text{dim}}); \)
24. \( X_{\text{newsizepop}, \text{dim}} = X_{\text{sizepop}, \text{dim}} + \text{stepsize} \times K; \)
25. For \( i = 1: \text{sizepop} \)
26. \( f_{\text{new}} = \text{Function}(X_{\text{new}, \text{dim}}); \)
27. if \( f_{\text{new}} \leq \text{fitness}(i) \)
28. \( \text{fitness}(i) = f_{\text{new}}; \)
29. \( p_{\text{best}, i, \text{dim}} = X_{\text{new}, \text{dim}}; \)
30. Endif
31. Endfor
32. \( [\text{newmin}, \text{fminIndex}] = \text{min}(\text{fitness}); \)
33. \( g_{\text{best}} = X_{f_{\text{minIndex}}, \text{dim}}; \)
34. if \( \text{newmin} \leq f_{\text{min}} \)
35. \( g_{\text{best}} = \text{newbest}; \)
36. Endif
37. Endwhile
4. Experiments and discussions

In order to verify the feasibility of the PSOCS algorithm to handle the PV problem, this section conducts experiments in five different sets of data (RTC France, Photowatt-PWP 201, SM55, KC200GT, ST40) [96]. The RTC France data set is 26 pairs of current-voltage values measured on a commercial silicon solar cell with an irradiance of 1000 W/m², a temperature of 33°C, and a diameter of 57 mm. The Photowatt-PWP 201 data set is 25 pairs of current-voltage values measured at an irradiance of 1000 W/m² and a temperature of 45 °C for 36 photovoltaic panels made of polycrystalline silicon cells connected in series. SM55, KC200GT, and ST40 are three non-standard data sets of current-voltage for different temperature or irradiance conditions. When the temperature or irradiance dynamically changes, the range of model parameters also changes. To demonstrate the competitiveness of the PSOCS algorithm, the PSO [106], CS [107], improved JAYA algorithm (IJAYA) [109], generalized oppositional teaching-learning based optimization (GOTLBO) [110], multiple learning backtracking search algorithm (MLBSA) [111] are chosen for comparison.

To ensure the fairness of the experiments [112-115], the entire testing process is implemented in the MATLAB R2016a compilation environment, with an average of 30 tests per set of experiments, the number of particles set to 30, and the number of evaluations set to 20,000, and the accuracy of the results is assessed using absolute error of current (I\text sub{AE}), max, min, mean, and standard deviation (\text{Std}).

4.1. SDM on RTC France cell data set

In this section, tests are performed on the RTC France cell dataset to investigate the performance of the PSOCS algorithm to identify SDM. The search range for unknown parameters in the SDM on the RTC France cell dataset is included in Table 3. Table 4 lists the parameter results and RMSE extracted by all algorithms. The statistical indicator data are summarized in Table 5. Fig. 5 reveals the I-V and P-V fitting arcs of the measured data against the estimated data. Fig. 6 shows the absolute error values for the current (I\text sub{AE}) and the absolute error values for the power (P\text sub{AE}). Finally, Fig. 7 shows the convergence curves of all algorithms over the entire process.

In Table 4, the PSOCS algorithm identifies RMSE of 9.8602E-04, which is the smallest compared to the RMSE of other algorithms. The MLBSA algorithm identifies the same results as the PSOCS algorithm. The RMSEs of the IJAYA and GOTLBO algorithms are 9.8632E-04 and 9.8645E-04, respectively, which are very competitive. The PSO and CS algorithms have more inferior results with 1.0941E-03 and 1.1085E-03, respectively.

The data from 30 independent tests in Table 5 show that the PSOCS algorithm has the smallest results.
for all four metrics compared to the other algorithms. Among them, the results of std are much smaller than other algorithms. The results of the IJAYA algorithm, GOTLBO algorithm, and MLBSA algorithm are similar, but the std of the MLBSA algorithm is better. The results of the CS algorithm are better overall compared with the PSO algorithm.

**Table 3** Unknown parameter range in the SDM on the RTC France cell dataset

<table>
<thead>
<tr>
<th>SDM</th>
<th>RTC France</th>
<th>Lower Bound</th>
<th>Upper Bound</th>
</tr>
</thead>
<tbody>
<tr>
<td>$I_{ph}$ (A)</td>
<td>0</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>$I_{sd}$ (μA)</td>
<td>0</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>$R_s$ (Ω)</td>
<td>0</td>
<td>0.5</td>
<td></td>
</tr>
<tr>
<td>$R_{sh}$ (Ω)</td>
<td>0</td>
<td>100</td>
<td></td>
</tr>
<tr>
<td>$n$</td>
<td>1</td>
<td>2</td>
<td></td>
</tr>
</tbody>
</table>

**Table 4** The parameters and RMSE in the SDM on the RTC France cell dataset

<table>
<thead>
<tr>
<th>algorithm</th>
<th>PSOCS</th>
<th>PSO</th>
<th>CS</th>
<th>IJAYA</th>
<th>GOTLBO</th>
<th>MLBSA</th>
</tr>
</thead>
<tbody>
<tr>
<td>$I_{ph}$ (A)</td>
<td>7.6078E-01</td>
<td>7.6054E-01</td>
<td>7.6075E-01</td>
<td>7.6080E-01</td>
<td>7.6078E-01</td>
<td></td>
</tr>
<tr>
<td>$R_s$ (Ω)</td>
<td>3.6377E-02</td>
<td>3.5409E-02</td>
<td>3.6320E-02</td>
<td>3.6343E-02</td>
<td>3.6377E-02</td>
<td></td>
</tr>
<tr>
<td>$R_{sh}$ (Ω)</td>
<td>5.3719E+01</td>
<td>6.2253E+01</td>
<td>5.7238E+01</td>
<td>5.3944E+01</td>
<td>5.3881E+01</td>
<td>5.3718E+01</td>
</tr>
<tr>
<td>$n$</td>
<td>1.4812E+00</td>
<td>1.5062E+00</td>
<td>1.4877E+00</td>
<td>1.4819E+00</td>
<td>1.4822E+00</td>
<td>1.4812E+00</td>
</tr>
</tbody>
</table>

**Table 5** The statistical indicator data in the SDM on the RTC France cell dataset

<table>
<thead>
<tr>
<th>algorithm</th>
<th>max</th>
<th>min</th>
<th>mean</th>
<th>std</th>
</tr>
</thead>
<tbody>
<tr>
<td>PSO</td>
<td>3.8151E-02</td>
<td>1.0941E-03</td>
<td>9.2377E-03</td>
<td>1.4710E-02</td>
</tr>
<tr>
<td>CS</td>
<td>1.8980E-03</td>
<td>1.1085E-03</td>
<td>1.4564E-03</td>
<td>1.7281E-04</td>
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<tr>
<td>IJAYA</td>
<td>1.4891E-03</td>
<td>9.8632E-04</td>
<td>1.0944E-03</td>
<td>1.5919E-04</td>
</tr>
<tr>
<td>GOTLBO</td>
<td>1.4214E-03</td>
<td>9.8645E-04</td>
<td>1.1180E-03</td>
<td>1.0277E-04</td>
</tr>
<tr>
<td>MLBSA</td>
<td>1.1282E-03</td>
<td>9.8602E-04</td>
<td>1.0006E-03</td>
<td>3.0781E-05</td>
</tr>
</tbody>
</table>

**Fig.5** The fitting curves of I-V (left) and P-V (right) in SDM on the RTC France cell dataset
As can be seen from Fig.5, the I-V and P-V curves are well-fitted between the estimated data of the PSOCS algorithm optimized SDM and the measured data. The IAE for each set of voltage and power is minimal in Fig.6. The maximum of $I_{IAE}$ is $2.5074 \times 10^{-3}$, and the minimum is $8.7704 \times 10^{-5}$. The maximum of $P_{IAE}$ is $1.4626 \times 10^{-3}$, and the minimum is $1.9723 \times 10^{-6}$. The range of $I_{IAE}$ and $P_{IAE}$ is small, which indicates that the PSOCS algorithm has good stability.

In the convergence curves of Fig.7, the PSOCS algorithm converges better than the original PSO and CS algorithms and more accurately than the IJAYA, GOTLBO, and MLBSA algorithms. The PSOCS algorithm gradually converges to obtain a higher accuracy solution when the number of iterations is about 13000. The IJAYA algorithm converges fastest in the early stage. The convergence performance of the MLBSA algorithm is better than that of the GOTLBO algorithm. The PSO algorithm has the worst convergence performance.

4.2. DDM on RTC France cell data set

This section is tested on the RTC France cell dataset to investigate the performance of the PSOCS algorithm to identify DDM. In addition, this section tests the optimization effect of the algorithm in the
DDM on the RTC France cell dataset. Table 6 contains the search range for unknown parameters in the DDM on the RTC France cell dataset. The parameter results extracted by all algorithms with the RMSE are presented in Table 7. The statistical indicator data are outlined in Table 8. Fig 8 draws the I-V and P-V fitting curves of the measured data against the estimated data. Fig 9 shows the absolute error values for the current and the absolute error values for the power. Finally, Fig 10 shows the convergence curves of all algorithms in the DDM on the RTC France cell dataset.

Table 6 Unknown parameter range in the DDM on the RTC France cell dataset

<table>
<thead>
<tr>
<th></th>
<th>DDM</th>
<th>RTC France</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Lower Bound</td>
<td>Upper Bound</td>
</tr>
<tr>
<td>$I_{ph}$ (A)</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>$I_{sd}$ (μA)</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>$I_{sd}$ (μA)</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>$R_s$ (Ω)</td>
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<tr>
<td>$R_{sh}$ (Ω)</td>
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<td>$n_1$</td>
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<td>2</td>
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<tr>
<td>$n_2$</td>
<td>1</td>
<td>2</td>
</tr>
</tbody>
</table>

Table 7 The parameters and RMSE in DDM on the RTC France cell dataset

<table>
<thead>
<tr>
<th></th>
<th>PSOCS</th>
<th>PSO</th>
<th>CS</th>
<th>IJAYA</th>
<th>GOTLBO</th>
<th>MLBSA</th>
</tr>
</thead>
<tbody>
<tr>
<td>$I_{ph}$ (A)</td>
<td>7.6078E-01</td>
<td>7.6080E-01</td>
<td>7.6066E-01</td>
<td>7.6088E-01</td>
<td>7.6075E-01</td>
<td>7.6080E-01</td>
</tr>
<tr>
<td>$I_{sd}$ (μA)</td>
<td>1.0000E-00</td>
<td>3.0290E-01</td>
<td>7.5652E-01</td>
<td>4.9360E-01</td>
<td>2.7055E-01</td>
<td>5.8964E-01</td>
</tr>
<tr>
<td>$I_{sd}$ (μA)</td>
<td>1.9815E-01</td>
<td>8.8734E-02</td>
<td>3.6856E-01</td>
<td>2.3083E-01</td>
<td>2.3687E-01</td>
<td>2.3692E-01</td>
</tr>
<tr>
<td>$R_s$ (Ω)</td>
<td>3.6874E-02</td>
<td>3.6513E-02</td>
<td>3.4899E-02</td>
<td>3.6667E-02</td>
<td>3.6502E-02</td>
<td>3.6663E-02</td>
</tr>
<tr>
<td>$R_{sh}$ (Ω)</td>
<td>5.6172E+01</td>
<td>5.3173E+01</td>
<td>7.5456E+01</td>
<td>5.4070E+01</td>
<td>5.5591E+01</td>
<td>5.5083E+01</td>
</tr>
<tr>
<td>$n_1$</td>
<td>2.0000E+00</td>
<td>1.4753E+00</td>
<td>1.9859E+00</td>
<td>1.9107E+00</td>
<td>1.4669E+00</td>
<td>1.9699E+00</td>
</tr>
<tr>
<td>$n_2$</td>
<td>1.4401E+00</td>
<td>2.0000E+00</td>
<td>1.5003E+00</td>
<td>1.4536E+00</td>
<td>1.8697E+00</td>
<td>1.4553E+00</td>
</tr>
</tbody>
</table>

Table 7 shows that the PSOCS algorithm identifies an RMSE of 9.8297E-04, which is the smallest compared to the fitness values of the other algorithms. The PSO, IJAYA, GOTLBO, and MLBSA algorithms all have more competitive results with fitness values of 9.8638E-04, 9.8506E-04, 9.9183E-04, and 9.8299E-04, respectively. The CS algorithm showed more unsatisfactory results with an adaptation value of only 1.3426E-03.

By counting the results of 30 average tests, Table 8 shows that the max of the PSOCS algorithm is 1.4133E-03, the min is 9.8297E-04, the mean is 1.0286E-03 and the std is 9.9217E-05. Compared with other algorithms, the result of min is the best. The MLBSA algorithm has optimal results for max, mean, std. The results of IJAYA and GOTLBO algorithms are approximate for the four metrics. The PSO algorithm is the worst.

Table 8 The statistical indicator data in DDM on the RTC France cell dataset

<table>
<thead>
<tr>
<th>algorithm</th>
<th>max</th>
<th>min</th>
<th>mean</th>
<th>std</th>
</tr>
</thead>
<tbody>
<tr>
<td>PSOCS</td>
<td>1.4133E-03</td>
<td>9.8297E-04</td>
<td>1.0286E-03</td>
<td>9.9217E-05</td>
</tr>
<tr>
<td>Method</td>
<td>PSO</td>
<td>CS</td>
<td>IJAYA</td>
<td>GOTLBO</td>
</tr>
<tr>
<td>--------</td>
<td>-----------</td>
<td>-----------</td>
<td>-----------</td>
<td>-----------</td>
</tr>
<tr>
<td></td>
<td>3.8151E-02</td>
<td>9.8638E-04</td>
<td>1.3021E-02</td>
<td>1.5665E-02</td>
</tr>
<tr>
<td></td>
<td>3.3817E-03</td>
<td>1.3426E-03</td>
<td>2.2706E-03</td>
<td>5.1830E-04</td>
</tr>
<tr>
<td></td>
<td>1.6044E-03</td>
<td>9.8506E-04</td>
<td>1.1485E-03</td>
<td>1.6704E-04</td>
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<tr>
<td></td>
<td>1.7998E-03</td>
<td>9.9183E-04</td>
<td>1.3388E-03</td>
<td>2.2717E-04</td>
</tr>
<tr>
<td></td>
<td><strong>1.4121E-03</strong></td>
<td><strong>9.8299E-04</strong></td>
<td><strong>1.0210E-03</strong></td>
<td><strong>8.4100E-05</strong></td>
</tr>
</tbody>
</table>

Fig. 8 The fitting curves of I-V (left) and P-V (right) in DDM on the RTC France cell dataset

Fig. 9 The IAE for the current (left) and the power (right) in DDM on the RTC France cell dataset
The optimization results of the PSOCS algorithm in Fig.8 are highly fitted to the I-V and P-V curves between the estimated data and measured data. The values of the IAE for each set of voltage and power are minimal in Fig.9. The maximum absolute error of current is 2.5571E-03, and the minimum absolute error is 5.5699E-05. The maximum absolute error of power is 1.4916E-03, and the minimum absolute error is 1.8192E-06. Thus, the range of absolute errors of current and power is small, indicating that the PSOCS algorithm has good stability.

In Fig.10, the convergence accuracy of the PSOCS algorithm is approximately the same as that of the MSLBSA algorithm. The PSOCS algorithm gradually converges to obtain a higher accuracy solution when the number of iterations is about 14000. The IJAYA algorithm converges fastest at the beginning. The convergence performance of the MLBSA algorithm is better than that of the GOTLBO algorithm. The convergence performance of the PSO algorithm is the worst. The convergence performance of the CS algorithm is average.

### 4.3. PV module on the Photo-watt-PWP 201 data sets

In this section, experiments are conducted on the Photo-watt-PWP 201 dataset to investigate the performance of the PSOCS algorithm to identify the PV module. In addition, this section experimentally tests the optimization effect of the algorithm in the Photo-watt-PWP 201 data set. Tables 9, 10, and 11 contain the search scope for unknown parameters, optimization results, and indicator statistics. Fig.11, Fig.12, and Fig.13 plot the fitted curves, absolute error values, and convergence curves, respectively.

#### Table 9 Unknown parameter range in the PV module on the Photo-watt-PWP 201 data set

<table>
<thead>
<tr>
<th>PV module</th>
<th>Photowatt-PWP 201</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Lower Bound</td>
</tr>
<tr>
<td>$I_{ph}$ (A)</td>
<td>0</td>
</tr>
<tr>
<td>$I_{sd}$ (μA)</td>
<td>0</td>
</tr>
<tr>
<td>$R_s$ (Ω)</td>
<td>0</td>
</tr>
<tr>
<td>$R_{sh}$ (Ω)</td>
<td>0</td>
</tr>
<tr>
<td>$n$</td>
<td>1</td>
</tr>
</tbody>
</table>
The parameters and RMSE in PV module on the Photo-watt-PWP 201 dataset

<table>
<thead>
<tr>
<th>Algorithm</th>
<th>( I_p ) (A)</th>
<th>( I_s ) (μA)</th>
<th>( R_s ) (Ω)</th>
<th>( R_{sh} ) (Ω)</th>
<th>( n )</th>
<th>RMSE</th>
</tr>
</thead>
<tbody>
<tr>
<td>PSOCS</td>
<td>1.0305E+00</td>
<td>3.4823E-00</td>
<td>1.2013E+00</td>
<td>9.8198E+02</td>
<td>4.8643E+01</td>
<td>2.4251E-03</td>
</tr>
<tr>
<td>PSO</td>
<td>1.0303E+00</td>
<td>3.6399E-00</td>
<td>1.1967E+00</td>
<td>1.0322E+03</td>
<td>4.8813E+01</td>
<td>2.4282E-03</td>
</tr>
<tr>
<td>CS</td>
<td>1.0294E+00</td>
<td>3.7326E-00</td>
<td>1.1959E+00</td>
<td>1.1486E+03</td>
<td>4.8908E+01</td>
<td>2.4450E-03</td>
</tr>
<tr>
<td>IJAYA</td>
<td>1.0307E+00</td>
<td>3.5367E-00</td>
<td>1.1996E+00</td>
<td>9.7704E+02</td>
<td>4.8703E+01</td>
<td>2.4268E-03</td>
</tr>
<tr>
<td>GOTLBO</td>
<td>1.0305E+00</td>
<td>3.4441E-00</td>
<td>1.2025E+00</td>
<td>9.8005E+02</td>
<td>4.8600E+01</td>
<td>2.4255E-03</td>
</tr>
<tr>
<td>MLBSA</td>
<td>1.0305E+00</td>
<td>3.4823E-00</td>
<td>1.2013E+00</td>
<td>9.8198E+02</td>
<td>4.8643E+01</td>
<td>2.4251E-03</td>
</tr>
</tbody>
</table>

The RMSE values in Table 10 indicate that the PSOCS algorithm is better optimized than other algorithms. The PSOCS algorithm identifies PV with an adaptation value of 2.4251E-03, which is the smallest compared to the adaptation values of the other algorithms. The MLBSA algorithm identifies the same results as the PSOCS algorithm. The PSO, CS, IJAYA, and GOTLBO algorithms identify 2.4282E-03, 2.4450E-03, 2.4268E-03, and 2.4255E-03, which are not optimum, but the difference with the results of the PSOCS algorithm is minimal.

The standard deviation values in Table 11 demonstrate the strong robustness of the PSOCS algorithm. The PSOCS algorithm has the best value of optimization compared to other algorithms in all four statistical indicators. The results of max, mean, and std of the PSO algorithm are worse than the other algorithms. The results of the four metrics are similar between the CS algorithm and the GOTLBO algorithm. The results of each metric of the MLBSA algorithm are slightly better than the results of the IJAYA algorithm.

The curves in Fig.11 and Fig.12 show that there is a high fit between the SDM optimized by the PSOCS algorithm and the actual model. Fig.13 shows that the convergence accuracy of the PSOCS algorithm is higher than the basic PSO algorithm and CS algorithm and slightly better than GOTLBO and MLBSA algorithms. The PSOCS algorithm gradually converges to obtain a higher accuracy solution at about 12,000 iterations. The GOTLBO algorithm and MLBSA algorithm converge with similar speed and convergence accuracy. The PSO algorithm has the worst convergence performance.
Fig. 11 The fitting curves of I-V (left) and P-V (right) in PV module on the Photo-watt-PWP 201 dataset.

Fig. 12 The IAE for the current (left) and the power (right) in PV module on the Photo-watt-PWP 201 dataset.
4.4. Analysis of the number of different particles

This section experiments the performance of the algorithms to identify the SDM, DDM, and PV module parameters under the condition that the number of evaluations is 20,000 and the particles are set to 10, 20, 30, 40, 50, and 60. Fig.14, Fig.15, and Fig.16 plot the convergence curves of all algorithms for different particle conditions.

The curves show that the PSOCS algorithm has the best comprehensive convergence performance when the number of particles is set to 30. In Fig.14, as the number of particles is 10, the convergence performance of the PSOCS algorithm is only better than that of the PSO algorithm. With the condition that the number of particles is more than 20, the convergence accuracy of the PSOCS algorithm is optimal while the convergence speed gradually decreases. In Fig.15 and Fig.16, the PSOCS algorithm shows the highest convergence accuracy only when the particle is larger than 30, but the convergence speed also decreases gradually. Therefore, the appropriate value for the particle size is 30 by combining the analysis of the PSOCS algorithm to identify the SDM, DDM, and PV module convergence performance.
4.5. SDM and DDM on the manufacturer's data

This section tests the PSOCS algorithm for parameter recognition of SDM and DDM at different irradiances and temperatures on SM55, KC200GT, ST40 data sets. Table 12 contains the search range for unknown parameters. $I_p$ is related to the short-circuit current ($I_{SC}$) and is calculated, as shown in Eq. (16). $G$ and $T$ represent dynamic irradiance and temperature, respectively, $\alpha$ denotes the temperature coefficient of short-circuit current, and the subscript $STC$ denotes standard conditions.

$$I_{SC}(G, T) = I_{SCSTC} \times \frac{G}{G_{STC}} + \alpha \times (T - T_{STC})$$  \hspace{1cm} (16)

<table>
<thead>
<tr>
<th>SDM / DDM</th>
<th>Manufacturer's data</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Lower Bound</td>
</tr>
<tr>
<td>$I_p$ (A)</td>
<td>0</td>
</tr>
<tr>
<td>$I_o$ (μA) / $I_{sd}$ (μA), $I_{sh}$ (μA)</td>
<td>0</td>
</tr>
<tr>
<td>$R_s$ (Ω)</td>
<td>0</td>
</tr>
<tr>
<td>$R_{sh}$ (Ω)</td>
<td>0</td>
</tr>
<tr>
<td>$n$ / $n_{1,2}$</td>
<td>1</td>
</tr>
</tbody>
</table>

Table 13 means the parameter results of the PSOCS algorithm to identify the SDM and DDM on the ST 40 dataset with the irradiance at a constant value of 1000 W/m$^2$ at temperatures of 25 °C, 40 °C, 50 °C, and 70 °C, respectively.

The PSOCS algorithm identifies the smallest RMSE value for SDM at the condition of 70°C. In contrast, the RMSE value for the PSOCS algorithm to identify DDM is smallest at the condition of 25°C.

Table 14 shows the results of the PSOCS algorithm for identifying SDM and DDM on the ST 40 dataset with a constant temperature of 25°C and irradiances of 200 W/m$^2$, 400 W/m$^2$, 600 W/m$^2$, 800 W/m$^2$, and 1000 W/m$^2$.

It can be seen that the PSOCS algorithm performs better in optimizing the SDM than in optimizing the DDM. The RMSE value of the PSOCS algorithm to identify SDM and DDM is minimum at 200W/m$^2$. Overall, the discrimination accuracy of the PSOCS algorithm increases as the irradiance decreases.

Table 15 represents the parameter results of the PSOCS algorithm to identify the SDM and the DDM on the SM 55 dataset at a constant irradiance of 1000 W/m$^2$ and temperatures of 25°C, 40°C, and 60°C,
respectively.

At 60°C, the PSOCS algorithm discriminates the smallest fitness values for SDM, DDM, and 3.7804E-03 and 3.7827E-03, respectively. As the temperature increases, the discrimination accuracy of the PSOCS algorithm increases.

Table 16 contains the parameters and fitness values for the PSOCS algorithm to discriminate SDM and DDM on the SM55 dataset. Among the non-standard conditions, the temperature is 25°C, and the irradiances are 1000 W/m², 800 W/m², 600 W/m², 400 W/m², and 200 W/m², respectively. Therefore, the RMSE value of the PSOCS algorithm to identify SDM and DDM is minimum at 200W/m², 5.6955E-04, and 5.3206E-04, respectively.

Table 17 represents the results of the PSOCS algorithm on the KC200GT dataset for identifying parameters at a constant irradiance of 1000 W/m² and temperatures of 25°C, 50°C, and 75°C, respectively.

The PSOCS algorithm recognizes the SDM with the smallest fitness value at 75°C. The accuracy of the PSOCS algorithm increases with the increase of temperature. The adaptation value of the PSOCS algorithm to recognize DDM is the smallest at 50°C.

Table 18 consists of the accurate parameters and adaptation values of the PSOCS algorithm for identifying SDM and DDM on the KC200GT dataset. Among the non-standard conditions, the temperature is 25°C, and the irradiance is 1000 W/m², 800 W/m², 600 W/m², 400 W/m² and 200 W/m², respectively.

At 200 W/m², the values of both discriminative SDM and DDM adaptation are minimum. Overall, the discrimination accuracy of the PSOCS algorithm increases as the irradiance decreases.

Fig. 17, Fig. 18, Fig. 19, Fig. 20, Fig. 21, and Fig. 22 show that the PSOCS algorithm exhibits stable optimization performance in response to different irradiances and temperatures.

Table 13 The parameters and RMSE on the ST 40 dataset at different temperature

<table>
<thead>
<tr>
<th>ST 40 / 1000 W/m²</th>
<th>SDM</th>
<th>DDM</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>25 °C</td>
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</tr>
<tr>
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<td></td>
<td></td>
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<td>3.6882E+02</td>
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<td></td>
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<td>1.7697E+00</td>
</tr>
<tr>
<td></td>
<td>RMSE</td>
<td>1.0815E-03</td>
</tr>
<tr>
<td></td>
<td></td>
<td>2.6753E+00</td>
</tr>
</tbody>
</table>

Fig. 17 The fitting curves of SDM (left) and DDM (right) on the ST 40 dataset at different temperature
Table 14 The parameters and RMSE on the ST 40 dataset at different irradiance

<table>
<thead>
<tr>
<th>Irradiance</th>
<th>SDM</th>
<th>DDM</th>
</tr>
</thead>
<tbody>
<tr>
<td>1000 W/m²</td>
<td>2.6758E+00</td>
<td>2.6743E+00</td>
</tr>
<tr>
<td>800 W/m²</td>
<td>2.1376E+00</td>
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<tr>
<td>600 W/m²</td>
<td>1.6042E+00</td>
<td>1.6025E+00</td>
</tr>
<tr>
<td>400 W/m²</td>
<td>1.0667E+00</td>
<td>1.0675E+00</td>
</tr>
<tr>
<td>200 W/m²</td>
<td>5.3280E-01</td>
<td>5.3319E-01</td>
</tr>
</tbody>
</table>

Table 15 The parameters and RMSE on the SM 55 dataset at different temperature

<table>
<thead>
<tr>
<th>Temperature</th>
<th>SDM</th>
<th>DDM</th>
</tr>
</thead>
<tbody>
<tr>
<td>25 °C</td>
<td>3.4419E+00</td>
<td>3.4842E+00</td>
</tr>
<tr>
<td>40 °C</td>
<td>3.4682E+00</td>
<td>3.4945E+00</td>
</tr>
<tr>
<td>60 °C</td>
<td>3.4946E+00</td>
<td>3.5044E+00</td>
</tr>
</tbody>
</table>

Fig.18 The fitting curves of SDM (left) and DDM (right) on the ST 40 dataset at different irradiance.
### Table 16: The parameters and RMSE on the SM 55 dataset at different irradiance

<table>
<thead>
<tr>
<th>Irradiance</th>
<th>1000 W/m²</th>
<th>800 W/m²</th>
<th>600 W/m²</th>
<th>400 W/m²</th>
<th>200 W/m²</th>
</tr>
</thead>
<tbody>
<tr>
<td>SM 55 / 25°C</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

**SDM**

- \( R_0 \) (Ω): 2.8468E-01, 3.0545E-01, 3.1874E-01
- \( R_s \) (Ω): 1.0724E+03, 5.8094E+02, 4.8429E+02
- \( n \): 1.4990E+00, 1.4346E+00, 1.4050E+00
- \( I_{p0} \) (A): 3.4365E+00, 3.4684E+00, 3.4947E+00
- \( I_{s0} \) (µA): 1.3066E+00, 0.0000E+00, 6.8490E-00
- \( I_{sd1} \) (µA): 1.3066E+00, 0.0000E+00, 6.8490E-00
- \( n_1 \): 1.1100E+00, 4.0000E+00, 1.4042E+00
- \( n_2 \): 1.7530E+00, 1.4296E+00, 4.0000E+00
- RMSE: 6.0297E-03, 3.9452E-03, 3.7804E-03

**DDM**

- \( R_0 \) (Ω): 3.5589E-01, 3.0772E-01, 3.1899E-01
- \( R_s \) (Ω): 5.0000E+03, 5.7325E+02, 4.8237E+02
- \( n \): 1.4586E+00, 1.4652E+00, 1.4389E+00
- \( I_{p0} \) (A): 3.4459E+00, 2.7549E+00, 2.0696E+00
- \( I_{s0} \) (µA): 1.3066E+00, 0.0000E+00, 6.8490E-00
- \( I_{sd1} \) (µA): 1.3066E+00, 0.0000E+00, 6.8490E-00
- \( n_1 \): 1.1100E+00, 4.0000E+00, 1.4042E+00
- \( n_2 \): 1.7530E+00, 1.4296E+00, 4.0000E+00
- RMSE: 5.3503E-03, 3.8691E-03, 3.7827E-03

**Fig. 19** The fitting curves of SDM (left) and DDM (right) on the SM 55 dataset at different temperature.
Fig. 20 The fitting curves of SDM (left) and DDM (right) on the SM 55 dataset at different irradiance.

Table 17 The parameters and RMSE on the KC200GT dataset at different temperature

<table>
<thead>
<tr>
<th>KC200GT / 1000 W/m²</th>
<th>Temperature</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>25 °C</td>
</tr>
<tr>
<td>SDM</td>
<td></td>
</tr>
<tr>
<td>$I_p$ (A)</td>
<td>8.2156E+00</td>
</tr>
<tr>
<td>$I_o$ (μA)</td>
<td>5.0936E-02</td>
</tr>
<tr>
<td>$R_s$ (Ω)</td>
<td>2.8360E-01</td>
</tr>
<tr>
<td>$R_a$ (Ω)</td>
<td>4.9925E+03</td>
</tr>
<tr>
<td>$n_1$</td>
<td>1.2519E+00</td>
</tr>
<tr>
<td>RMSE</td>
<td>2.5402E-02</td>
</tr>
<tr>
<td>DDM</td>
<td></td>
</tr>
<tr>
<td>$I_p$ (A)</td>
<td>8.2130E+00</td>
</tr>
<tr>
<td>$I_o$ (μA)</td>
<td>0.0000E+00</td>
</tr>
<tr>
<td>$I_o2$ (μA)</td>
<td>4.7518E-02</td>
</tr>
<tr>
<td>$R_s$ (Ω)</td>
<td>2.8525E-01</td>
</tr>
<tr>
<td>$R_a$ (Ω)</td>
<td>2.9592E+03</td>
</tr>
<tr>
<td>$n_1$</td>
<td>2.1805E+00</td>
</tr>
<tr>
<td>$n_2$</td>
<td>1.2474E+00</td>
</tr>
<tr>
<td>RMSE</td>
<td>2.4901E-02</td>
</tr>
</tbody>
</table>

Fig. 21 The fitting curves of SDM (left) and DDM (right) on the KC200GT dataset at different temperature.

Table 18 The parameters and RMSE on the KC200GT dataset at different irradiance.
<table>
<thead>
<tr>
<th>KC200GT / 25°C</th>
<th>Irradiance</th>
<th>1000 W/m²</th>
<th>800 W/m²</th>
<th>600 W/m²</th>
<th>400 W/m²</th>
<th>200 W/m²</th>
</tr>
</thead>
<tbody>
<tr>
<td>SDM</td>
<td>(I_{ph}) (A)</td>
<td>8.2126×10⁰⁰</td>
<td>6.5696×10⁰⁰</td>
<td>4.9246×10⁰⁰</td>
<td>3.2770×10⁰⁰</td>
<td>1.6435×10⁰⁰</td>
</tr>
<tr>
<td></td>
<td>(I_d) (μA)</td>
<td>7.9566×10⁻⁰²</td>
<td>3.3751×10⁻⁰²</td>
<td>4.9246×10⁻⁰²</td>
<td>3.2770×10⁻⁰²</td>
<td>9.4206×10⁻⁰³</td>
</tr>
<tr>
<td></td>
<td>(R_s) (Ω)</td>
<td>2.7337×10⁻⁰¹</td>
<td>2.8445×10⁻⁰¹</td>
<td>2.6703×10⁻⁰¹</td>
<td>2.2851×10⁻⁰¹</td>
<td>1.0158×10⁻⁰¹</td>
</tr>
<tr>
<td></td>
<td>(R_a) (Ω)</td>
<td>5.0000×10⁰³</td>
<td>2.2272×10⁰³</td>
<td>5.0000×10⁰³</td>
<td>5.0000×10⁰³</td>
<td>8.5900×10⁰³</td>
</tr>
<tr>
<td></td>
<td>(n)</td>
<td>1.2818×10⁰⁰</td>
<td>1.2273×10⁰⁰</td>
<td>1.2469×10⁰⁰</td>
<td>1.2144×10⁰⁰</td>
<td>1.1537×10⁰⁰</td>
</tr>
<tr>
<td></td>
<td>RMSE</td>
<td>2.9522×10⁻⁰²</td>
<td>2.4739×10⁻⁰²</td>
<td>1.3865×10⁻⁰²</td>
<td>8.5884×10⁻⁰³</td>
<td>3.6947×10⁻⁰³</td>
</tr>
<tr>
<td>DDM</td>
<td>(I_{ph}) (A)</td>
<td>8.2191×10⁰⁰</td>
<td>6.5694×10⁰⁰</td>
<td>4.9220×10⁰⁰</td>
<td>3.2746×10⁰⁰</td>
<td>1.6437×10⁰⁰</td>
</tr>
<tr>
<td></td>
<td>(I_d) (μA)</td>
<td>9.1526×10⁻⁰²</td>
<td>6.5933×10⁻⁰²</td>
<td>4.7072×10⁻⁰²</td>
<td>5.1369×10⁻⁰²</td>
<td>0.0000×10⁰⁰</td>
</tr>
<tr>
<td></td>
<td>(R_s) (Ω)</td>
<td>2.7337×10⁻⁰¹</td>
<td>2.8445×10⁻⁰¹</td>
<td>2.6703×10⁻⁰¹</td>
<td>2.2851×10⁻⁰¹</td>
<td>1.0158×10⁻⁰¹</td>
</tr>
<tr>
<td></td>
<td>(R_a) (Ω)</td>
<td>5.0000×10⁰³</td>
<td>2.0719×10⁰³</td>
<td>5.0000×10⁰³</td>
<td>5.0000×10⁰³</td>
<td>8.1768×10⁰²</td>
</tr>
<tr>
<td></td>
<td>(n_1)</td>
<td>1.2913×10⁰⁰</td>
<td>1.2708×10⁰⁰</td>
<td>1.2526×10⁰⁰</td>
<td>1.4012×10⁰⁰</td>
<td>3.6681×10⁰⁰</td>
</tr>
<tr>
<td></td>
<td>(n_2)</td>
<td>4.0000×10⁰⁰</td>
<td>4.0000×10⁰⁰</td>
<td>3.9860×10⁰⁰</td>
<td>1.0527×10⁰⁰</td>
<td>1.1410×10⁰⁰</td>
</tr>
<tr>
<td></td>
<td>RMSE</td>
<td>3.1070×10⁻⁰²</td>
<td>2.9588×10⁻⁰²</td>
<td>1.4339×10⁻⁰²</td>
<td>6.3516×10⁻⁰³</td>
<td>3.5119×10⁻⁰³</td>
</tr>
</tbody>
</table>

Fig. 22 The fitting curves of SDM (left) and DDM (right) on the KC200GT dataset at different irradiance.

### 4.6. Discussions

Testing the algorithm’s feasibility to handle the PV problem on five different data sets reveals that the PSOCS algorithm has better discrimination performance. The results of the PSOCS algorithm for identifying SDM and DDM on the RTC France cell dataset and identifying PV module on the Photo-watt-PWP 201 dataset are better than the identification results of the selected metaheuristic algorithms. By counting the results of 30 average tests, the PSOCS algorithm is competitive with other algorithms for all four metrics. The range of absolute errors of current and power is small, indicating that the PSOCS algorithm has good stability. The convergence curves display that the PSOCS algorithm gradually converges to higher accuracy solutions between iterations of 12,000 and 14,000. The discrimination of SDM and DDM parameters on the SM55, KC200GT, and ST40 datasets show that the discrimination accuracy of the PSOCS algorithm increases with decreasing irradiance when the temperature condition is 25°C, while the accuracy increases with increasing temperature when the irradiance is 1000 W/m².

As per good results of the proposed optimization core, the proposed PSOCS can also be applied to other optimization problems, such as medical diagnosis [116-119], service ecosystem [120, 121], image dehazing [122-124], covert communication system [125-127], image editing [128-130], and micro-expression spotting.
Also, it can be further enhanced to deal with complex scenarios such as brain function prediction [133, 134], regression tasks [135], Lunar impact crater identification and age estimation [136], engineering optimization problems [137, 138], shape registration [139], energy storage planning and scheduling [140], large scale network analysis [141], and feature selection [142-144]. The proposed PSO-based optimizer shows unique exploratory and exploitative trends without dependency on the solved problems. Hence, it can also be utilized for dynamic and complex control problems [145-149] and engineering device design [150-154].

5. Conclusions and future work

In this paper, a new hybrid PSO-based algorithm based on random reselection mechanisms is designed to take advantage of the strengths of the PSO algorithm and revise the core method using the unique features of the CS algorithm. The PSO algorithm can handle high-precision problems, while the CS algorithm is better at handling multi-modal problems. The PSOCS algorithm reconstructs the particle swarm search method in the PSO algorithm, and the random reselection mechanisms appeared in cuckoo's randomly reselected parasitic nest strategy in the CS algorithm to balance the relationship between exploration and exploitation. The results of the PSOCS algorithm applied to the PV demonstrate the effectiveness of the new PSO-based method. Statistical data on the optimization of the SDM, DDM, and PV module shows that the convergence accuracy and robustness of the developed parameter identifier algorithm are superior to those obtained by the original PSO, CS algorithms, and other meta-heuristics. The PSOCS algorithm also exhibits strong stability under various conditions and the external conditions of temperature and irradiance.

The combination of the particle search of the PSO algorithm with the random reselection of the parasitic nest strategy of the CS algorithm makes the time complexity of the PSOCS algorithm higher than that of the PSO algorithm and reduces the convergence speed of the whole algorithm. Therefore, we hope further to balance the exploration and exploitation of the PSOCS algorithm to improve the convergence speed while ensuring the convergence accuracy of the PSOCS algorithm in future work.
Acknowledgments

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1. A new algorithm (PSOCS) is proposed for accurate extraction the parameters of solar photovoltaic system model.
2. PSOCS is proposed based on the core components of the particle swarm optimizer and cuckoo search.
3. PSOCS has higher convergence accuracy and better results than other peers.
4. PSOCS were evaluated under different irradiance levels and temperature levels.
Declaration of interests

☑ The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

☐ The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: