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# A comprehensive survey on meta-heuristic algorithms for parameter extraction of photovoltaic models

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ABSTRACT

Photovoltaic (PV) cells are widely used for their clean and sustainable advantages, forcing researchers to accurately model their characteristics. The behavior of PV cells can be derived from their current–voltage characteristics, depending on their unknown circuit model parameters. Due to the simulation, evaluation, control, and optimization of PV systems, it is essential to accurately and reliably extract the parameters of PV models. However, because of the non-linear, multi-variable, and multi-modal characteristics, it is still a very challenging task. With the rapid development of intelligent computing, various meta-heuristic algorithms have been devoted to extracting the parameters of different PV models. The purpose of this paper is to comprehensively review the meta-heuristic algorithms and their related variants that have been used to extract the parameters of different PV models. Different from the existing research works, this paper presents a comprehensive review based on the reliability, robustness, computational resources, and time complexity of the algorithm. These features are essential to design an algorithm for efficient parameter extraction of PV models. Based on the conducted review, some useful recommendations are provided, which have important reference significance when designing the new parameter extraction methods of PV models and are of great significance for further improving the performance, control, and design of PV cells.

## 1. Introduction

Due to the large amount of traditional energy used in the past, it has caused significant environmental impacts, such as environmental pollution. As a result, in order to strengthen the protection of the environment, the use of alternative renewable energy sources has received great attention in recent years [1,2]. Among the currently popular renewable energy sources, such as solar, wind, wave, nuclear, tidal, and geothermal, solar energy is considered as one of the most profitable renewable energy resources, thanks to its wide availability and cleanness [3,4]. Therefore, it has been applied for many practical applications, such as oil industry [5], hot water provision [6], agriculture [7], wireless sensor [8], and photovoltaic (PV) systems [9–12]. In these applications, solar PV systems play an important role in the world's renewable energy development, because it can directly convert solar energy into electricity energy [13,14].

For a PV system, accurate modeling is essential. Over the past few decades, significant progress has been made in understanding the behavior of the PV system characteristics through mathematical modeling. The widely used models are to simulate the behavior of real PV cells, that is, to fit their measured current–voltage ($I$-$V$) data under all operating conditions [15]. Equivalent circuit models, which are made of diodes, are usually used. In this regard, the most commonly used models are the single diode model (SDM) [16] and the double diode model (DDM) [17]. Besides, the triple diode model (TDM) [18,19] is also proposed to describe the $I$-$V$ characteristic curve. Based on these equivalent models, there are five, seven, and nine parameters that need to be estimated, respectively. Accurate parameter extraction of PV models is of great significance not only for the evaluation of PV cell performance, but also for PV cell design improvements, optimization of manufacturing processes, and quality control [20,21]. Therefore, feasible parameter identification techniques become particularly urgent.

Due to its non-linear, multi-variable, and multi-modal characteristics, parameter extraction of PV models is still an important and challenging task. In recent years, various approaches have been employed for parameter extraction of PV models. From these reported approaches, they can be categorized into two main types: key-point based methods and $I$-$V$ characteristic curves based methods. In order to vividly illustrate the development trend of these two methods, Fig. 1

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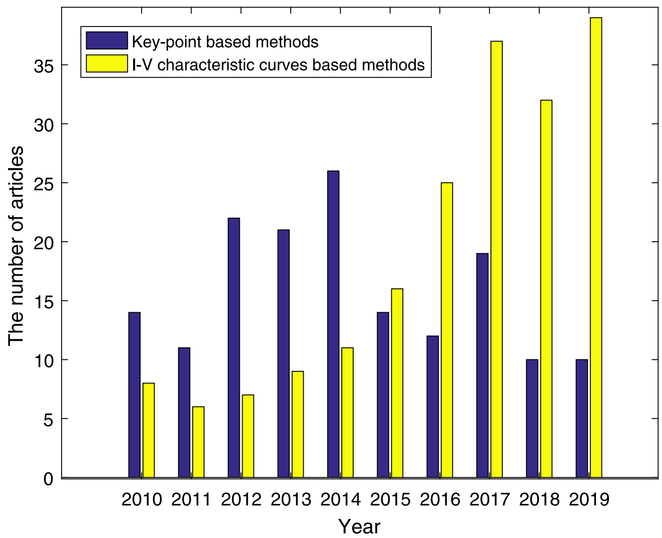


**Fig. 1.** The number of articles for both methods over the years in WoS.

shows the number of articles published based on these two methods in the past ten years. From Fig. 1, two points can be drawn: 1) the number of the key-point based method is more than the $I$-$V$ characteristic curves based method before 2014, and after 2014, the latter exceeds the former; 2) the $I$-$V$ characteristic curves based method is attracting more and more attention. The two types of methods are described below:

(i) *Key-point based methods*: These methods [22–25] are relatively simple and easy to be implemented, but the extracted parameters are not accurate enough. It reduces the model parameters by analyzing and simplifying the model equations, and then extracts PV models parameters via several key points, such as short-circuit current, open-circuit voltage, and maximum power point.

ii) *$I$-$V$ characteristic curves based methods*: Different from the above methods, $I$-$V$ characteristic curves based methods are to minimize the overall error between the simulated current and the measured current by numerical optimization techniques. This type of method does not require complex analysis and derivation, but may consume more computing resources. Commonly used numerical optimization techniques are deterministic and meta-heuristic methods.

For the deterministic methods [26–29], they can quickly find the optimal solution. But their performance are highly sensitive to the given initial guess. When employing these methods, it may face a risk that once the initial guess given is not better, it will trap into a local optimum. With the development of intelligent computing, meta-heuristic methods, inspired by natural phenomena, have received great attention and have been widely applied to engineering optimization, especially in highly non-linear and complex problems [4,30]. The prominent advantages of meta-heuristic methods are that they are simple, effective, easy to be implemented, and do not rely on the characteristics of the mathematical model of the studied system. Thus, in the last few years, various meta-heuristic algorithms have been used for parameter extraction of PV models.

In order to provide a state-of-the-art introduction of these studies, in this paper, a comprehensive review on meta-heuristic algorithms and related variants that have been developed for the PV models parameter extraction, is carried out. Different from some existing works [4,16,17,21], this paper attempts to analyze, discuss, and summarize some representative meta-heuristic methods for PV models parameter extraction according to the statistical results rather than a certain evaluation criteria. In other words, in some existing reviews, most are reviewed based on the best objective function value, such as the best root mean square error, provided by the researcher, while ignoring some important statistical results including the maximum, average, standard deviation, maximum number of function evaluations, and CPU time. It is undeniable that the best objective function value can reflect the accuracy of the algorithm to a certain extent. However, it cannot indicate the reliability, robustness, computational resources, and time complexity of the algorithm. Therefore, these statistical results should be taken into consideration, which is meaningful for a more comprehensive analysis of these meta-heuristic algorithms on PV models parameter extraction. Based on the above considerations, according to the statistical results, some representative meta-heuristic methods used for PV models parameter extraction in recent years are selected to review for further research in the future.

The main contributions of this paper are given as follows:

- Some common PV models, such as the single diode, the double diode, the triple diode, and the PV module model, and their parameter optimization problems are described.
- According to the statistical results, some representative meta-heuristic methods for parameter extraction of PV models in recent years are reviewed.
- The paper summarizes the various important discoveries made so far in the field of parameter extraction of PV models and provides some future research directions.

The rest of this paper is organized as follows. Section 2 gives the mathematical formulation of different PV models. The optimization problem of PV model parameter extraction is described in Section 3. Section 4 reviews some representative meta-heuristic algorithms for PV models parameter extraction. Section 5 provides the discussion about different parameter extraction techniques and some future researches. Finally, Section 6 concludes this paper.

## 2. Mathematical formulation of PV models

As mentioned in Section 1, three equivalent circuit models are used to fit the $I$-$V$ characteristic curve of the PV cell, i.e, SDM, DDM, and TDM. In this section, the detailed mathematical formulation of different PV models are described.

### 2.1. Single diode model

One of the most commonly used PV models is the SDM which has a simple structure and is easy to implement. As shown in Fig. 2(a), the equivalent circuit of the SDM is composed of a diode $D$, a current source, a series resistor $R_s$, and a shunt resistor $R_{sh}$. The output current $I$ can be formulated as follows [31]:

$$I = I_{ph} - I_d - I_{sh} \tag{1}$$

where $I_{ph}$ is the photo-generated current, $I_d$ is the diode current, and $I_{sh}$ is the shunt resistor current.

Then, complying with the Shockley equation and Kirchhoff's Voltage Law, $I_d$ and $I_{sh}$ can be calculated as follows:

$$I_d = I_{sd}\left[\exp\left(\frac{V + I R_s}{n V_t}\right) - 1\right] \tag{2}$$

$$I_{sh} = \frac{V + I R_s}{R_{sh}} \tag{3}$$

where $I_{sd}$ is the diode reverse saturation current; $n$ represents the non-physical diode ideality factor; $V$ denotes the cell output voltage, and $V_t$ is the junction thermal voltage which is formulated as below:

$$V_t = \frac{k \cdot T}{q} \tag{4}$$

where $k = 1.3806503\times10^{-23}$ J/K is the Boltzmann constant; $T$ represents the temperature of junction in Kelvin; and $q = 1.60217646 \times 10^{-19}$ C indicates the electron charge.

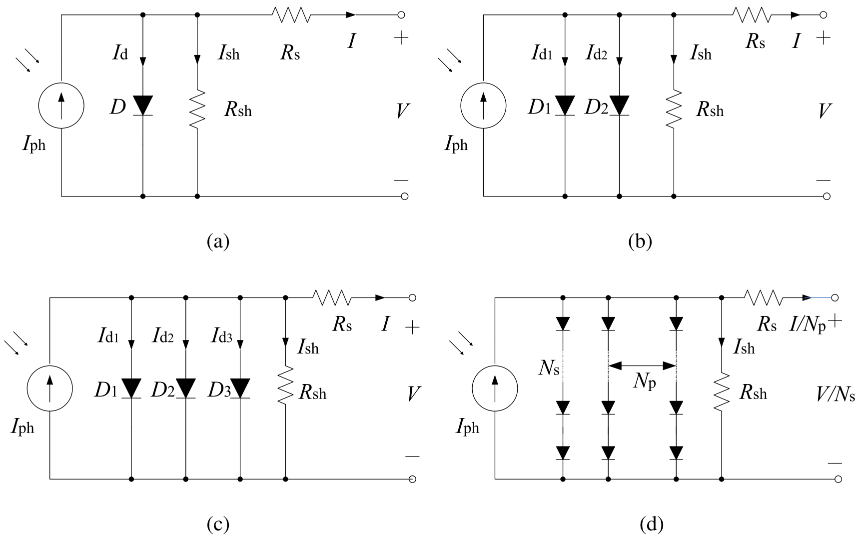


**Fig. 2.** Equivalent circuit of PV models: (a) SDM, (b) DDM, (c) TDM, (d) SMM.

Based on Eqs. (1)–(4), the output current $I$ can be calculated as follows:

$$I = I_{ph} - I_{sd}\left[\exp\left(\frac{V + IR_s}{nV_t}\right) - 1\right] - \frac{V + IR_s}{R_{sh}} \tag{5}$$

where five unknown parameters, including $I_{ph}$, $I_{sd}$, $R_s$, $R_{sh}$, and $n$, need to be identified in the SDM.

### 2.2. Double diode model

Considering the effect of recombination current loss in the depletion region, the DDM has been put forward, which is considered to be more precise than the SDM. The equivalent circuit of the DDM is given in Fig. 2(b), where it can be seen that there are two diodes ($D_1$ and $D_2$) in this model. The output current $I$ is formulated as follows [31,32]:

$$I = I_{ph} - I_{d_1} - I_{d_2} - I_{sh} \tag{6}$$

where $I_{d_1}$, $I_{d_2}$ represent the first and second diode currents, respectively. Similar to the definition of $I_d$, the $I_{d_1}$, $I_{d_2}$ are calculated as follow:

$$I_{d_1} = I_{sd_1}\left[\exp\left(\frac{V + IR_s}{n_1 V_t}\right) - 1\right] \tag{7}$$

$$I_{d_2} = I_{sd_2}\left[\exp\left(\frac{V + IR_s}{n_2 V_t}\right) - 1\right] \tag{8}$$

Thus, the output current $I$ can be calculated as follows:

$$I = I_{ph} - I_{sd_1}\left[\exp\left(\frac{V + IR_s}{n_1 V_t}\right) - 1\right] - I_{sd_2}\left[\exp\left(\frac{V + IR_s}{n_2 V_t}\right) - 1\right] - \frac{V + IR_s}{R_{sh}} \tag{9}$$

where $I_{sd_1}$, $I_{sd_2}$ are diffusion and saturation currents, respectively; and $n_1$, $n_2$ represent respectively the first and second non-physical diode ideality factors.

From Eq. (9), there are seven unknown parameters ($I_{ph}$, $I_{sd_1}$, $I_{sd_2}$, $R_s$, $R_{sh}$, $n_1$, and $n_2$).

### 2.3. Triple diode model

Besides the SDM and DDM, another PV model, the TDM which takes the influence of grain boundaries and large leakage current into consideration, is proposed in [18]. The equivalent circuit of the TDM is given in Fig. 2(c), it is clear that a third diode ($D_3$) is added in parallel with the two diodes of the DDM, and its output current $I$ is calculated as follows:

$$I = I_{ph} - I_{d_1} - I_{d_2} - I_{d_3} - I_{sh} \tag{10}$$

where $I_{d_1}$, $I_{d_2}$, $I_{d_3}$ are the first, second, third diode currents, respectively, and $I_{d_3}$ is formulated as follow:

$$I_{d_3} = I_{sd_3}\left[\exp\left(\frac{V + IR_s}{n_3 V_t}\right) - 1\right] \tag{11}$$

Then, the output current $I$ can be expressed as follows:

$$I = I_{ph} - I_{sd_1}\left[\exp\left(\frac{V + IR_s}{n_1 V_t}\right) - 1\right] - I_{sd_2}\left[\exp\left(\frac{V + IR_s}{n_2 V_t}\right) - 1\right] - I_{sd_3}\left[\exp\left(\frac{V + IR_s}{n_3 V_t}\right) - 1\right] - \frac{V + IR_s}{R_{sh}} \tag{12}$$

where $I_{sd_3}$, $n_3$ represent the third saturation currents and non-physical diode ideality factors, respectively.

From Eq. (12), it is clear that the TDM has nine unknown parameters namely $I_{ph}$, $I_{sd_1}$, $I_{sd_2}$, $I_{sd_3}$, $R_s$, $R_{sh}$, $n_1$, $n_2$, and $n_3$.

### 2.4. PV module model

As a matter of fact, in addition to the above three PV models, there is also a practically used PV module model based on the SDM (SMM), which is designed to solve the problem that a PV cell can provide a limited voltage magnitude. Shown as Fig. 2(d), there are multiple diodes connected in series or in parallel in this model. The relationship of current and voltage of SMM is formulated as follows:

$$I = I_{ph}N_p - I_{sd}N_p\left[\exp\left(\frac{VN_p + IR_sN_s}{nN_sN_pV_t}\right) - 1\right] - \frac{VN_p + IR_sN_s}{R_{sh}N_s} \tag{13}$$

where $N_s$, $N_p$ represent the count of PV cells connected in series or in parallel, respectively. It can be seen that there are five unknown parameters in this model, i.e, $I_{ph}$, $I_{sd}$, $R_s$, $R_{sh}$, and $n$, similar to the SDM.

### 2.5. Summary of these models

Fig. 3 reports the proportion of these models used in published literature, where it can be seen that the SDM and DDM are the most widely used, followed by SMM and TDM. The SDM has a simple structure with five unknown parameters. Based on the SDM, the DDM with seven unknown parameters takes the effect of recombination current loss into consideration. The SMM is proposed to solve the problem that the voltage provided by the SDM is insufficient for practical applications. In recent years, its related research, namely the maximum power point tracking problem [33], has been favored by many researchers. As for the TDM with nine unknown parameters, due to its complex structure,

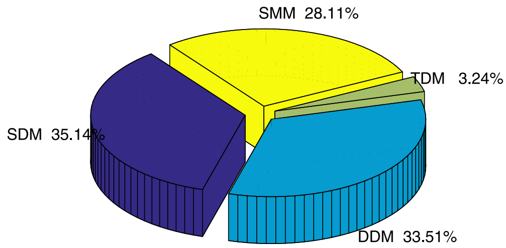


**Fig. 3.** The proportion of different models used in literature.

high nonlinearity, and multi-modal characteristics, it has been rarely studied. For a more detailed introduction of these models, it can be seen in [16,18,19,23].

## 3. PV model parameter extraction problem

PV models play an important role not only in the evaluation of cells performance, but also in the simulation, control, and optimization of PV systems. Further, PV models can be used to fit the behavior of the PV cells current–voltage characteristics. Nonetheless, the accuracy of the model depends on the precision of the unknown model parameters extracted. Therefore, it is essential to accurately extract these parameters. Currently the most common method is to compare the simulated current data obtained by the extracted parameters with the measured current dataset. If the two are closer, the more accurate the extracted parameters are. There are many objective functions used to describe the error. For example, absolute error (AE) can represent the difference between the measured data and the simulated data; based on AE, mean absolute error (MAE) can better reflect the situation of the measured data and the simulated data; sum squared error (SSE) can evaluate the degree of data change, the smaller the value of SSE, indicating that the simulated data describes the measured data with better accuracy; root mean square error (RMSE) can explain the degree of dispersion of the measured data and the simulated data. The definition of these objective functions are described as follows:

$$\mathrm{AE} = \sum_{i=1}^{N} \left| f_m(V_i, I_i, \mathbf{x}) \right| \tag{14}$$

$$\mathrm{MAE} = \frac{1}{N} \sum_{i=1}^{N} \left| f_m(V_i, I_i, \mathbf{x}) \right| \tag{15}$$

$$\mathrm{SSE} = \sum_{i=1}^{N} f_m^2(V_i, I_i, \mathbf{x}) \tag{16}$$

$$\mathrm{RMSE} = \sqrt{\frac{1}{N} \sum_{i=1}^{N} f_m^2(V_i, I_i, \mathbf{x})} \tag{17}$$

where $N$ represents the number of measured $I$-$V$ dataset; $\mathbf{x}$ is a vector that consists of the parameter to be identified; $m$ indicates the selected model, $f_m(V, I, \mathbf{x})$ denotes the error function, which is defined as below:

- For SDM:

$$\begin{cases} f(V, I, \mathbf{x}) = I_{\mathrm{ph}} - I_{\mathrm{sd}} \left[ \exp\left( \frac{V + I R_{\mathrm{s}}}{n V_{\mathrm{t}}} \right) - 1 \right] - \frac{V + I R_{\mathrm{s}}}{R_{\mathrm{sh}}} - I \\ \mathbf{x} = \left\{ I_{\mathrm{ph}}, I_{\mathrm{sd}}, R_{\mathrm{s}}, R_{\mathrm{sh}}, n \right\} \end{cases} \tag{18}$$

- For DDM:

$$\begin{cases} f(V, I, \mathbf{x}) = I_{\mathrm{ph}} - I_{\mathrm{sd}_1} \left[ \exp\left( \frac{V + I R_{\mathrm{s}}}{n_1 V_{\mathrm{t}}} \right) - 1 \right] \\ \quad - I_{\mathrm{sd}_2} \left[ \exp\left( \frac{V + I R_{\mathrm{s}}}{n_2 V_{\mathrm{t}}} \right) - 1 \right] - \frac{V + I R_{\mathrm{s}}}{R_{\mathrm{sh}}} - I \\ \mathbf{x} = \left\{ I_{\mathrm{ph}}, I_{\mathrm{sd}_1}, I_{\mathrm{sd}_2}, R_{\mathrm{s}}, R_{\mathrm{sh}}, n_1, n_2 \right\} \end{cases} \tag{19}$$

- For TDM:

$$\begin{cases} f(V, I, \mathbf{x}) = I_{\mathrm{ph}} - I_{\mathrm{sd}_1} \left[ \exp\left( \frac{V + I R_{\mathrm{s}}}{n_1 V_{\mathrm{t}}} \right) - 1 \right] - I_{\mathrm{sd}_2} \left[ \exp\left( \frac{V + I R_{\mathrm{s}}}{n_2 V_{\mathrm{t}}} \right) - 1 \right] \\ \quad - I_{\mathrm{sd}_3} \left[ \exp\left( \frac{V + I R_{\mathrm{s}}}{n_3 V_{\mathrm{t}}} \right) - 1 \right] - \frac{V + I R_{\mathrm{s}}}{R_{\mathrm{sh}}} - I \\ \mathbf{x} = \left\{ I_{\mathrm{ph}}, I_{\mathrm{sd}_1}, I_{\mathrm{sd}_2}, I_{\mathrm{sd}_3}, R_{\mathrm{s}}, R_{\mathrm{sh}}, n_1, n_2, n_3 \right\} \end{cases} \tag{20}$$

- For SMM:

$$\begin{cases} f(V, I, \mathbf{x}) = I_{\mathrm{ph}} - I_{\mathrm{ph}} \left[ \exp\left( \frac{V + I R_{\mathrm{s}} N_{\mathrm{s}}}{n N_{\mathrm{s}} V_{\mathrm{t}}} \right) - 1 \right] - \frac{V + I N_{\mathrm{s}}}{R_{\mathrm{sh}} N_{\mathrm{s}}} - I \\ \mathbf{x} = \left\{ I_{\mathrm{ph}}, I_{\mathrm{sd}}, R_{\mathrm{s}}, R_{\mathrm{sh}}, n \right\} \end{cases} \tag{21}$$

## 4. Meta-heuristic algorithms for PV models parameter extraction

Since traditional methods depend on the characteristics of the problem, meta-heuristic algorithms have received great attention. The main advantage of meta-heuristics is that they are easy to implement and not affected by the characteristics of the problem. In recent years, a great quantity of meta-heuristic algorithms are applied to the PV cells parameter extraction. In this section, a brief description of the most widely used meta-heuristics, i.e., genetic algorithm, differential evolution, particle swarm optimization, teaching–learning-based optimization, whale optimization algorithm, shuffled complex evolution, backtracking search algorithm, JAYA, and other optimization algorithms, applied for extracting the parameters of different PV models is presented.

### *4.1. Genetic algorithm*

Genetic algorithm (GA) is a population-based evolutionary algorithm inspired by the natural phenomenon of 'survival of the fittest' proposed by Darwin [34]. In GA, the decision variables are encoded as chromosomes, and the fitness value is used to evaluate and select between offsprings and parents. For the sake of clarity, Fig. 4 gives the flowchart of GA, where it can be seen that GA works with three main steps namely selection, crossover, and mutation in iteration process, which are described as follows:

*Selection*: First, randomly generate the population $\mathbb{P}$ within the specified search range; then evaluate the population by the fitness value; finally, filter the chromosomes by the fitness value to select for the next generation.

*Crossover*: In GA, there are two ways to generate offspring. Crossover as one of them, mainly selects two parents ($P_1$ and $P_2$) in the population ($\mathbb{P}$) to generate two offspring ($S_1$ and $S_2$) through a defined crossover probability $\alpha$ shown as Eq. (22).

$$\mathrm{Offspring} = \begin{cases} S_1 = \alpha \cdot P_1 + (1 - \alpha) \cdot P_2 \\ S_2 = (1 - \alpha) \cdot P_1 + \alpha \cdot P_2 \end{cases} \tag{22}$$

*Mutation*: In natural evolution, some genes may mutate. Similar to natural, in GA, mutation operations are performed through a mutation rate $\beta$, in which a parent ($P_1$) is selected to generate the offspring. The mutation operation is formulated as follow:

$$\mathrm{Offspring} = P_1 \pm \beta \cdot P_1 \tag{23}$$

The GA method was used to identify the electrical parameters ($I_{\mathrm{ph}}$, $I_{\mathrm{sd}}$, $R_{\mathrm{s}}$, $R_{\mathrm{sh}}$, $n$) of PV solar cells and modules in [35]. The authors extracted the parameters of the CT 801 solar cells and a commercial 50 Wp PV module manufactured by ANIT-Italy with a homemade GAs program developed on Matlab environment. Then, the extracted parameters are used to track the maximum power point of these cells. However, different irradiance and temperature are not taken

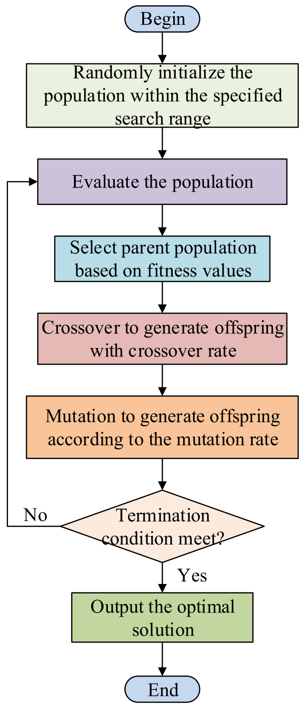


**Fig. 4.** Flowchart of GA.

into consideration in this paper. In [36], GA with an effective iterative technique, namely Newton Raphson (NR) method, was developed to identify the parameters of Mono-crystalline Sanyo HIT 215, Poly-crystalline Kyocera KC200GT, and Thin-film shell solar ST40 PV cells. In this method, parameters $R_s$, $R_{sh}$, and $n$ were extracted by GA while $I_{ph}$ and $I_{sd}$ were extracted by using NR method. It is worth mentioning that the shading effects on a PV panel has successfully validated through the KC200GT PV module under partial shading conditions. In [37], a GA with the interior-point method (IPM) was employed to accurately extract the parameters of the PV modules. There are two main ways to improve accuracy: (1) the standard and nominal operating cell temperature conditions of a PV have been considered by a multi-objective based optimization; (2) the IPM can traverse a set of internal points within the boundary to achieve the global best solution, which can improve the accuracy of the solution to a certain extent. Even so, the convergence of the algorithm is still a problem that needs to be improved. Recently, an adaptive genetic algorithm (AGA) based on multi-objective optimization measure was developed for optimal PV design parameter extraction [38]. In this paper, the objective function consists of two different functions, least mean error reduction and residual error reduction in a ratio of 0.7 and 0.3. The simulation results indicated that AGA based approach fits curve efficiently at different temperature conditions than the traditional approaches and can provide the optimal parameter values. Table 1 summarizes the different GA methods applied for PV models parameter extraction, and Table 2 shows the factors used or not taken into account when employing these methods, where NS is not specific.

### *4.2. Differential evolution*

Followed by GA, as another population-based optimization, differential evolution (DE) known for simple in structure, ease of use, fast convergence, was proposed by Storn and Price in 1997 [39]. Fig. 5 shows the process of DE finding the optimal solution. From Fig. 5, it is clear that its working process is mainly through four operations, i.e., initialization, mutation, crossover, and selection, which are described in detail as follows:

*Initialization*: In classic DE, the population size $Np$ is kept constant, and each individual is considered as a solution vector consisting of $D$ decision variables, where $D$ depends on the size of the problem to be solved. Before the loop iteration, all individuals in the population are initialized. For example, the $j$th decision variable of the $i$th individual is initialized as below:

$$x_{i,j} = LB_j + rand \cdot (UB_j - LB_j) \tag{24}$$

where $i$ belongs to 1 to $Np$, $j$ is an integer less than or equal to $D$, and $LB_j$, $UB_j$ are the lower and upper bound of the $j$th decision variable, respectively.

*Mutation*: Mutation is a core operation of DE. It is by picking the difference between two vectors and adding it to another vector with a certain weight. The most classic mutation operator is as follows:

$$\mathbf{v}_i = \mathbf{x}_1 + F \cdot (\mathbf{x}_2 - \mathbf{x}_3) \tag{25}$$

where $\mathbf{v}_i$ is the $i$th mutation vector, $F$ is the scale factor.

*Crossover*: In order to maintain the diversity of the population, the crossover operation is employed to generate trial vectors after mutation. There are two common crossover methods including binomial crossover and exponential crossover, and the binomial crossover is defined as follows:

$$u_{i,j} = \begin{cases} v_{i,j}, & \text{if } rand \le CR \;\|\; j == jrand \\ x_{i,j}, & \text{otherwise} \end{cases} \tag{26}$$

where $\mathbf{u}_i$ is the $i$th trial vector, $CR$ is the crossover rate, $jrand$ represents an integer randomly selected from set $\{1, \ldots, D\}$, which ensures that at least one dimension comes from the mutation vector.

*Selection*: After mutation and crossover, the selection is to determine who will survive the next generation by comparing the objective function values of the offsprings and the parents. The selection process is formulated as below:

$$\mathbf{x}_i = \begin{cases} \mathbf{u}_i, & \text{if } f(\mathbf{u}_i) \le f(\mathbf{x}_i) \\ \mathbf{x}_i, & \text{otherwise} \end{cases} \tag{27}$$

Due to its remarkable advantages, DE and its variants are widely applied to the PV models parameter extraction problem [40–51]. In [40], a penalty based DE (P-DE) was proposed to extract different PV models parameters. By the penalty function, more feasible solutions are generated, improving the diversity. Experimental results show that this method is better than some other meta-heuristics, both in accuracy and CPU time. Jiang et al. [41] proposed an improved adaptive DE (IADE) for parameter extraction of different PV cells. The control parameters $F$ and $CR$ can be adjusted automatically according to the fitness values during the optimization process. In [42], Gong and Cai developed a repaired adaptive DE (Rcr-IJADE) with the crossover rate repairing technique and ranking-based mutation to fast and accurately extract the solar cell parameters. The experimental results show its superiority in solution quality and convergence speed. An improved free search DE (IFSDE) proposed in [43], was used to identify the parameter of solar cells under two conditions. In [44], a new adaptive DE technique (DET) was proposed to extract the parameters of solar cell models accurately. In this method, the adaption consists of population, $CR$, and $F$. The feasibility of the DET has been verified by different PV models. Two improved DE variants DEIM, DEAM, were employed to estimate the PV modules parameters [45]. Combining the attraction–repulsion mechanism of the EM algorithm and adaptive mutation, DEIM and DEAM can offer the RMSE values less than other methods by 14% at least. Based on Rcr-IJADE, Muangkote et al. [46] developed a new variant ORcr-IJADE, in which an advanced onlooker-ranking-based mutation operator was proposed. ORcr-IJADE has been verified by 18 solar cell models and PV modules, and compared with 31 state-of-the-art algorithms. The results confirm its superiority on the accuracy, the success rate and the convergence speed. In [47], an enhanced

**Table 1**
Comparison of GA method in different approaches.

| Method | Ref. | Remarks |
|---|---|---|
| Genetic algorithm | GA [35] | A homemade GAs program developed on Matlab environment for parameters extraction of solar cells. |
| | GA+NR [36] | GA with an effective iterative technique Newton Raphson (NR) for different PV cells. |
| | GA+IPM [37] | GA with the interior-point method (IPM) was employed to accurately extract the parameters of the PV modules. |
| | AGA [38] | An adaptive GA based multi-objective optimization for PV cell parameter extraction. |

**Table 2**
Details of PV modes parameter extraction with GA methods.

| Algorithm | Cell dataset | Model | Objective function | Radiation | Temperature | CPU time |
|---|---|---|---|---|---|---|
| GA [35] | CT 801 | SDM, SMM | NS | No | No | Yes |
| GA+NR [36] | Mono-crystalline Sanyo HIT 215, Poly-crystalline Kyocera KC200GT, Thin-film shell solar ST40; | SDM, DDM, SMM | MAE | Yes | Yes | No |
| GA+IPM [37] | Poly-crystalline Kyocera KC200GT, Thin-film shell solar ST40, E20/333; | SDM, SMM | NS | Yes | No | Yes |
| AGA [38] | Standard solar cell data | SDM, DDM | Two objectives | No | Yes | No |

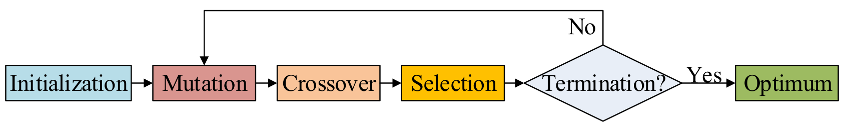


**Fig. 5.** Flowchart of DE.

adaptive DE (EJADE) with the crossover rate sorting mechanism and dynamic population reduction strategy was proposed to extract PV parameters fast, accurately and reliably. The simulated results indicate that EJADE exhibits competitive performance on accuracy, reliability and convergence speed when compared with other meta-heuristic algorithms. Biswas et al. [48] estimated the parameters of solar cells by using the linear population size reduction technique of success history based adaptive DE (L-SHADE), in which the three major points from the manufacturer datasheet has been used. The errors almost zero error at these three points indicates its feasibility. In [49], the authors used 11 advanced DE algorithms to extract the PV parameters and performed a comparative analysis. In view of the accuracy, convergence speed, and robustness, L-SHADE and Rcr-IJADE are the most competitive among these algorithms. In addition, this paper provided some useful insights that are helpful for designing more efficient alternative DE methods. Based on success history based adaptive DE (SHADE) [52], Li et al. [50] proposed a memetic adaptive DE (MADE) to estimate the parameters of different PV models. In MADE, SHADE is applied for the global search and the Nelder–Mead simplex method is employed for the local search. The experimental results demonstrate that MADE not only provides accurate and reliable parameter values, but also consumes minimal computational resources. In [51], a new similarity-guided evolutionary multi-task optimization framework with DE (SGDE) was proposed to extract the parameters of multiple different PV models simultaneously. The comprehensive experiments verified the superiority of the SGDE. Table 3 summarizes the different DE methods applied for PV models parameter extraction, and Table 4 gives the details of PV modes parameter extraction with DE methods. The statistical results including minimum (Min), maximum (Max), average value (Mean), standard deviation (Std), maximum number of function evaluations (Max_NFE) and the CPU time for the number of independent runs, of DEs on 57 mm diameter R.T.C France solar cell is provided in Table 5. From Table 5, it is obvious that MADE consumed the least CPU time and provided the best results, followed by EJADE, Rcr-IJADE, ORcr-IJADE, L-SHADE, SGDE, and IADE. Note that in order to facilitate comparison and analysis, only the results of 57 mm diameter R.T.C France solar cell are reported because it is used by most literatures.

### 4.3. Particle swarm optimization

Particle swarm optimization (PSO) as a swarm intelligence optimization algorithm, was first proposed by Eberhart and Kennedy in 1995 [53]. It is inspired by the social behavior of birds foraging. When the flock of birds is foraging, each bird in the flock is moving at a random position at a random speed until they get a considerable experience to food (objective), and then others birds follow the closest bird to the food. In PSO, an individual, called a particle has a position and a speed, and it adjusts its position according to its own experience and its neighbors, including the current velocity ($\mathbf{v}_i^g$), position ($\mathbf{x}_i^g$), the best previous position ($\mathbf{x}_{i,pbest}$) and global optimal position ($\mathbf{x}_{gbest}$). The velocity and position of $i$th particle are updated as follows:

$$\mathbf{v}_i^{g+1} = w \cdot \mathbf{v}_i^g + c_1 \cdot r_1 \cdot (\mathbf{x}_{i,pbest} - \mathbf{x}_i^g) + c_2 \cdot r_2 \cdot (\mathbf{x}_{gbest} - \mathbf{x}_i^g) \tag{28}$$

$$\mathbf{x}_i^{g+1} = \mathbf{v}_i^{g+1} + \mathbf{x}_i^g \tag{29}$$

where $g$ represents the current generation; $w$ is an inertia weight; $c_1$, $c_2$ are the learning factors; $r_1$ and $r_2$ denote the random numbers between 0 and 1.

In order to better understand the PSO process, the flowchart is provided in Fig. 6.

Due to its easy implementation, robustness, and computational efficiency, PSO has gained much attention and applied to the PV model parameter extraction problem. In [54], the problem was solved by using the PSO method based on the synthetic and experimental current–voltage data. Compared with GAs, PSO shows competitive performance in terms of accuracy and computational effectiveness. In [55], an improved PSO with chaotic search strategy (CPSO) was used to identify the parameters of solar cells. This method can avoid local optima and prove to be effective. A PSO with binary constraints [56] has been presented to identify the unknown parameters of different PV models including multi-crystalline and mono-crystalline, in which different radiation and temperature are taken into consideration. The results indicate that the proposed PSO can yield high accurate parameter values irrespective of temperature variations. Jordehi [57] proposed an improved PSO variant with enhanced leader (ELPSO) to solve PV

**Table 3**
Comparison of DE method in different approaches.

| Method | Ref. | Remarks |
|---|---|---|
| Differential evolution | P-DE [40] | The authors proposed a penalty based differential evolution (P-DE) for extracting the parameters of solar PV modules at different environmental conditions. |
| | IADE [41] | An adaptive DE according to fitness values to automatically adjust the control parameters during the optimization process. |
| | Rcr-IJADE [42] | The authors proposed the crossover rate repairing technique and the ranking-based mutation, then incorporate it into the JADE. |
| | IFSDE [43] | An improved FSDE with a different strategy for the Potential Solution Generator to make use of local search. |
| | DET [44] | An adaptive DE technique by improving population diversity and parameters CR and F adaptation was proposed to extract the parameters of solar cell models accurately. |
| | DEIM, DEAM [45] | Two improved DE, DEIM, DEAM, combined the attraction–repulsion mechanism of the EM algorithm were employed to estimate the PV modules parameters quickly and accurately. |
| | ORcr-IJADE [46] | The authors proposed an advanced onlooker-ranking-based mutation operator based on the Rcr-IJADE and it was used to quickly and accurately extract the parameters of solar cell models. |
| | EJADE [47] | An enhanced adaptive DE (EJADE) with the crossover rate sorting mechanism and dynamic population reduction strategy was proposed to extract photovoltaic parameters fast, accurately and reliably. |
| | L-SHADE [48] | The authors estimated the parameters of solar cells by an advanced adaptive DE (L-SHADE). This method used the minimum available information from the manufacturer datasheet. |
| | L-SHADE [49] | 11 state-of-the-art DE algorithms have been applied for parameter extraction of PV models. L-SHADE and Rcr-IJADE can achieve a better results. |
| | MADE [50] | A memetic adaptive DE (MADE) was proposed, where SHADE was used to global search and the Nelder–Mead simplex method was employed for local search. The computational resources has been saved in this method. |
| | SGDE [51] | A new similarity-guided evolutionary multitask optimization framework with DE was developed to identify parameters of different PV models. This method can extract the parameters of multiple models simultaneously. |

**Table 4**
Details of PV modes parameter extraction with DE methods.

| Algorithm | Cell Dataset | Model | Objective function | Radiation | Temperature | CPU time |
|---|---|---|---|---|---|---|
| P-DE [40] | Multi-crystalline S75, S115 Mono-crystalline SM55, SQ150PC Thin-film ST36, ST40; | DDM, SMM | RMSE | Yes | No | Yes |
| IADE [41] | Multi-crystalline SL80CE-36M 57mm diameter R.T.C France solar cell Photowatt-PWP 201; | SDM, SMM | RMSE | Yes | Yes | No |
| Rcr-IJADE [42] | 57mm diameter R.T.C France solar cell Photowatt-PWP 201; | SDM, DDM, SMM | RMSE | No | No | No |
| IFSDE [43] | – | SDM | RMSE | No | No | No |
| DET [44] | 5.8 cm diameter silicon solar cell Mono-crystalline SM55 Poly-crystalline Kyocera KC200GT; | SDM, DDM, SMM | RMSE | Yes | No | Yes |
| DEIM, DEAM [45] | Multi-crystalline Kyocera KC120-1; | SMM | AE, RMSE | Yes | Yes | Yes |
| ORcr-IJADE [46] | 57mm diameter R.T.C France solar cell Photowatt-PWP 201 Thin-film ST40 Mono-crystalline Shell SP70 Mono-crystalline Shell SQ85; | SDM, DDM, SMM | RMSE | No | Yes | No |
| EJADE [47] | 57mm diameter R.T.C France solar cell Photowatt-PWP201 Mono-crystalline STM6-40/36 Ploy-crystalline STP6-120/36 Multi-crystalline KC200GT Mono-crystalline SM55; | SDM, DDM, SMM | RMSE | Yes | Yes | Yes |
| L-SHADE [48] | Poly-crystalline Kyocera KC200GT Monocrystalline Shell SQ85 Thin-film Shell ST40; | SDM, DDM, SMM | ERR | No | No | Yes |
| L-SHADE [49] | 57mm diameter R.T.C France solar cell Photowatt-PWP201 Mono-crystalline STM6-40/36 Ploy-crystalline STP6-120/36 Multi-crystalline KC200GT Mono-crystalline SM55; | SDM, DDM, SMM | RMSE | Yes | Yes | Yes |
| MADE [50] | 57mm diameter R.T.C France solar cell Photowatt-PWP201 Mono-crystalline STM6-40/36 Ploy-crystalline STP6-120/36; | SDM, DDM, SMM | RMSE | No | No | Yes |
| SGDE [51] | 57mm diameter R.T.C France solar cell Photowatt-PWP201; | SDM, DDM, SMM | RMSE | No | No | No |

**Table 5**
Statistical results of DEs on 57mm diameter R.T.C France solar cell.

| Algorithm | Model | RMSE | | | | Max_NFE | CPU time(s) |
|---|---|---|---|---|---|---|---|
| | | Min | Max | Mean | Std | | |
| IADE [41] | SDM | 9.8900E−04 | – | – | – | – | – |
| Rcr-IJADE [42] | SDM | 9.860219E−04 | 9.860219E−04 | 9.860219E−04 | 5.12E−16 | 10 000 | – |
| | DDM | 9.824849E−04 | 9.860244E−04 | 9.826140E−04 | 9.86E−05 | 20 000 | – |
| ORcr-IJADE [46] | SDM | 9.860219E−04 | 9.860219E−04 | 9.860219E−04 | 4.509089E−17 | 150 000 | – |
| | DDM | 9.824849E−04 | 9.860219E−04 | 9.835106E−04 | 1.613054E−06 | 150 000 | – |
| EJADE [47] | SDM | 9.8602E−04 | 9.8602E−04 | 9.8602E−04 | 5.13E−17 | 10 000 | 11.82 (30) |
| | DDM | 9.8248E−04 | 9.8602E−04 | 9.8363E−04 | 1.36E−06 | 20 000 | 23.16 (30) |
| L-SHADE [49] | SDM | 9.8602E−04 | 9.8602E−04 | 9.8602E−04 | 4.58E−16 | 10 000 | 35.40 (50) |
| | DDM | 9.8248E−04 | 2.4351E−03 | 1.0772E−03 | 2.73E−04 | 20 000 | 62.66 (50) |
| MADE [50] | SDM | 9.8602E−04 | 9.8602E−04 | 9.8602E−04 | 2.74E−15 | 5000 | 0.1267 (1) |
| | DDM | 9.8261E−04 | 9.8786E−04 | 9.8608E−04 | 8.02E−05 | 10 000 | 0.1890 (1) |
| SGDE [51] | SDM | 9.86035398E−04 | 9.8602187789E−04 | 9.86022E−04 | 2.47465E−09 | 150 000 | – |
| | DDM | 9.84413E−04 | 9.86022E−04 | 9.85774E−04 | 4.01504E−07 | 150 000 | – |

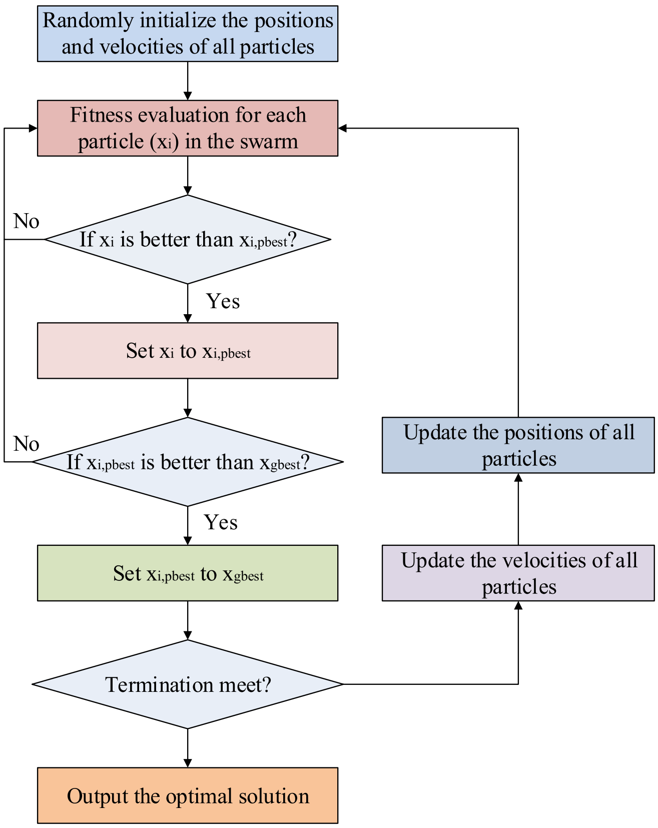


**Fig. 6.** Flowchart of PSO.

models parameter estimation problem. In ELPSO, the premature convergence problem of PSO is alleviated by enhancing the leader through a five-staged successive mutation strategy. From the results, ELPSO achieved a smaller RMSE value than other meta-heuristic algorithms. In [58], the authors proposed a guaranteed convergence PSO (GCPSO) to determine the parameters of PV cells and modules. This method can also effectively avoid premature convergence. In view of the reported results, GCPSO can not only obtain more accurate parameter values, but also reduce the computational cost. Merchaoui et al. [59] proposed an improved mutated PSO (MPSO) algorithm with adaptive mutation strategy for parameter estimation of PV solar cell and module circuit model. The adaptive mutation strategy is used to alleviate the premature convergence and balance the global exploration and local exploitation abilities. From the comparison results, MPSO can provide the lowest RMSE values. In [60], a flexible PSO (FPSO) algorithm was proposed to find the optimal parameters of PV cell models, in which an elimination phase is added. In addition, according to the value of these parameters, the search space of the parameters in each particle is changed. The accuracy and robustness of FPSO has been illustrated by estimating parameters of different PV models. A novel chaotic heterogeneous comprehensive learning PSO (C-HCLPSO) was presented for static and dynamic PV models parameters identification in [61]. It is worth mentioning that the dynamic PV models (IOM, FOM) are used. In terms of RMSE, MAE, convergence speed and lower execution time, C-HCLPSO obtained a competitive result. In [62], Liang et al. proposed a classified perturbation mutation based PSO (CPMPSO) algorithm, in which the high-quality or low-quality particles positions are updated by different perturbation mutation strategies. The superiority of CPMPSO has been evaluated by extracting parameters of five different PV models. A novel PSO namely fractional chaotic ensemble PSO (FC-EPSO) was proposed in [63], in which the fractional chaos maps are incorporated into EPSO to enhance its accuracy and reliability. The effectiveness of FC-EPSO has been verified through parameter identification of different PV models. Note that the TDM is adopted in this paper. Lin and Wu [64] proposed niche-based PSO in parallel computing (NPSOPC) to identify the parameters of PV models, in which particles are divided and distributed into different workers, and then searched in parallel. The experimental results show that NPSOPC can provide the best accuracy and reliability parameter values when compared with other algorithms. Table 6 summarizes the different PSO methods applied for PV models parameter extraction, and Table 7 gives the details of PV modes parameter extraction with PSO methods. The statistical results of PSO methods are reported in Table 8, where ELPSO, GCPSO, MPSO, C-HCLPSO, and FC-EPSO achieved the smallest RMSE values on SDM, followed by FPSO, CPMPSO, and NPSOPC. For DDM, GCPSO provided the best result. However, in terms of the Max_NFE and CPU time, FC-EPSO exhibits superior performance.

### *4.4. Teaching–learning-based optimization*

Teaching–learning-based optimization (TLBO), as a simple and efficient optimization method, was proposed by Rao et al. [65]. It is also a population-based optimization algorithm for nonlinear optimization problems and its idea comes from the teachers influence on the learner in the class. In general, there are $Np$ learners (expressed as $\mathbf{x}_i$, $i = 1, \ldots, Np$) in a class, and the best learner is deemed as the teacher ($\mathbf{x}_{\text{teacher}}$). TLBO solves the problem mainly through two phases: the teacher phase and the learner phase, which are described in detail as follows:

*Teacher phase*: In the teacher phase, the teacher shares her/his knowledge with the learners to improve the mean value of the class ($\mathbf{x}_{\text{mean}}$). In the teaching process, each learner is taught as follows:

$$\mathbf{x}_{i,new} = \mathbf{x}_i + rand \cdot (\mathbf{x}_{\text{teacher}} - T_F \cdot \mathbf{x}_{\text{mean}}) \tag{30}$$

where $\mathbf{x}_{i,new}$ represents the $i$th updated learner; $rand$ is a random number in the range $[0, 1]$; $T_F$ denotes the teaching factor; and $\mathbf{x}_{\text{mean}}$ is defined as below:

$$\mathbf{x}_{\text{mean}} = \frac{1}{Np} \sum_{i=1}^{Np} \mathbf{x}_i \tag{31}$$

*Learner phase*: For the learner phase, learners learns from each other. Generally, learners randomly select another learner to interact for enhancing her/his knowledge by some ways, such as discussions, formal communications et al. The learning process is introduced as follows:

$$\mathbf{x}_{i,new} = \begin{cases} \mathbf{x}_i + rand \cdot (\mathbf{x}_i - \mathbf{x}_j), & \text{if } f(\mathbf{x}_i) < f(\mathbf{x}_j) \\ \mathbf{x}_i + rand \cdot (\mathbf{x}_j - \mathbf{x}_i), & \text{otherwise,} \end{cases} \tag{32}$$

where $\mathbf{x}_j$ is the $j$-th learner different from $\mathbf{x}_i$, $f(\mathbf{x})$ is the objective function value of $\mathbf{x}$.

There are also some TLBO variants [66–70] that are developed to extract the parameters of PV models. Patel et al. [66] extracted all five parameters of a solar cell from a single illuminated $I$-$V$ characteristic using TLBO algorithm. The effectiveness of TLBO has been validated by estimating the parameters of solar cell, plastic solar cell, and PV module. In [67], an improved and simplified TLBO (STLBO) algorithm was proposed to identify and optimize parameters of PEM fuel cell and solar cell models. In STLBO, the quality of population was improved by employing an elite strategy, and the diversity of the local search was improved by introducing a chaotic map. The reported results demonstrate the effectiveness and scalability of the STLBO. Chen et al. [68] developed a new TLBO with generalized oppositional (GOTLBO) to identify parameters of solar cell models. To enhance the convergence speed, GOTLBO employs the generalized oppositional mechanism in the initialization step and generation jumping. The simulation results show the performance of GOTLBO when compared other

**Table 6**
Comparison of PSO method in different approaches.

| Method | Ref. | Remarks |
|---|---|---|
| Particle swarm optimization | PSO [54] | The traditional PSO algorithm was employed to extract the parameters of solar cells. |
| | CPSO [55] | A chaos PSO algorithm(CPSO) was used for extracting PV model parameters. |
| | PSO [56] | A PSO with binary constraints was presented to identify the unknown parameters of different PV models. |
| | ELPSO [57] | The authors proposed an improved PSO variant with enhanced leader (ELPSO), in which the premature convergence problem is mitigated. |
| | GCPSO [58] | A guaranteed convergence PSO (GCPSO) that can avoid premature convergence, was developed to determine the parameters of PV cells and modules. |
| | MPSO [59] | An improved mutated PSO (MPSO) algorithm with adaptive mutation strategy is proposed to identify the optimal parameters of different photovoltaic models. |
| | FPSO [60] | The authors proposed a flexible PSO (FPSO) algorithm to estimate the parameters of PV cell model. Compared with classic PSO, an elimination phase is added in FPSO. |
| | C-HCLPSO [61] | A novel chaotic heterogeneous comprehensive learning PSO was introduced to identify static and dynamic PV models parameters. Ten different chaos maps were used. |
| | CPMPSO [62] | A classified perturbation mutation based PSO (CPMPSO) is proposed to extract the parameters of PV models. The high-quality or low-quality solution updated by different perturbation mutation strategies. |
| | FC-EPSO [63] | The authors proposed a novel fractional chaotic ensemble PSO (FC-EPSO) to identify the parameters of solar PV modules accurately. TDM is tested in this method. |
| | NPSOPC [64] | An optimization algorithm based on niche PSO in parallel computing (NPSOPC) was proposed to identify the parameters of PV models. |

**Table 7**
Details of PV modes parameter extraction with PSO methods.

| Algorithm | Cell dataset | Model | Objective function | Radiation | Temperature | CPU time |
|---|---|---|---|---|---|---|
| PSO [54] | – | SDM, DDM | RMSE | No | No | Yes |
| CPSO [55] | – | SDM | SSE | No | No | No |
| PSO [56] | Mono-crystalline KD210GH-2PU Polycrystalline Shell SP70 and SQ85; | SDM, SMM | Others | Yes | Yes | No |
| ELPSO [57] | 57mm diameter R.T.C France solar cell Mono-crystalline STM6-40/36 PVM 752 GaAs thin film cell; | SDM, DDM, SMM | RMSE | No | No | No |
| GCPSO [58] | 57mm diameter R.T.C France solar cell Photowatt-PWP 201 Sharp ND-R250A5; | SDM, DDM, SMM | RMSE | Yes | Yes | Yes |
| MPSO [59] | 57mm diameter R.T.C France solar cell Photowatt-PWP 201 Multi-crystalline IFRI250-60 Mono-crystalline SM55 Multi-crystalline KC200GT Thin-film Shell ST40; | SDM, DDM, SMM | RMSE | Yes | Yes | No |
| FPSO [60] | 57mm diameter R.T.C France solar cell Mono-crystalline STM6-40/36 Mono-crystalline SM55 Multi-crystalline KC200GT Ploy-crystalline SW255; | SDM, DDM, SMM | MAE, RMSE | Yes | Yes | No |
| C-HCLPSO [61] | 57mm diameter R.T.C France solar cell; | SDM, DDM | MAE, SSE, RMSE | No | No | Yes |
| CPMPSO [62] | 57mm diameter R.T.C France solar cell Photowatt-PWP201 Mono-crystalline STM6-40/36 Ploy-crystalline STP6-120/36 Multi-crystalline KC200GT Mono-crystalline SM55 Thin-film Shell ; | SDM, DDM, SMM | RMSE | Yes | Yes | Yes |
| FC-EPSO [63] | 57mm diameter R.T.C France solar cell Mono-crystalline STM6-40/36 Multi-crystalline CS6Pe240P; | SDM, DDM, TDM, SMM | MAE, SSE, RMSE | Yes | Yes | Yes |
| NPSOPC [64] | 57mm diameter R.T.C France solar cell Photowatt-PWP201; | SDM, DDM, SMM | RMSE | No | No | No |

**Table 8**
Statistical results of PSOs on 57mm diameter R.T.C France solar cell.

| Algorithm | Model | RMSE | | | | Max_NFE | CPU time(s) |
|---|---|---|---|---|---|---|---|
| | | Min | Max | Mean | Std | | |
| ELPSO [57] | SDM | 7.7301E−04 | 7.7455E−04 | 7.7314E−04 | 3.4508E−07 | 101 000 | – |
| | DDM | 7.4240E−04 | 7.9208E−04 | 7.5904E−04 | 9.4291E−06 | 151 500 | – |
| GCPSO [58] | SDM | 7.730063E−04 | 7.730065E−04 | 7.730063E−04 | 4.055839E−11 | – | 61 (100) |
| | DDM | 7.182745E−04 | 7.417141E−04 | 7.301380E−04 | 5.371802E−06 | – | 216 (100) |
| MPSO [59] | SDM | 7.73006E−04 | – | – | – | 120 000 | – |
| | DDM | 7.3257E−04 | – | – | – | 120 000 | – |
| FPSO [60] | SDM | 9.8602E−04 | – | – | 2.0142E−08 | – | – |
| | DDM | 9.8253E−04 | – | – | 3.1469E−08 | – | – |
| C-HCLPSO [61] | SDM | 7.73007E−04 | – | – | 1.85970E−11 | – | – |
| | DDM | 7.4283E−04 | – | – | 8.2667E−11 | – | – |
| CPMPSO [62] | SDM | 9.86022E−04 | 9.86022E−04 | 9.86022E−04 | 2.17556E−17 | 50000 | – |
| | DDM | 9.82485E−04 | 9.86022E−04 | 9.83137E−04 | 1.3398E−06 | 50 000 | – |
| FC-EPSO [63] | SDM | 7.7301E−04 | – | – | 1.5688E−10 | 6000 | 11.5197 (30) |
| | DDM | 7.4489E−04 | – | – | 2.1153E−10 | 6000 | 12.0364 (30) |
| | TDM | 7.4300E−04 | – | – | 9.1140E−11 | 6000 | 39.5212 (30) |
| NPSOPC [64] | SDM | 9.8856E−04 | – | – | – | – | – |
| | DDM | 9.82084E−04 | – | – | – | – | – |

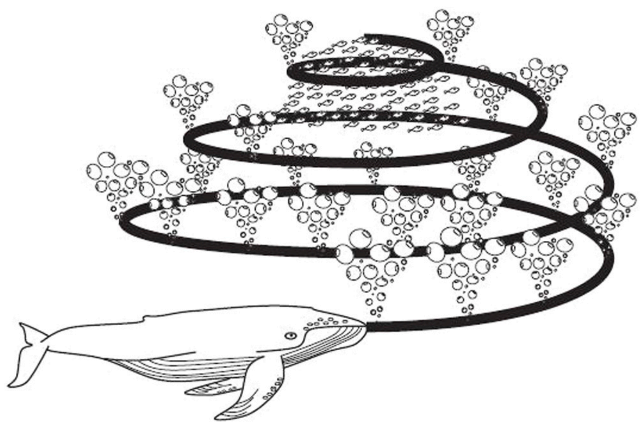

**Fig. 7.** Bubble-net feeding behavior of humpback whales [71].

evolutionary algorithms. In order to save function evaluations, a self-adaptive TLBO (SATLBO) was proposed in [69], in which the learners can self-adaptively select teacher phase or learner phase according to their knowledge level. The performance of SATLBO was evaluated on 34 benchmark functions and parameters identification of different PV models. From the comparison results, SATLBO exhibits high accuracy and reliability. In [70], Li et al. proposed an improved TLBO (ITLBO) to extract the parameters of PV models. In ITLBO, the teacher uses different teaching strategies based on learner levels in the teacher phase, and a new learning strategy is proposed to balance exploration and exploitation in the learner phase. Compared with TLBO variants and other evolution algorithms, ITLBO can obtain better performance with respect to accuracy and reliability. Table 9 summarizes the different TLBO methods applied for PV models parameter extraction, and Table 10 gives the details of PV modes parameter extraction with TLBO methods. The statistical results of TLBO methods are reported in Table 11. From Table 11, it can be seen that STLBO, ITLBO can obtain the best Min RMSE, but ITLBO has obvious advantages in Max, Mean, and Std. At the same time, only ITLBO took the CPU time into account.

### 4.5. Whale optimization algorithm

Whale optimization algorithm (WOA) a new algorithm inspired by nature, which simulates the behavior of the humpback whales [71]. In WOA, the optimization process of whales looking for the prey, it is regarded as an exploration of the search space. There are two behaviors i.e., creating bubble-nets and encircling, for whales locating the prey location and attacking them.

*Bubble-nets behavior*: The bubble-net feeding is a unique behavior of humpback whales. In WOA, the behavior is mathematically modeled by using a spiral bubble-net shown as Fig. 7, where it can be seen that the whales update their positions via a spiral way by mimicking the helix-shaped movement of humpback whales around their preys as follows:

$$\mathbf{x}_w(g+1) = D \cdot e^{bl} \cdot cos(2\pi l) + \mathbf{x}_p(g) \tag{33}$$

where $g$ is the current iteration, $D$ is the Euler distance between the whale ($\mathbf{x}_w$) and the prey ($\mathbf{x}_p$, the current best solution) positions, $b$ represents a constant for defining the shape of the logarithmic spiral, and $l$ denotes a random number in [−1, 1].

*Encircling behavior*: The humpback whales will encircle the prey when they recognize the location of prey. This behavior is represented as follows:

$$\mathbf{x}_w(g+1) = \mathbf{x}_p(g) - (2a \cdot \mathbf{r} - a) \cdot D' \tag{34}$$

where $a$ is linearly decreased from 2 to 0 over the iterations, $D' = \left|2\mathbf{r} \cdot \mathbf{x}_p(g) - \mathbf{x}_w(g)\right|$, and $r$ is a random vector in [0,1].

Besides, to simulate the simultaneous occurrence of these two behaviors, WOA uses a probabilistic mechanism to select between either the shrinking encircling mechanism or the spiral mode to update the whales position. This process is defined as follows:

$$\mathbf{x}_w(g+1) = \begin{cases} \mathbf{x}_p(g) - (2a \cdot \mathbf{r} - a) \cdot D', & \text{if } p < 0.5 \\ D \cdot e^{bl} \cdot cos(2\pi l) + \mathbf{x}_p(g), & \text{otherwise} \end{cases} \tag{35}$$

where p is a random number in [0, 1]. There is a fact that the humpback whales search for prey randomly. Therefore, a random position is selected instead of the best position. So the location of a whale is modified as below:

$$\mathbf{x}_w(g+1) = \mathbf{x}_{rand}(g) - (2a \cdot \mathbf{r} - a) \cdot D'' \tag{36}$$

where $D'' = \left|2\mathbf{r} \cdot \mathbf{x}_{rand}(g) - \mathbf{x}_w(g)\right|$.

Elazab et al. [72] introduced a novel application of the WOA for estimating the parameters of SDM, DDM, and TDM of a PV module. The simulation results of WOA compared with GA, SA, and PSO, has verified its effectiveness. In [73], an improved chaotic WOA (CWOA) was proposed for parameter estimation of PV cells. In CWOA, the internal parameters of WOA can be automatically adapted by introducing the chaotic maps, as well as the capability to search for the best solution is also improved. The experimental results show the improved performance of CWOA in terms of accuracy and robustness. An improved WOA with the opposition-based learning (OBWOA) was presented to estimate the parameters of solar cells diode models [74]. In order to enhance the exploration of the search space, the opposition-based learning mechanism was introduced in OBWOA. The performance of this method has been verified through parameter estimation of different PV models including the SDM, DDM, TDM, and SMM. In [75], Xiong et al. proposed an improved version of WOA (IWOA), in which two prey searching strategies were designed to effectively balance the local exploitation and global exploration. To verify the performance of IWOA, it was applied for parameter extraction of three PV models including SDM, DDM, SMM, and two practical PV power station models. From the reported results, the improved WOA can provide more accurate parameter values compared to other WOA variants. Table 12 summarizes the different WOA methods applied for PV models parameter extraction, and Table 13 gives the details of PV modes parameter extraction with WOA methods. The statistical results of WOA methods are reported in Table 14, where IWOA achieved the best results on SDM and DDM. In addition, CWOA consumed the least computing resources, while OBWOA experimented with TDM.

### 4.6. Shuffled complex evolution

As an effective and efficient global optimization algorithm, shuffled complex evolution (SCE) was proposed by Duan et al. in 1993 [76]. This algorithm mainly considers four concepts namely integration of deterministic and random, clustering, systematic evolution, and competitive evolution. On the one hand, SCE can apply the deterministic strategy to employ the information of response surface effectively as guidance to search. On the other hand, the random strategy increases the flexibility and robustness of SCE. Clustering can be used to select the optimal regions for searching, instead of the whole search space. The systematic complex evolution strategy is employed to improve the robustness of the search. The implementation of the competitive evolution strategy will enhance the efficiency of global convergence. It is these four concepts that make SCE an powerful global search algorithm. The main steps of SCE are as follows:

*Step 1*: Initializing the algorithm parameters.

*Step 2*: Generate a sample of points in the feasible space, and calculate the objective value at each sample point.

*Step 3*: Sort the sample points in order of increasing according to the function values, and store them in an array.

*Step 4*: Partition the sorted array into the predefined number of complexes.

**Table 9**
Comparison of TLBO method in different approaches.

| Method | Ref. | Remarks |
|---|---|---|
| Teaching–learning-based optimization | TLBO [66] | The TLBO was used to extract all five parameters of a solar cell from a single illuminated current–voltage ($I$-$V$) characteristic. |
| | STLBO [67] | The authors proposed an improved and simplified TLBO (STLBO) algorithm to identify and optimize parameters for these two types of cell models (PEM fuel cell and solar cell). |
| | GOTLBO [68] | A generalized oppositional TLBO (GOTLBO) was presented to identify parameters of solar cell models. |
| | SATLBO [69] | A self-adaptive TLBO (SATLBO) was proposed, in which learners can self-adaptively select different learning phases based on their knowledge level. |
| | ITLBO [70] | The authors proposed an improved TLBO (ITLBO) for parameter extraction of PV models. The novelty of ITLBO lies primarily in the improved teaching and learning strategies. |

**Table 10**
Details of PV modes parameter extraction with TLBO methods.

| Algorithm | Cell dataset | Model | Objective function | Radiation | Temperature | CPU time |
|---|---|---|---|---|---|---|
| TLBO [66] | 57mm diameter R.T.C France solar cell Photowatt-PWP201 Plastic solar cell; | SDM, SMM | SSE | No | No | No |
| STLBO [67] | 57mm diameter R.T.C France solar cell; | SDM, DDM | RMSE | No | No | No |
| GOTLBO [68] | 57mm diameter R.T.C France solar cell; | SDM, DDM | RMSE | No | No | No |
| SATLBO [69] | 57mm diameter R.T.C France solar cell Photowatt-PWP201; | SDM, DDM, SMM | RMSE | No | No | No |
| ITLBO [70] | 57mm diameter R.T.C France solar cell Photowatt-PWP201 Mono-crystalline STM6-40/36 Ploy-crystalline STP6-120/36; | SDM, DDM, SMM | RMSE | No | No | Yes |

**Table 11**
Statistical results of TLBOs on 57mm diameter R.T.C France solar cell.

| Algorithm | Model | RMSE | | | | Max_NFE | CPU time(s) |
|---|---|---|---|---|---|---|---|
| | | Min | Max | Mean | Std | | |
| STLBO [67] | SDM | 9.8602E−04 | – | – | – | 50 000 | – |
| | DDM | 9.8248E−04 | – | – | – | 50 000 | – |
| GOTLBO [68] | SDM | 9.87442E−04 | 1.98244E−03 | 1.33488E−03 | 2.99407E−04 | 10 000 | – |
| | DDM | 9.83177E−04 | 1.78774E−03 | 1.24360E−03 | 2.09115E−04 | 20 000 | – |
| SATLBO [69] | SDM | 9.86022E−04 | 9.94939E−04 | 9.87795E−04 | 2.30015E−06 | 50 000 | – |
| | DDM | 9.828037E−04 | 1.047045E−03 | 9.981111E−04 | 1.951533E−05 | 50 000 | – |
| ITLBO [70] | SDM | 9.8602E−04 | 9.8602E−04 | 9.8602E−04 | 2.19E−17 | 50 000 | 5.95 (30) |
| | DDM | 9.8248E−04 | 9.8812E−04 | 9.8497E−04 | 1.54E−06 | 50 000 | 6.60 (30) |

**Table 12**
Comparison of WOA method in different approaches.

| Method | Ref. | Remarks |
|---|---|---|
| Whale optimization algorithm | WOA [72] | The WOA was applied for estimating the parameters of the single, double, and three diode PV models of a PV module. |
| | CWOA [73] | The authors proposed an improved WOA with chaotic system (CWOA) for parameter estimation of PV cells. The internal parameters of WOA are adapted. |
| | OBWOA [74] | An improved opposition-based WOA (OBWOA) was developed for parameter estimation of solar cells diode models including the SDM, DDM, TDM, and SMM. |
| | IWOA [75] | The authors proposed an improved WOA (IWOA) to accurately extract the parameters of different PV models. The local exploitation and global exploration was balanced. |

**Table 13**
Details of PV modes parameter extraction with WOA methods.

| Algorithm | Cell Dataset | Model | Objective function | Radiation | Temperature | CPU time |
|---|---|---|---|---|---|---|
| WOA [72] | Multi-crystalline KC200GT; | SDM, DDM, TDM | RMSE | Yes | Yes | No |
| CWOA [73] | 57mm diameter R.T.C France solar cell Mono-crystalline STM6-40/36 Ploy-crystalline STP6-120/36; | SDM, DDM, SMM | MAE, RMSE | No | No | No |
| OBWOA [74] | 57mm diameter R.T.C France solar cell Mono-crystalline STM6-40/36 Ploy-crystalline STP6-120/36 Multi-crystalline S75; | SDM, DDM, TDM, SMM | RMSE | Yes | Yes | No |
| IWOA [75] | 57mm diameter R.T.C France solar cell Photowatt-PWP201 Poly-crystalline CS6U-320P Mono-crystalline JAM6-60-295W-4BB; | SDM, DDM, SMM | RMSE | No | No | No |

*Step 5*: Evolve each complex according to the competitive complex evolution strategy.

*Step 6*: Shuffle complexes via replacing the sorting array elements by the evolved complexes.

*Step 7*: Check convergence. If the convergence criteria is met, end; otherwise, return to *Step 4*.

In [77], the authors extracted the parameters of PV models by using the SCE algorithm. The result obtained by SCE was compared with the Levenberg Marquardt, analytical method, GA, DE, and PSO. From the comparison results, the SCE algorithm provided the best accuracy with minimum computational time. Chen et al. [78] proposed an improved SCE enhanced by the opposition-based learning (ESCE-OBL).

**Table 14**
Statistical results of WOAs on 57mm diameter R.T.C France solar cell.

| Algorithm | Model | RMSE | | | | Max_NFE | CPU time(s) |
|---|---|---|---|---|---|---|---|
| | | Min | Max | Mean | Std | | |
| CWOA [73] | SDM | 9.8604E−04 | – | – | 1.0216E−08 | 45 000 | – |
| | DDM | 9.8279E−04 | – | – | 1.1333E−07 | 45 000 | – |
| OBWOA [74] | SDM | 9.8603E−04 | – | – | 1.0196E−08 | 1 500 000 | – |
| | DDM | 9.8294E−04 | – | – | 1.1278E−07 | 1 500 000 | – |
| | TDM | 9.850E−04 | – | – | 2.4739E−05 | 1 500 000 | – |
| IWOA [75] | SDM | 9.8602E−04 | 1.0331E−03 | 9.9524E−04 | 1.1267E−05 | 100 000 | – |
| | DDM | 9.8255E−04 | 1.0889E−03 | 9.9693E−04 | 1.9297E−05 | 100 000 | – |

So as to improve the exploration capability, a new enhanced competitive complex evolution was introduced in ESCE-OBL. The results demonstrated that ESCE-OBL can achieve fast convergence and provide accurate parameter values. In addition, an improved SCE (ISCE) [79] was proposed for parameter extraction of different PV models. In ISCE, a new improved competitive complex evolution strategy was developed to overcome the shortcomings of original SCE algorithm. ISCE exhibited the highest computational efficiency to obtain the most accurate parameter values when compared with the best reported algorithms such as Rcr-IJADE and EHA-NMS. Table 15 summarizes the different SCE methods applied for PV models parameter extraction, and Table 16 gives the details of PV modes parameter extraction with SCE methods. The statistical results of SCE methods are reported in Table 17, where ESCE-OBL and ISCE consumed the same Max_NFE but ISCE achieved a better statistical results.

### *4.7. Backtracking search algorithm*

Backtracking search algorithm (BSA) is also a population-based optimization proposed by Civicioglu in 2013 [80]. Different from other population-based optimization algorithms, BSA consists of two populations: current population and historical population. The flowchart of BSA is given in Fig. 8, where the BSA optimization process is mainly composed of five parts: initialization, selection-I, mutation, crossover and selection-II. The detailed description is as follows:

*Initialization*: Similar to Eq. (24) of DE, the current population and historical population are initialized in the specific boundary. Then the fitness values of the two populations are evaluated.

*Selection-I*: This part is to reform the historical population $OldP$ through the current population $P$, which is formulated as follows:

$$OldP = \begin{cases} P, & \text{if } \theta < \varphi |\ \theta,\ \varphi \sim U(0,1) \\ OldP, & \text{otherwise} \end{cases} \tag{37}$$

where $\theta$, $\varphi$ are the random number in 0 and 1. Then the $OldP$ is used to randomly change the order of the individuals in $oldP$ as below:

$$OldP = permuting(OldP) \tag{38}$$

where the permuting function is a random shuffling function.

*Mutation and Crossover*: Different from the DE, the mutation of BSA is related with the current population and the historical population, which is defined as follows:

$$M = P + F \cdot (OldP - P) \tag{39}$$

where $M$ is the mutation population, $F$ represents a scale factor. After mutation, the trial population $V$ is generated by $M$ and $P$ by a binary integer-valued matrix ($Map$), which is shown as Eq. (40).

$$V_{i,j} = \begin{cases} P_{i,j}, & \text{if } Map_{i,j} == 1 \\ M_{i,j}, & \text{otherwise} \end{cases} \tag{40}$$

*Selection-II*: Finally, the Selection-II is used to select the new current population $P_{\text{new}}$ between the $V$ and $P$ according to the fitness value as below:

$$P_{i,\text{new}} = \begin{cases} V_i, & \text{if } f(V_i) < f(P_i) \\ P_i, & \text{otherwise} \end{cases} \tag{41}$$

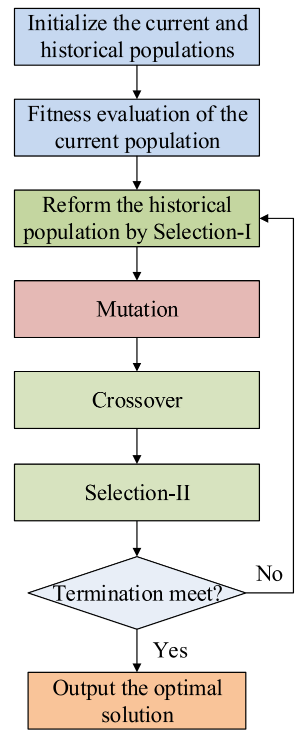


**Fig. 8.** Flowchart of BSA.

There two BSA variants [81,82] are developed for parameter extraction of PV models. In [81], Yu et al. proposed a multiple learning BSA (MLBSA), in which three improvements have been put forward. i) To maintain the population diversity and enhance the exploration ability, some individuals learn from the current population and the historical population simultaneously. ii) To enhance the exploitation ability, other individuals learn from the best individual of current population. iii) In order to refine the quality of current population, an elite strategy based on chaotic local search is developed. The performance of MLBSA has been verified by extracting the parameter of different PV models, and the results indicate that MLBSA outperforms than other state-of-the-art algorithms such as STLBO and GOTLBO et al. A new BSA variant called BSA with Lévy flight (LFBSA) was presented for parameter estimation of PV modes in [82]. Different from MLBSA, LFBSA improved the population diversity by introducing an information sharing mechanism with Lévy flight. In addition, to avoid trapping into local optimum, mutation operator based on the hunting mechanism of gray wolves was employed. Compared with BSA and other algorithms, LFBSA shows its superiority in terms of accuracy and reliability. Table 18 summarizes the different BSA methods applied for PV models parameter extraction, and Table 19 gives the details of PV modes parameter extraction with BSA methods. Table 20 provides the statistical results of BSA methods. From this table, it can be seen that

**Table 15**
Comparison of SCE method in different approaches.

| Method | Ref. | Remarks |
| --- | --- | --- |
| Shuffled complex evolution | SCE [77] | The SCE algorithm was applied for parameter extraction of DDM. |
| | ESCE-OBL [78] | The authors proposed an improved SCE by introducing the opposition-based learning (ESCE-OBL) to extract the parameters of PV models. |
| | ISCE [79] | An improved SCE (ISCE) algorithm was presented for parameter extraction of different PV models, including SDM, DDM, and SMM. The novelty of ISCE lied primary in the improved competitive complex evolution strategy. |

**Table 16**
Details of PV modes parameter extraction with SCE methods.

| Algorithm | Cell Dataset | Model | Objective function | Radiation | Temperature | CPU time |
| --- | --- | --- | --- | --- | --- | --- |
| SCE [77] | Poly-crystalline Kyocera KC120-1; | DDM | MAE, SSE, RMSE | Yes | Yes | Yes |
| ESCE-OBL [78] | 57mm diameter R.T.C France solar cell Photowatt-PWP201; | SDM, DDM, SMM | RMSE | No | No | No |
| ISCE [79] | 57mm diameter R.T.C France solar cell Photowatt-PWP201 Mono-crystalline STM6-40/36 Ploy-crystalline STP6-120/36; | SDM, DDM, SMM | RMSE | No | No | No |

**Table 17**
Statistical results of SCEs on 57mm diameter R.T.C France solar cell.

| Algorithm | Model | RMSE | | | | Max_NFE | CPU time(s) |
| --- | --- | --- | --- | --- | --- | --- | --- |
| | | Min | Max | Mean | Std | | |
| ESCE-OBL [78] | SDM | 9.8602E−04 | – | 9.8602E−04 | 3.15E−14 | 5000 | – |
| | DDM | 9.824848E−04 | – | 9.836941E−04 | – | 10 000 | – |
| ISCE [79] | SDM | 9.860219E−04 | 9.860219E−04 | 9.860219E−04 | 3.98E−17 | 5000 | – |
| | DDM | 9.824849E−04 | 9.861092E−04 | 9.827740E−04 | 4.61E−07 | 10 000 | – |

LFBSA is better than MLBSA in various statistical indexes under the same function evaluation times.

### 4.8. JAYA

JAYA algorithm is a simple yet powerful population-based optimization algorithm proposed by Rao for solving the constrained and unconstrained optimization problems. The conceptual background of this algorithm comes from that the solution obtained for a given problem should move towards the best solution as well as should avoid the worst solution [83]. Different from the previously mentioned population-based meta-heuristic algorithms, the JAYA algorithm has a unique advantage that it is free from the algorithm-specific control parameters except the population size. In addition, all the individual of the population are updated by using only one formula, which is described as follows:

$$x_{i,j}^{g+1} = x_{i,j}^{g} + rand1 \cdot (x_{\text{best},j}^{g} - \left|x_{i,j}^{g}\right|) - rand2 \cdot (x_{\text{worst},j}^{g} - \left|x_{i,j}^{g}\right|) \quad (42)$$

where $g$ is the number of generation; $rand1$, $rand2$ represent the random number in [0, 1]; $\mathbf{x}_{best}$, $\mathbf{x}_{worst}$ denote the best and worst solutions in current population, respectively.

Yu et al. [84] proposed an improved JAYA (IJAYA) algorithm to accurately and reliably identify the parameters of different PV models. In IJAYA, a self-adaptive weight was employed to adjust the tendency of approaching the best solution and avoiding the worst solution at different search stages. The population diversity was maintained by an experience-based learning strategy. Finally, the best solution was refined by a chaotic elite learning method. The accuracy and reliability of IJAYA has been confirmed by comparing with other advanced algorithm. In [85], the authors presented a novel elite opposition-based JAYA (EO-JAYA) algorithm for parameter estimation of PV cell models. In EO-JAYA, the elite opposition learning strategy was employed to diversify the solutions when updating the solutions. Besides the IJAYA, Yu et al. proposed another JAYA variant named performance-guide JAYA (PGJAYA) in [86] for parameters identification of PV cell and module. In PGJAYA, the performance of each individual was quantified through ranking probability. Then the individuals can self-adaptively select different evolution strategies according to the ranking probability. Additionally, to improve the quality of whole population, a self-adaptive chaotic perturbation mechanism was introduced. The statistical results for different PV models show that PGJAYA is superior to IJAYA in accuracy and reliability. Recently, Jian and Weng [87] developed a logistic chaotic JAYA algorithm (LCJAYA) for parameters identification of PV cell and module models, in which a logistic chaotic map strategy was introduced to improve the population diversity. Moreover, a chaotic mutation strategy was employed to make trade-off between the exploration ability and the exploitation ability. From the reported results, LCJAYA achieved better results than PGJAYA regardless of different PV models. Table 21 summarizes the different JAYA methods applied for PV models parameter extraction, and Table 22 gives the details of PV modes parameter extraction with JAYA methods. The statistical results of JAYA methods are reported in Table 23.

### 4.9. Other optimization algorithms

Besides the aforementioned methods, there are other meta-heuristic algorithms employed to extract the parameters of PV models. In [88], a pattern search (PS) algorithm was used for optimal extraction of solar cell parameters. A simulated annealing (SA) algorithm was proposed for PV parameters identification [89]. Askarzadeh et al. [90] proposed a harmony search (HS) algorithm to identify the unknown parameters of the solar cell. Subsequently, Askarzadeh et al. developed a artificial bee swarm optimization (ABSO) algorithm for parameters identification of solar cell models in [91]. In [92], a new optimization method flower pollination algorithm (FPA) was proposed to extract the optimal parameters of SDM and DDM. The fireworks algorithm (FWA) was applied for the accurate identification of these unknown parameters [93]. To overcome the disadvantage of ant lion optimization (ALO) algorithm, an improved ALO (IALO) was presented for parameter identification of PV cell models [94]. In [95], Fathy and Rezkand presented a reliable methodology based on imperialist competitive algorithm (ICA) for estimating the optimal parameters of PV models. Derick et al. [96] proposed a wind driven optimization (WDO) technique for identifying the parameters of solar PV. In [97], an efficient method based on salp swarm algorithm (SSA) was proposed for extracting the parameters of PV cell based DDM. A novel coyote optimization algorithm (COA)

**Table 18**
Comparison of BSA method in different approaches.

| Method | Ref. | Remarks |
|---|---|---|
| Backtracking search algorithm | MLBSA [81] | A multiple learning BSA (MLBSA) was proposed for parameter estimation of PV models. Three improvements were introduced in MLBSA. |
| | LFBSA [82] | The authors proposed a BSA variant (LFBSA) to estimate the parameters of PV models. In LFBSA, the Lévy flight was employed to enhance the performance of BSA. |

**Table 19**
Details of PV modes parameter extraction with BSA methods.

| Algorithm | Cell Dataset | Model | Objective function | Radiation | Temperature | CPU time |
|---|---|---|---|---|---|---|
| MLBSA [81] | 57mm diameter R.T.C France solar cell Photowatt-PWP201; | SDM, DDM, SMM | RMSE | No | No | Yes |
| LFBSA [82] | 57mm diameter R.T.C France solar cell Photowatt-PWP201; | SDM, DDM, SMM | RMSE | No | No | No |

**Table 20**
Statistical results of BSAs on 57mm diameter R.T.C France solar cell.

| Algorithm | Model | RMSE | | | | Max_NFE | CPU time(s) |
|---|---|---|---|---|---|---|---|
| | | Min | Max | Mean | Std | | |
| MLBSA [81] | SDM | 9.8602E−04 | 9.8602E−04 | 9.8602E−04 | 9.1461E−12 | 50 000 | – |
| | DDM | 9.8249E−04 | 9.8798E−04 | 9.8518E−04 | 1.3482E−06 | 50 000 | – |
| LFBSA [82] | SDM | 9.8602E−04 | 9.8602E−04 | 9.8602E−04 | 2.3613E−17 | 50 000 | – |
| | DDM | 9.82485E−04 | 9.86023E−04 | 9.84127E−04 | 1.46344E−06 | 50 000 | – |

**Table 21**
Comparison of JAYA method in different approaches.

| Method | Ref. | Remarks |
|---|---|---|
| JAYA | IJAYA [84] | An improved JAYA (IJAYA) algorithm was proposed to accurately and reliably identify the parameters of different PV models. |
| | EO-JAYA [85] | A novel elite opposition-based JAYA (EO-JAYA) algorithm was presented for parameter estimation of PV cell models. The elite opposition learning strategy was employed to diversify the solutions when updating. |
| | PGJAYA [86] | The authors proposed a performance-guide JAYA (PGJAYA) for parameters identification of PV cell and module, In which the individual performance in the whole population is quantified through probability. |
| | LCJAYA [87] | A logistic chaotic JAYA algorithm (LCJAYA) was developed for parameters identification of PV cell and module models. In LCJAYA, logistic chaotic map strategy and chaotic mutation strategy were introduced. |

**Table 22**
Details of PV modes parameter extraction with JAYA methods.

| Algorithm | Cell Dataset | Model | Objective function | Radiation | Temperature | CPU time |
|---|---|---|---|---|---|---|
| IJAYA [84] | 57mm diameter R.T.C France solar cell Photowatt-PWP201; | SDM, DDM, SMM | RMSE | No | No | No |
| EO-JAYA [85] | 57mm diameter R.T.C France solar cell; | SDM, DDM | RMSE | No | No | No |
| PGJAYA [86] | 57mm diameter R.T.C France solar cell Photowatt-PWP201 Multi-crystalline KC200GT Mono-crystalline SM55 Thin-film Shell ST40; | SDM, DDM, SMM | RMSE | Yes | Yes | Yes |
| LCJAYA [87] | 57mm diameter R.T.C France solar cell Photowatt-PWP201; | SDM, DDM, SMM | RMSE | No | No | No |

**Table 23**
Statistical results of JAYAs on 57mm diameter R.T.C France solar cell.

| Algorithm | Model | RMSE | | | | Max_NFE | CPU time(s) |
|---|---|---|---|---|---|---|---|
| | | Min | Max | Mean | Std | | |
| IJAYA [84] | SDM | 9.8603E−04 | 1.0622E−03 | 9.9204E−04 | 1.4033E−05 | 50 000 | – |
| | DDM | 9.8293E−05 | 1.4055E−03 | 1.0269E−03 | 9.8325E−05 | 50 000 | – |
| EO-JAYA [85] | SDM | 9.8603E−04 | – | – | – | 1 500 000 | – |
| | DDM | 9.8262E−04 | – | – | – | 1500000 | – |
| PGJAYA [86] | SDM | 9.8602E−04 | 9.8602E−04 | 9.8602E−04 | 1.4485E−09 | 50 000 | – |
| | DDM | 9.8263E−04 | 9.9499E−04 | 9.8582E−04 | 2.5375E−06 | 50 000 | – |
| LCJAYA [87] | SDM | 9.8602E−04 | 9.8602E−04 | 9.8602E−04 | 5.6997E−16 | 50 000 | – |
| | DDM | 9.8250E−04 | 9.8602E−04 | 9.8308E−04 | 1.3118E−06 | 50 000 | – |

was employed to extract the nine unknown parameters of the TDM of PV models [98]. After ICA, Fathy and Rezkand [99] proposed an enhanced moth search algorithm (EMSA) for identifying the optimal parameters of TDM under different operating conditions. In [100], an improved Lozi map based chaotic optimization algorithm (ILCOA) was presented to estimate the unknown parameters of the solar cells. A new parameter extraction method based bacterial foraging optimization (BFO) was presented in [101]. In [102], the moth-flame optimization (MFO) algorithm was employed to extract the parameters of the TDM for the multi-crystalline solar cell/module. Xiong et al. [103] developed a winner-leading competitive swarm optimizer with dynamic Gaussian mutation (WLCSODGM) algorithm to solve the parameter extraction problem of PV models. In [104], an opposition-based learning modified slap swarm algorithm (OLMSSA) was proposed for accurate identification of DDM of the PV models. The cuckoo search (CS) was introduced to estimate the parameter of PV models in [105].

**Table 24**
Details of PV modes parameter extraction with other methods.

| Algorithm | Cell Dataset | Model | Objective function | Radiation | Temperature | CPU time |
|---|---|---|---|---|---|---|
| PS [88] | 57mm diameter R.T.C France solar cell Photowatt-PWP201; | SDM, DDM, SMM | MAE, RMSE | No | No | No |
| SA [89] | 57mm diameter R.T.C France solar cell Photowatt-PWP201; | SDM, DDM, SMM | RMSE | No | No | No |
| HS [90] | 57mm diameter R.T.C France solar cell; | SDM, DDM | RMSE | No | No | No |
| ABSO [91] | 57mm diameter R.T.C France solar cell; | SDM, DDM | RMSE | No | No | No |
| FPA [92] | 57mm diameter R.T.C France solar cell Photowatt-PWP201 Multi-crystalline KC200GT Mono-crystalline SM55 Thin-film Shell ST40; | SDM, DDM, SMM | SSE, RMSE | Yes | Yes | No |
| FWA [93] | Multi-crystalline KC200GT Mono-crystalline SM55 Polycrystalline Shell SP70; | DDM | AE | No | No | No |
| IALO [94] | NS | SDM | – | Yes | Yes | No |
| ICA [95] | Mono-crystalline SQ150-PC 57mm diameter R.T.C France solar cell Multi-crystalline KC200GT Thin-film Shell ST40; | SDM, DDM | MAE | Yes | Yes | No |
| WDO [96] | 57mm diameter R.T.C France solar cell Multi-crystalline KC200GT; | SDM, DDM | RMSE | Yes | Yes | No |
| SSA [97] | NS | DDM | AE, RMSE | Yes | Yes | No |
| COA [98] | Multi-crystalline KC200GT, MSX-60; | TDM | RMSE | No | No | No |
| EMSA [99] | NS | TDM | RMSE | Yes | Yes | No |
| ILCOA [100] | 57mm diameter R.T.C France solar cell Mono-crystalline STM6-40/36; | SDM, DDM, SMM | MAE, RMSE | No | No | No |
| BFO [101] | Polycrystalline Shell SQ85, SP70 SSI-M6-205 and Shell ST40; | SMM | – | Yes | Yes | Yes |
| MFO [102] | Multi-crystalline solar cell Q6-1380 Multi-crystalline PV solar CS6P-240P; | DDM, TDM | RMSE | Yes | Yes | No |
| WLCSODGM [103] | 57mm diameter R.T.C France solar cell Photowatt-PWP201 Multi-crystalline KC200GT, MSX-60; | SDM, DDM, SMM | RMSE | Yes | Yes | No |
| OLMSSA [104] | TITAN-12-50 solar panel; | DDM | RMSE | Yes | Yes | No |
| CS [105] | 57mm diameter R.T.C France solar cell Multi-crystalline KC200GT; | SDM, SMM | RMSE | Yes | Yes | No |
| ImCSA [106] | 57mm diameter R.T.C France solar cell Photowatt-PWP201 Mono-crystalline STM6-40/36 Ploy-crystalline STP6-120/36; | SDM, DDM, SMM | RMSE | | | |
| MSSO [107] | 57mm diameter R.T.C France solar cell; | SDM, DDM | RMSE | No | No | Yes |
| SSSO [108] | 57mm diameter R.T.C France solar cell; | SDM, DDM | RMSE | No | No | Yes |
| ER-WCA [109] | 57mm diameter R.T.C France solar cell Photowatt-PWP201; | SDM, DDM, SMM | MAE, RMSE | Yes | Yes | No |

**Table 25**
Statistical results of other methods on 57mm diameter R.T.C France solar cell.

| Algorithm | Model | RMSE | | | | Max_NFE | CPU time(s) |
|---|---|---|---|---|---|---|---|
| | | Min | Max | Mean | Std | | |
| PS [88] | SDM | 0.2863 | – | – | – | – | – |
| | DDM | – | – | – | – | – | – |
| SA [89] | SDM | 1.7E−03 | – | – | – | – | – |
| | DDM | – | – | – | – | – | – |
| HS [90] | SDM | 9.8635E−04 | – | – | – | 150 000 | – |
| | DDM | 9.9306E−04 | – | – | – | 150000 | – |
| ABSO [91] | SDM | 9.9124E−04 | – | – | – | 150 000 | – |
| | DDM | 9.8344E−04 | – | – | – | 150000 | – |
| FPA [92] | SDM | 7.7301E−04 | – | – | – | 25 000 | – |
| | DDM | 7.8425E−04 | – | – | – | 25 000 | – |
| WDO [96] | SDM | 8.664E−06 | – | – | – | – | – |
| | DDM | 6.5237E−06 | – | – | – | – | – |
| ILCOA [100] | SDM | 9.8602E−04 | – | – | 1.0107E−08 | – | – |
| | DDM | 9.8257E−04 | – | – | 6.2543E−07 | – | – |
| WLCSODGM [103] | SDM | 9.8602E−04 | 9.8602E−04 | 9.8602E−04 | 2.6371E−17 | 50 000 | – |
| | DDM | 9.8248E−04 | 9.8782E−04 | 9.8429E−04 | 1.5419E−06 | 50 000 | – |
| CS [105] | SDM | 0.0010 | – | – | – | – | – |
| ImCSA [106] | SDM | 9.860219E−04 | 9.860219E−04 | 9.860219E−04 | 2.987589E−12 | 37 500 | – |
| | DDM | 9.8249E−04 | 9.8396E−04 | 9.8258E−04 | 2.8197E−07 | 200 000 | – |
| MSSO [107] | SDM | 9.8608E−04 | 9.8802E−04 | 9.8663E−04 | 5.2095E−07 | – | 1.0 (1) |
| | DDM | 9.8327E−04 | 9.9026E−04 | 9.8658E−04 | 1.7124E−06 | – | 1.0 (1) |
| SSSO [108] | SDM | 9.86E−04 | 9.86E−04 | 9.86E−04 | 5.04E−17 | 5000 | 0.722758 (1) |
| | DDM | 9.8248E−04 | 1.0561E−03 | 9.8681E−04 | 1.16E−05 | 10 000 | 0.914258 (1) |
| ER-WCA [109] | SDM | 9.8602E−04 | – | – | – | 8000 | – |
| | DDM | 9.824849E−04 | – | – | – | 7500 | – |

**Table 26**
Comparison of hybrid method in different approaches.

| Method | Ref. | Remarks |
|---|---|---|
| Hybrid optimization | BPFPA [110] | Flower Pollination Algorithm (FPA) + Artificial Bee Colony (ABC). |
| | GOFPANM [111] | Flower Pollination Algorithm (FPA) + Nelder–Mead (NM) simplex method. |
| | ABC-TRR [112] | Artificial Bee Colony (ABC) + Trust-Region Reflective (TRR). |
| | TLABC [113] | Teaching–Learning-Based Optimization (TLBO) + Artificial Bee Colony (ABC). |
| | DE/WOA [114] | Differential Evolution (DE) + Whale Optimization Algorithm (WOA). |
| | HFAPS [115] | Pattern Search (PS) + Firefly Algorithm (FA). |
| | BHCS [116] | Cuckoo Search (CS) + Biogeography-Based Optimization (BBO). |
| | GWOCS [117] | Gray Wolf Optimizer (GWO) + Cuckoo Search (CS). |

**Table 27**
Details of PV modes parameter extraction with hybrid methods.

| Algorithm | Cell Dataset | Model | Objective function | Radiation | Temperature | CPU time |
|---|---|---|---|---|---|---|
| BPFPA [110] | 57mm diameter R.T.C France solar cell Multi-crystalline KC200GT Mono-crystalline SM55 Thin-film Shell ST40 Polycrystalline Shell SP70; | SDM, DDM, SMM | RMSE | Yes | Yes | No |
| GOFPANM [111] | 57mm diameter R.T.C France solar cell Photowatt-PWP201 Multi-crystalline KC200GT Multi-crystalline S75 Thin-film Shell ST40; | SDM, DDM, SMM | RMSE | Yes | Yes | No |
| ABC-TRR [112] | 57mm diameter R.T.C France solar cell Photowatt-PWP201 GL-M100 PV module; | SDM, DDM, SMM | SSE, RMSE | Yes | Yes | No |
| TLABC [113] | 57mm diameter R.T.C France solar cell Photowatt-PWP201; | SDM, DDM, SMM | RMSE | No | No | No |
| DE/WOA [114] | 57mm diameter R.T.C France solar cell Photowatt-PWP201 JA Solar JAM6-60-295W-4BB; | SDM, DDM, SMM | RMSE | Yes | Yes | No |
| HFAPS [115] | 57mm diameter R.T.C France solar cell Photowatt-PWP201 Mono-crystalline STM6-40/36 Multi-crystalline KC200GT M/S BP SX3200N M/S 1Soltech 1STH-235WH; | SDM, DDM, SMM | RMSE | Yes | Yes | No |
| BHCS [116] | 57mm diameter R.T.C France solar cell Mono-crystalline STM6-40/36 Ploy-crystalline STP6-120/36; | SDM, DDM, SMM | RMSE | No | No | No |
| GWOCS [117] | 57mm diameter R.T.C France solar cell Photowatt-PWP201 Mono-crystalline STM6-40/36; | SDM, DDM, SMM | RMSE | No | No | No |

**Table 28**
Statistical results of hybrid methods on 57mm diameter R.T.C France solar cell.

| Algorithm | Model | RMSE | | | | Max_NFE | CPU time(s) |
|---|---|---|---|---|---|---|---|
| | | Min | Max | Mean | Std | | |
| BPFPA [110] | SDM | 7.27E−04 | – | – | – | 20 000 | – |
| | DDM | 7.23E−04 | – | – | – | 20 000 | – |
| GOFPANM [111] | SDM | 9.860219E−04 | 9.860219E−04 | 9.860219E−04 | 5.591415E−15 | 10 000 | – |
| | DDM | 9.824849E−04 | 1.340531E−03 | 9.954827E−04 | 6.518742E−05 | 20 000 | – |
| ABC-TRR [112] | SDM | 9.860219E−04 | 9.860219E−04 | 9.860219E−04 | 6.15E−17 | 1000 | – |
| | DDM | 9.824849E−04 | 9.860219E−04 | 9.825556E−04 | 4.95E−07 | 5000 | – |
| TLABC [113] | SDM | 9.86022E−04 | 1.03970E−03 | 9.98523E−04 | 1.86022E−05 | 50 000 | – |
| | DDM | 9.84145E−04 | 1.50482E−03 | 1.05553E−03 | 1.55034E−04 | 50 000 | – |
| DE/WOA [114] | SDM | 9.860219E−04 | 9.860219E−04 | 9.860219E−04 | 3.545178E−17 | 100 000 | – |
| | DDM | 9.824849E−04 | 9.860377E−04 | 9.829703E−04 | 9.152178E−07 | 100 000 | – |
| HFAPS [115] | SDM | 9.8602E−04 | – | – | – | 250 000 | – |
| | DDM | 9.8248E−04 | – | – | – | 250 000 | – |
| BHCS [116] | SDM | 9.86022E−04 | 9.86022E−04 | 9.86022E−04 | 2.61254E−17 | 50 000 | – |
| | DDM | 9.82485E−04 | 9.86865E−04 | 9.83800E−04 | 1.53897E−06 | 50 000 | – |
| GWOCS [117] | SDM | 9.8607E−04 | 9.9095E−04 | 9.8874E−04 | 2.4696E−06 | 50 000 | – |
| | DDM | 9.8334E−04 | 1.0017E−03 | 9.9411−04 | 9.5937E−06 | 50 000 | – |

Another CS variant named a novel improved cuckoo search algorithm (ImCSA) was proposed for parameter estimation of PV models [106]. Lin et al. [107] proposed a modified SSO (MSSO) for parameters extraction of solar cell models. In addition to MSSO, in [108], a simplex simplified swarm optimization (SSSO) was developed to accurately and reliably identify the parameters of solar cell models. Kler et al. [109] proposed a new and powerful meta-heuristic optimization technique, namely evaporation rate based water cycle algorithm (ER-WCA), for effective parameters estimation of PV models. Table 24 gives the details of PV models parameter extraction with other methods. The statistical results of other methods are reported in Table 25, in which SSSO and WLCSODGM have obtained satisfactory results in terms of the statistical results while SSSO consumed the less computing resources. In addition, an interesting finding is that WDO has achieved very small RMSE values on SDM (8.664E−06) and DDM (6.5237E−06), and almost all methods have not reached this accuracy.

### 4.10. Hybrid optimization

In addition to the use of a single meta-heuristic algorithm mentioned as above for PV models parameter extraction, there are some hybrid algorithms that are also used to solve this problem. Ram et al. [110] presented a new hybrid bee pollinator flower pollination algorithm (BPFPA) which combines the flower pollination algorithm (FPA) and the artificial bee colony (ABC) method, for the PV parameter extraction problem. In [111], a new optimization algorithm GOFPANM was proposed for efficiently and accurately estimating the parameters of PV models. In GOFPANM, the Nelder–Mead (NM) simplex method was incorporated with the FPA and the generalized opposition-based learning mechanism was also introduced. In [112], the authors proposed a new hybrid algorithm (ABC-TRR) by combining the ABC meta-heuristic algorithm with the trust-region reflective (TRR) deterministic algorithm for parameter extraction of PV models. Chen et al. [113] proposed a hybrid teaching–learning-based artificial bee colony (TLABC) for the solar PV parameter estimation problems. It is an amalgamated approach of teaching–learning-based optimization (TLBO) and ABC. In [114], Xiong et al. extracted the parameters of PV models by a hybrid differential evolution (DE) with whale optimization algorithm (WOA). A hybrid optimization algorithm named HFAPS [115] was proposed to identify the parameters of solar cell models, in which the pattern search (PS) good at local search was embedded in the firefly algorithm (FA). To accurately and reliably estimate the parameters of solar PV models, a hybrid meta-heuristic algorithm called biogeography-based heterogeneous cuckoo search (BHCS) was developed in [116]. In addition, Long et al. [117] extracted the parameters of different PV models with the experimental data under different operating conditions via a new hybrid algorithm based on gray wolf optimizer and cuckoo search (GWOCS). Table 26 summarizes the different hybrid methods applied for PV models parameter extraction,

**Table 29**
Statistical results of various algorithms on 57mm diameter R.T.C France solar cell.

| Algorithm | $I_{ph}$ (A) | $I_{sd_1}$ ($\mu$A) | $I_{sd_2}$ ($\mu$A) | $R_s$ ($\Omega$) | $R_{sh}$ ($\Omega$) | $n_1$ | $n_2$ | RMSE | | | | Max_NFE | CPU time (s) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | | | Min | Max | Mean | Std | | |
| SDM | | | | | | | | | | | | | |
| EJADE [47] | 0.7608 | 0.3230 | – | 0.0364 | 53.7185 | 1.4812 | – | 9.8602E–04 | 9.8602E–04 | 9.8602E–04 | 5.13E–17 | 10 000 | 11.82 (30) |
| MADE [50] | 0.7608 | 0.3230 | – | 0.0364 | 53.7185 | 1.4812 | – | 9.8602E–04 | 9.8602E–04 | 9.8602E–04 | 2.74E–15 | 5000 | 0.1267 (1) |
| FC-EPSO [63] | 0.76079 | 0.31131 | – | 0.036538 | 52.944 | 1.4773 | – | 7.7301E–04 | – | – | 1.5688E–10 | 6000 | 11.5197 (30) |
| CPMPSO [62] | 0.760776 | 0.323021 | – | 0.036377 | 53.71852 | 1.481184 | – | 9.86022E–04 | 9.86022E–04 | 9.86022E–04 | 2.17556E–17 | 50 000 | – |
| ITLBO [70] | 0.7608 | 0.3230 | – | 0.0364 | 53.7185 | 1.4812 | – | 9.8602E–04 | 9.8602E–04 | 9.8602E–04 | 2.19E–17 | 50 000 | 5.95 (30) |
| CWOA [73] | 0.76077 | 0.3239 | – | 0.03636 | 53.7987 | 1.4812 | – | 9.8604E–04 | – | – | 1.0216E–08 | 45 000 | – |
| ISCE [79] | 0.76077553 | 0.32302083 | – | 0.03637709 | 53.71852771 | 1.48118360 | – | 9.860219E–04 | 9.860219E–04 | 9.860219E–04 | 3.98E–17 | 5000 | – |
| LFBSA [82] | 0.760776 | 0.323021 | – | 0.036377 | 53.71852 | 1.481184 | – | 9.8602E–04 | 9.8602E–04 | 9.8602E–04 | 2.3613E–17 | 50 000 | – |
| PGJAYA [86] | 0.7608 | 0.3230 | – | 0.0364 | 53.7185 | 1.4812 | – | 9.8602E–04 | 9.8602E–04 | 9.8602E–04 | 1.4485E–09 | 50 000 | – |
| LCJAYA [87] | 0.7608 | 0.3230 | – | 0.0364 | 53.7185 | 1.4819 | – | 9.8602E–04 | 9.8602E–04 | 9.8602E–04 | 5.6997E–16 | 50 000 | – |
| SSSO [108] | 0.760776 | 0.323021 | – | 0.036377 | 53.718530 | 1.481184 | – | 9.86E–04 | 9.86E–04 | 9.86E–04 | 5.04E–17 | 5000 | 0.722758 (1) |
| WLC-SODGM [103] | 0.76077553 | 0.32302078 | – | 0.03637709 | 53.71852194 | 1.48118358 | – | 9.8602E–04 | 9.8602E–04 | 9.8602E–04 | 2.6371E–17 | 50 000 | – |
| ABC-TRR [112] | 0.760776 | 0.323021 | – | 0.036377 | 53.718521 | 1.481184 | – | 9.860219E–04 | 9.860219E–04 | 9.860219E–04 | 6.15E–17 | 1000 | – |
| GOF-PANM [111] | 0.7607755 | 0.3230208 | – | 0.0363771 | 53.7185203 | 1.4811836 | – | 9.860219E–04 | 9.860219E–04 | 9.860219E–04 | 5.591415E–15 | 10 000 | – |
| DE/WOA [114] | 0.760776 | 0.323021 | – | 0.036377 | 53.718524 | 1.481184 | – | 9.860219E–04 | 9.860219E–04 | 9.860219E–04 | 3.545178E–17 | 100 000 | – |
| BHCS [116] | 0.76078 | 0.32302 | – | 0.03638 | 53.71852 | 1.48118 | – | 9.86022E–04 | 9.86022E–04 | 9.86022E–04 | 2.61254E–17 | 50 000 | – |
| DDM | | | | | | | | | | | | | |
| EJADE [47] | 0.7608 | 0.2260 | 0.7493 | 0.0367 | 55.4854 | 1.4510 | 2.0000 | 9.8248E–04 | 9.8602E–04 | 9.8363E–04 | 1.36E–06 | 20 000 | 23.16 (30) |
| MADE [50] | 0.7608 | 0.7394 | 0.2246 | 0.0368 | 55.4329 | 1.9963 | 1.4505 | 9.8261E–04 | 9.8786E–04 | 9.8608E–04 | 8.02E–05 | 10 000 | 0.1890 (1) |
| FC-EPSO [63] | 0.76082 | 0.10974 | 0.93626 | 0.037567 | 54.928 | 1.3948 | 1.8450 | 7.4489E–04 | – | – | 2.1153E–10 | 6000 | 12.0364 (30) |
| CPMPSO [62] | 0.76078 | 0.74935 | 0.22597 | 0.03674 | 55.48544 | 2 | 1.45102 | 9.82485E–04 | 9.86022E–04 | 9.83137E–04 | 1.3398E–06 | 50 000 | – |
| ITLBO [70] | 0.7608 | 0.2260 | 0.7493 | 0.0367 | 55.4854 | 1.4510 | 2.0000 | 9.8248E–04 | 9.8812E–04 | 9.8497E–04 | 1.54E–06 | 50 000 | 6.60 (30) |
| CWOA [73] | 0.76077 | 0.24150 | 0.60000 | 0.03666 | 55.2016 | 1.45651 | 1.9899 | 9.8279E–04 | – | – | 1.1333E–07 | 45 000 | – |
| ISCE [79] | 0.76078108 | 0.22597409 | 0.74934898 | 0.03674043 | 55.48544409 | 1.45101670 | 2.000000 | 9.824849E–04 | 9.861092E–04 | 9.827740E–04 | 4.61E–07 | 10 000 | – |
| LFBSA [82] | 0.760781 | 0.225974 | 0.749345 | 0.036740 | 55.48543 | 1.451017 | 2 | 9.82485E–04 | 9.86023E–04 | 9.84127E–04 | 1.46344E–06 | 50 000 | – |
| PGJAYA [86] | 0.7608 | 0.21031 | 0.88534 | 0.0368 | 55.8135 | 1.4450 | 2.0000 | 9.8263E–04 | 9.9499E–04 | 9.8582E–04 | 2.5375E–06 | 50 000 | – |
| LCJAYA [87] | 0.7608 | 0.22596 | 0.74640 | 0.0367 | 55.4815 | 1.4518 | 2.0000 | 9.8250E–04 | 9.8602E–04 | 9.8308E–04 | 1.3118E–06 | 50 000 | – |
| SSSO [108] | 0.760779225 | 0.350185688 | 0.307012100 | 0.036665270 | 54.886073220 | 1.629491315 | 1.559272611 | 9.8248E–04 | 1.0561E–03 | 9.8681E–04 | 1.16E–05 | 10 000 | 0.914258 (1) |
| WLC-SODGM [103] | 0.76078110 | 0.74920245 | 0.22599157 | 0.03674034 | 55.48504499 | 2.00000000 | 1.45102317 | 9.8248E–04 | 9.8782E–04 | 9.8429E–04 | 1.5419E–06 | 50 000 | – |
| ABC-TRR [112] | 0.760781 | 0.225974 | 0.749349 | 0.036740 | 55.485438 | 1.451017 | 2.000000 | 9.824849E–04 | 9.860219E–04 | 9.825556E–04 | 4.95E–07 | 5000 | – |
| GOF-PANM [111] | 0.7607811 | 0.7493476 | 0.2259743 | 0.0367404 | 55.4854485 | 2.000000 | 1.4510168 | 9.824849E–04 | 1.340531E–03 | 9.954827E–04 | 6.518742E–05 | 20 000 | – |
| DE/WOA [114] | 0.760781 | 0.225974 | 0.749346 | 0.036740 | 55.485437 | 1.451017 | 2.000000 | 9.824849E–04 | 9.860377E–04 | 9.829703E–04 | 9.152178E–07 | 100 000 | – |
| BHCS [116] | 0.76078 | 0.74935 | 0.22597 | 0.03674 | 55.48544 | 2.00000 | 1.45102 | 9.82485E–04 | 9.86865E–04 | 9.83800E–04 | 1.53897E–06 | 50 000 | – |

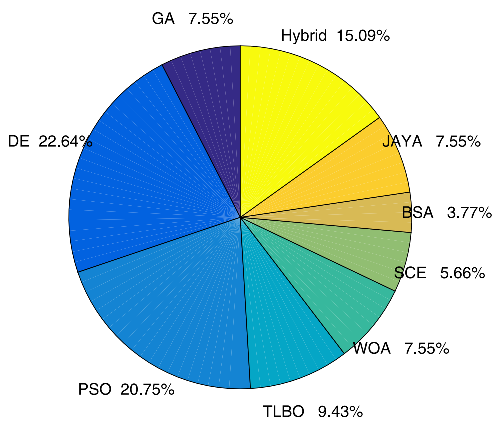


**Fig. 9.** The proportion of different optimization methods.

and Table 27 gives the details of PV modes parameter extraction with hybrid methods. Table 28 reports the statistical results of hybrid methods. From Table 28, it can be observed that BPFPA achieved the best RMSE values. Unfortunately, the authors of BPFPA did not give other statistical results in their paper. Taking the overall statistical results into consideration, ABC-TRR showed a clear advantage, followed by GOFPANM, BHCS, DE/WOA, and others.

## 5. Comprehensive analysis and future works

Various meta-heuristic methods used to solve the PV models parameters extraction problem have been described in previous section. In this section, some representative methods are selected from each type of meta-heuristic algorithm for comprehensive analysis, and some future research directions are proposed.

### 5.1. Comprehensive analysis

Fig. 9 shows a pie chart of various meta-heuristic optimization methods and related variants used in PV models parameter extraction in recent years. It can be observed that DE accounts for the largest proportion, followed by PSO, Hybrid, and others. However, each type of meta-heuristic algorithm has its own unique features. In order to more comprehensively analyze the performance of these parameter extraction algorithms, some representative methods such as EJADE [47], MADE [50], FC-EPSO [63], CPMPSO [62], ITLBO [70], CWOA [73], ISCE [79], LFBSA [82], PGJAYA [86], LCJAYA [87], SSSO [108], WLCSODGM [103], ABC-TRR [112], GOFPANM [111], DE/WOA [114], and BHCS [116], from each type of algorithm are selected. To facilitate the analysis of these methods, only the results of various algorithms on 57 mm diameter R.T.C France solar cell are recorded. The statistical results including the extracted optimal parameters, Min, Max, Mean, Std, Max_NFE and CPU time are reported in Table 29, where some conclusions can be made.

- In terms of RMSE, FC-EPSO can achieve the best RMSE values on the SDM (7.7301E−04) and the DDM (7.4489E−04). While the best RMSE values obtained by most other algorithms are 9.8602E−04 and 9.8248E−04 corresponding to SDM and DDM, respectively. With a view of the Max and Mean, all algorithms provide the best RMSE (9.8602E−04) values for the SDM. While for the DDM, EJADE, CPMPSO, LFBSA, LCJAYA and ABC-TRR obtained the best Max RMSE (9.8602E−04). In addition, ABC-TRR obtained the best Mean (9.825556E−04) RMSE, follow by ISCE (9.827740E−04), DE/WOA (9.829703E−04), and others. Unfortunately, FC-EPSO does not provide these two values in the study. As the Std, EJADE, CMPSO, ITLBO, ISCE, LFBSA, SSSO, WLCSODGM, ABC-TRR, DE/WOA and BHCS achieved the better results for the SDM and DDM, which showed that these algorithms have a good robustness.
- With respect to the Max_NFE consumed, ABC-TRR uses the least number of function evaluations, regardless of the model. For the SDM, MADE, ISCE, SSSO consumed 5000, 6000 for FC-EPSO, 10 000 for EJADE and GOFPANM, 50 000 for the most algorithms, and one or two consume more. For the DDM, FC-EPSO consumed 6000, 5000 for MADE, ISCE and SSSO, 10 000 for EJADE and GOFPANM. It is worth mentioning that Max_NFE means that the computing resources consumed by finding the optimal parameter values can reflect the computational burden of an algorithm to a certain extent.
- In regard to the CPU time, only some algorithms such as EJADE, MADE, FC-EPSO, ITLBO, and SSSO reported in their papers. From these reported results, MADE takes the shortest time, followed by ITLBO, FC-EPSO, EJADE, and SSSO. Note that the CPU time can indirectly indicate the complexity of an algorithm to some extent.

In addition, Table 30 summarizes the main advantages and disadvantages of some representative meta-heuristic optimization algorithms. According to this table, we can clearly understand the advantages and disadvantages of various algorithms, and some advanced and improved variants for the application of PV model parameter extraction. In addition, these reported disadvantages provide research directions for further improvement of these optimization algorithms.

### 5.2. Future works

After a comprehensive review on most of the meta-heuristic methods that used to extract the parameters of PV models, in this section, some insights in the future works are given as follows:

- For the GAs methods [36,37], the accuracy and consumed computational resources should be paid more attention. In addition, how to avoid falling into local optimum is noteworthy for these methods.
- For the DEs and PSOs methods such as Rcr-IJADE [42], EJADE [47], MADE [50], GCPSO [58], FC-EPSO [63], MPSO [59] and CPMPSO [62] the results obtained by these methods are very impressive. However, as far as RMSE is concerned, the accuracy of DEs has room for further improvement. While PSOs consume more computational resources and CPU time when compared to DEs. How to balance the two is worth further study.
- TLBOs [66–70] and JAYAs [84–87] methods are parameter-free. There is no need to adjust the parameters in advance, which is different from most algorithms. However, when improving such methods, convergence speed is a point of concern, which also applies to WOAs and BSAs.
- SCEs [78,79] and hybrid [110–117] methods also show remarkable performance on the PV model problem. Their algorithm structure is more complex, and there are many algorithm parameters to set. Therefore, when improving these algorithms, their parameters must be carefully adjusted and parameter-adaptive may be a good choice.
- Generally, PV cells are usually exposed outdoors, therefore the effect of changes in irradiation and temperature must be taken into consideration. In addition, few meta-heuristic methods are devoted to TDM research. However, it should be paid more attention.
- Most proposed methods only consider the RMSE as the objective function. It is recommended to study the influence of other objective functions.

**Table 30**
Summary of the advantages and disadvantages of some optimization algorithms.

| Algorithm | Advantages | Disadvantages |
|---|---|---|
| GAs | • Use a probabilistic mechanism with randomness<br>• The GA proposed in [38] is more accurate than the traditional approaches<br>• Easy to combine with other algorithms [36,37] | • Easy to trap into local optimum<br>• The value of the parameter seriously affects the quality of the solution<br>• Require more computational resources in improved versions [3] |
| DEs | • Easy to code<br>• Fast convergence<br>• Effective and efficient<br>• For PV models parameter extraction, DE variants provide better resulting terms of accuracy, reliability, and computational time [42,46,47,50] | • Easy to converge prematurely<br>• Three parameters need to be set |
| PSOs | • Good balance between the exploration and exploitation<br>• Fast search speed<br>• Considering the global optimal position and the best position of a particle, it has memory<br>• The TDM is adopted in [63]<br>• In [58,59,61,63], different PSO variants have obtained more accurate results on SDM and DDM | • Premature convergence<br>• Easy to trap local optimum on multi-modal problem<br>• Parameter setting depends on different problems |
| TLBOs | • Parameter-free<br>• Efficient and easy to implement<br>• In [69], a self-adaptive TLBO variant reduces the consumption of computing resources<br>• An improved TLBO increases the accuracy and reliability for SDM and DDM [70] | •Slow convergence<br>• Consume more computing resources [118] |
| WOAs | • A few parameter to tune<br>• Strong search ability<br>• Opposition-based learning mechanism can improve its exploration ability [74]<br>• In [74], WOA was verified by TDM | • Slow convergence<br>• Premature convergence on multi-modal problem |
| SCEs | • Integration of deterministic and random [76]<br>• Accurate and robust<br>• The improved SCE provides excellent results on SDM, DDM and SMM [79] | • The structure is complicated<br>• Slow convergence<br>• Performance is easily affected by parameters |
| BSAs | • Simple structure<br>• Use history information and search-direction matrix<br>• BSA is first used for PV models parameter extraction in [81]<br>• The improved variant of BSA has achieved better result on PV models [82] | • Slow convergence<br>• Performance depends on the random selection of historical population [81] |
| JAYAs | • Parameter-free<br>• Simple and effective<br>• Logistic chaotic map strategy improves the population diversity [87]<br>• The variants of JAYA have better performance than PSO and TLBO [86,87] | • Poor population diversity [86]<br>• The exploration and exploitation ability cannot be balanced well |
| Hybrid | • It has the advantages of multiple algorithms<br>• Many hybrid algorithms have obtained better performance [111–117]<br>• In [112], the computing resources and CPU time used for PV models parameter extraction are greatly reduced | • Complex algorithm structure<br>• Many parameters must be carefully adjusted |

- It is recommended to give statistical results such as the Min, Max, Mean, Std, CPU time and others in future researches, in order to more comprehensively analyze the accuracy, reliability and stability of the method.
- It is recommended to develop hybrid algorithms, especially combining meta-heuristics with some local search methods, such as Nelder–Mead (NM) simplex method, trust-region reflective (TRR), which are helpful to reduce the consumption of computing resources and improve accuracy.
- When conducting experiments, some more complex cell datasets should be used for algorithm performance evaluation, instead of some simple datasets such as 57 mm diameter R.T.C France solar cell, Photowatt-PWP201.

## 6. Conclusions

The PV system has largely pioneered the development of solar energy in the field of renewable energy, so it has received much attention recently. However, parameter extraction of PV models plays an important role in the simulation, evaluation, and control of PV systems. This paper focused on reviewing the different PV models and various meta-heuristic methods applied for PV models parameter extraction problem. The performance of each type of algorithm is analyzed and discussed. Among all the algorithms used for parameter extraction, FC-EPSO can provide the best RMSE values i.e., 7.7301E−04 for the SDM and 7.4489E−04 for the DDM. All DE algorithms and most other algorithms can only achieve satisfactory RMSE values, i.e., 9.8602E−04 and 9.8248E−04 corresponding to the SDM and DDM. However, the hybrid algorithm ABC-TRR uses the least computing resources and obtains considerable results. While MADE takes the shortest CPU calculation time. Furthermore, this review article comprehensively analyzes various meta-heuristic algorithms according to the statistical results. Based on this in-depth analysis, some directions for future work are provided, which will be beneficial for further research on this issue. The authors strongly believe that this review on PV models parameter extraction will provide a useful reference for researchers and engineers in this research field.

## CRediT authorship contribution statement

**Shuijia Li:** Resources, Project administration, Software, Data curation, Writing - original draft, Writing - review & editing. **Wenyin Gong:** Funding acquisition, Supervision, Conceptualization, Methodology, Writing - review & editing. **Qiong Gu:** Contributed data and analysis tools and performed the analysis, Writing - review & editing.

## Declaration of competing interest

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.

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