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Parameters identification of photovoltaic models using an improved JAYA optimization algorithm

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ABSTRACT

Parameters identification of photovoltaic (PV) models based on measured current-voltage characteristic curves is significant for the simulation, evaluation, and control of PV systems. To accurately and reliably identify the parameters of different PV models, an improved JAYA (IJAYA) optimization algorithm is proposed in the paper. In IJAYA, a self-adaptive weight is introduced to adjust the tendency of approaching the best solution and avoiding the worst solution at different search stages, which enables the algorithm to approach the promising area at the early stage and implement the local search at the later stage. Furthermore, an experience-based learning strategy is developed and employed randomly to maintain the population diversity and enhance the exploration ability. A chaotic elite learning method is proposed to refine the quality of the best solution in each generation. The proposed IJAYA is used to solve the parameters identification problems of different PV models, i.e., single diode, double diode, and PV module. Comprehensive experiment results and analyses indicate that IJAYA can obtain a highly competitive performance compared with other state-of-the-state algorithms, especially in terms of accuracy and reliability.

1. Introduction

To tackle the issues of climate change, global warming, and depletion of classical fossil fuels, increasing attention has been focused on the utilization of renewable energy sources. Solar energy can be generally presented as a promising alternative of inexhaustible and clean sources [1]. Solar energy is converted into electrical energy through photovoltaic (PV) systems such as solar cell. PV systems usually operate in harsh outdoor environment and their PV arrays are easy to be deteriorated, which greatly affect the solar energy utilization efficiency [2]. Hence, in order to control and optimize PV systems, it is vital to evaluate the actual behavior of PV arrays in operation using accurate model based on measured current-voltage data. There are several mathematical models that successfully describe the performance and nonlinear behavior of PV systems. The most common and widely adopted models are the single diode model and double diode model [3]. The accuracy of PV models mainly depends on their model parameters. However, these parameters usually are unavailable and change due to aging, faults, and volatile operating conditions. Hence, the accurate identification for parameters is indispensable to the simulation, evaluation, and control of PV systems, and various parameter identification methods have been developed over recent years [4,5].

Some attempts have been devoted to using deterministic techniques for parameter identification based on minimization of a suitably chosen function [6–8]. However, deterministic techniques impose various model restrictions such as differentiability and convexity in order to be correctly applied. Besides, since the parameter identification of PV models is a non-linear and multi-modal problem, leading to high probability of falling in local optimal when employing deterministic techniques.

As a promising alternative to deterministic techniques, heuristic methods inspired by various natural phenomenon have been widely used to identify parameters of PV models. They impose no restrictions on the problem characteristic, thus can be easily implemented for various real-world problems. In [9], a penalty based differential evolution (P-DE) was proposed for estimating the parameters of solar PV modules at different environmental conditions. In [10], an improved adaptive DE (IADE) based parameter estimation method was developed by introducing the new formulas for scaling factor and crossover rate. In [11], artificial bee swarm optimization (ABSO) was used to identify the solar cell parameters. In [12], bacterial foraging algorithm was proposed to model the solar PV characteristics accurately. In [13], a

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Nomenclature

I_d	diode current (A)
I_{d1}	first diode current (A)
I_{d2}	second diode current (A)
I_{ph}	photocurrent (A)
I_L	cell output current (A)
I_{sd}	reverse saturation current of diode (A)
I_{sd1}	diffusion current (A)
I_{sd2}	saturation current (A)
I_{sh}	shunt resistor current (A)
n	diode ideal factor
n_1	diffusion diode ideal factor
n_2	recombination diode ideal factor
k	Boltzmann constant
q	electron charge
N_p	the number of solar cells in parallel
N_s	the number of solar cells in series
N	the number of experimental data
R_S	series resistance (Ω)
R_{sh}	shunt resistance (Ω)
T	temperature of junction (K)
V_L	cell output voltage (V)
V_t	junction thermal voltage (V)
NP	population size
D	dimension of problem
$G_{\max}$	the maximal number of generation
Max_FES	the maximal number of function evaluations
RMSE	root mean square error
SD	standard deviation
IJAYA	improved JAYA
LETLBO	teaching-learning-based optimization with learning experience
GOTLBO	generalized oppositional teaching-learning-based optimization
LBSA	learning backtracking search algorithm
CLPSO	comprehensive learning particle swarm optimizer
BLPSO	biogeography-based learning particle swarm algorithm
DE/BBO	differential evolution with biogeography-based optimization
CMM-DE/BBO	DE/BBO with covariance matrix based migration
ABSO	artificial bee swarm optimization
IADE	improved adaptive differential evolution
IGHS	innovative global harmony search
PS	pattern search
SA	simulated annealing

biogeography-based optimization with mutation strategies (BBO-M) was developed by incorporating the mutation of DE and chaos theory into the BBO structure. BBO-M was first tested on benchmark functions, and then applied to the model parameter estimation of solar cell. In [14], an improved and simplified teaching-learning-based optimization (STLBO) with an elite strategy and a local search was designed for identifying the parameters of proton exchange membrane fuel and solar cells. In [15], TLBO was implemented by developing an interactive numerical simulation and then applied to the reported current-voltage data of different types of solar cells. In [16], a mutative-scale parallel chaos optimization algorithm (MPCOA) employing crossover and merging operation was developed for solving the designed parameter estimation problem. In [17], artificial bee colony (ABC) was utilized to extract the parameters of solar cells accurately. In [18], bird mating optimizer (BMO) was simplified and then employed to estimate the parameters of module model at different operation conditions. In [1], a DE with integrated mutation per generation (DEIM) was developed to identify the unknown parameters of double diode PV module model. In [19], the performance of six bio-inspired optimization algorithms were compared on the parameters identification of single diode model. In [20], month flame optimizer (MFO) was developed for the parameters estimation of three diode model. In [21], a generalized oppositional TLBO (GOTLBO) was proposed by introducing the generalized opposition-based learning into the initial step and generation jumping, and then used to extract the parameters of solar cell models. In [22], five different versions of the bacterial foraging algorithm (BFA) were developed to extract the parameters of PV module from nameplate data. In [23], a time varying acceleration coefficients particle swarm optimization (TVACPSO) was developed for estimating parameters of PV cells and modules. Although these attempts have achieved satisfied results, the performance of aforementioned algorithms are affected by their algorithm-specific or introduced parameters. It is difficult for users to set the appropriate parameters for a specific or new optimization problem, and the inappropriate tuning of parameters either increase the computational burden or achieve the local optimal solution.

JAYA algorithm is a new yet powerful heuristic method proposed by Rao for constrained and unconstrained optimization problems [24]. It does not require any algorithm-specific parameter except two common parameters namely the population size and the number of generation. Different from JAYA, many other algorithms require the algorithm-specific parameters in addition to common parameters. For example, DE requires the scaling factor and crossover probability, and PSO needs the inertia weight and acceleration coefficients. Hence, a significant benefit of JAYA algorithm can be achieved in terms of omitting the difficulty of adjusting parameters and decreasing the time necessary for conducting optimization process. Although TLBO algorithm is also free from algorithm-specific parameters, it requires two phases (i.e. teacher phase and learner phase) per generation, leading to two function evaluations (FE) for each individual in each generation. Thus, the computation cost of TLBO in a single generation is larger than that of an algorithm with one FE per generation. Unlike TLBO, JAYA algorithm needs only one phase, thus making it less computation time and implementation complexity. JAYA has been improved and widely applied to various real-world optimization problems such as thermal devices [25], two-area interconnected linear power system [26], modern machining processes [27], optimum power flow problem [28], heat exchangers [29–31], coefficients optimization of proportional plus integral controller [32], constrained mechanical design optimization [33], machining performance optimization during the tuning operation of CFRP composites [34], dimensional optimization of a micro-channel heat sink [35], and other problems [36,37]. However, as a new algorithm, JAYA has some disadvantages. The first is that there is only guidance as approach to the best solution and avoid the worst solution, although the convergence rate is accelerated, the population diversity may not be maintained efficiently, leads to local optimal solution. The second is that no strategy is used to improve the best solution during each generation, may result in the poor quality of final solution. Besides, to the best of our knowledge no attempts to employ JAYA in solving the parameter identification problems of PV models have been reported in the literature.

In this paper, an improved JAYA (IJAYA) algorithm is proposed to identify the parameters of PV models accurately and reliably. In IJAYA, a self-adaptive weight determined by the best and worst function values is introduced to adjust the tendency of approaching the best solution and avoiding the worst solution. This weight assists the algorithm to approach the potential area at the early stage and implement the local search at the later stage. In addition, a learning strategy based on the experience of other individuals is developed and used randomly to enhance the population diversity efficiently. A chaotic learning is employed to improve the quality of the best solution in each generation. In order to verify the effectiveness of the proposed IJAYA algorithm, it is compared with other well-established algorithms on parameters identification problems of different PV models, i.e., single diode, double diode, and PV module. Experimental results and analyses demonstrate that IJAYA exhibits superior performance in terms of accuracy and reliability. Thus, IJAYA can be an effective alternative for other complex optimization problems of PV systems.

The main contributions of this study are as follows:

(1) IJAYA algorithm is proposed for the parameters identification of PV models. In IJAYA, a self-adaptive weight is introduced to purposefully adjust the tendency of approaching the best solution and avoiding the worst solution at different search stages.
(2) An experience-based learning method is designed and implemented randomly to improve the population diversity efficiently.
(3) A chaotic elite learning strategy is proposed to refine the quality of the best solution in each generation.
(4) The effectiveness of IJAYA is demonstrated through comprehensive experiments and comparisons on parameters identification problems of different PV models.

The rest of this paper is organized as follows. The problem formulation of PV models is given in Section 2. Basic JAYA algorithm is introduced in Section 3. The proposed IJAYA algorithm is presented in Section 4. The experimental results on different PV models are shown and analyzed in Section 5. Finally, the conclusions are given in Section 6.

2. Problem formulation

In the literature, there are several PV models that describe the current-voltage characteristics of the solar cells and PV module. In practice, the most commonly used ones are the single diode model and double diode model. These models and their objective functions are introduced in this section.

2.1. Solar cell model

2.1.1. Single diode model

Single diode model has been widely used to represent the static characteristic of solar cell because of simplicity and accuracy [3]. This model includes a current source in parallel with a diode, a shunt resistor to represent the leakage current, and a series resistor to denote the losses of load current. The equivalent circuit of this model is presented in Fig. 1(a) and the output current is calculated as follows:

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

$$I_d = I_{sd}\cdot\left[\exp\left(\frac{q\cdot(V_L + R_S\cdot I_L)}{n\cdot k\cdot T}\right)-1\right] \tag{2}$$

$$I_{sh} = \frac{V_L + R_S\cdot I_L}{R_{sh}} \tag{3}$$

where I_L is the solar cell output current, I_{ph} is the total current generated by solar cell, I_d is the diode current calculated by Shockley Eq. (2), and I_{sh} is the shunt current calculated by Eq. (3). R_S and R_{sh} are the series and shunt resistances, respectively. V_L is the cell output voltage, I_{sd} is the reverse saturation current of diode. n is the diode ideal factor. k is the Boltzmann constant ($1.3806503 \times 10^{-23}$ J/K), q is the electron charge ($1.60217646 \times 10^{-19}$ C), and T is the cell absolute temperature in Kelvin. Hence, by combining Eqs. (2) and (3), the output current shown in Eq. (1) can be rewritten as:

$$I_L = I_{ph} - I_{sd}\cdot\left[\exp\left(\frac{q\cdot(V_L + R_S\cdot I_L)}{n\cdot k\cdot T}\right)-1\right] - \frac{V_L + R_S\cdot I_L}{R_{sh}} \tag{4}$$

Therefore, for this single diode model, five unknown parameters (I_{ph},I_{sd} R_S R_{sh} n) are needed to be estimated. Accurate identification of these parameters is vital to reflect the solar cell performance, this can be achieved by an optimization technique.

2.1.2. Double diode model

Double diode model is developed by considering the effect of recombination current loss in the depletion region [21]. In this model, there are two diodes in parallel with the current source and a shunt resistance. The equivalent circuit is shown in Fig. 1(b), and the output current can be described as follows:

$$I_L = I_{ph} - I_{d1} - I_{d2} - I_{sh} = I_{ph} - I_{sd1}\cdot\left[\exp\left(\frac{q\cdot(V_L + R_S\cdot I_L)}{n_1\cdot k\cdot T}\right)-1\right] - I_{sd2}\cdot\left[\exp\left(\frac{q\cdot(V_L + R_S\cdot I_L)}{n_2\cdot k\cdot T}\right)-1\right] - \frac{V_L + R_S\cdot I_L}{R_{sh}} \tag{5}$$

where I_{sd1} and I_{sd2} are the diffusion and saturation currents, respectively. n_1 and n_2 are the diffusion and recombination diode ideal factors, respectively. The other terms are introduced previously. Thus, for this double diode model, seven unknown parameters (I_{ph},I_{sd1} I_{sd2},R_S R_{sh} n_1,n_2) are needed to be identified to obtain the actual behavior of solar cell.

2.2. PV module model

As shown in Fig. 1(c), the single diode PV module model that consists of several solar cells connected in series and/or in parallel. The output current can be expressed as follows:

$$I_L/N_p = I_{ph} - I_{sd}\cdot\left[\exp\left(\frac{q\cdot(V_L/N_S + R_S\cdot I_L/N_p)}{n\cdot k\cdot T}\right)-1\right] - \frac{V_L/N_S + R_S\cdot I_L/N_p}{R_{sh}} \tag{6}$$

where N_p represents the number of solar cells in parallel; while N_S represents the number of solar cells in series. Same as to the single diode model, five unknown parameters (I_{ph},I_{sd} R_S R_{sh} n) are required to be estimated.

2.3. Objective function

The parameters identification problem of PV models is usually converted into as an optimization problem, and the goal is to minimize the difference between the experimental data and simulated data obtained by estimated parameters. The error function for each pair of

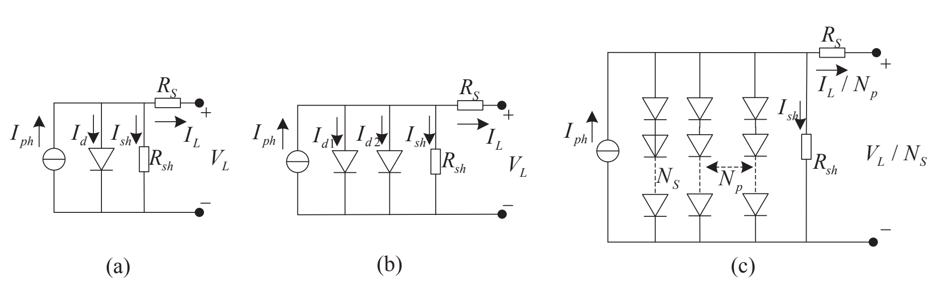

Fig. 1. Schematics for (a) single diode, (b) double diode, and (c) PV module.

experimental and simulated current data point is defined by Eqs. (7) and (8) for single diode model and double diode model, respectively.

$$\begin{cases} f_k(V_L,I_L,\mathbf{x}) = I_{ph}-I_{sd}\cdot[\exp(\frac{q\cdot(V_L+R_S\cdot I_L)}{n\cdot k\cdot T})-1]-\frac{V_L+R_S\cdot I_L}{R_{sh}}-I_L \\ \mathbf{x} = \{I_{ph},I_{sd},R_S,R_{Sh},n\} \end{cases} \tag{7}$$

$$\begin{cases} f_k(V_L,I_L,\mathbf{x}) = I_{ph}-I_{sd1}\cdot\left[\exp\left(\frac{q\cdot(V_L+R_S\cdot I_L)}{n_1\cdot k\cdot T}\right)-1\right]-I_{sd2}\cdot\left[\exp\left(\frac{q\cdot(V_L+R_S\cdot I_L)}{n_2\cdot k\cdot T}\right)-1\right] \\ \qquad -\frac{V_L+R_S\cdot I_L}{R_{sh}}-I_L \\ \mathbf{x} = \{I_{ph},I_{sd1},I_{sd2},R_S,R_{Sh},n_1,n_2\} \end{cases} \tag{8}$$

In this study, the root mean square error (RMSE) defined by Eq. (9) is used as the objective function to quantify the overall difference between the experimental and simulated current data, the objective function has been widely used in literature [10,11,14,21]. The optimization problem is to minimize the objective function RMSE($\mathbf{x}$) by searching the solution vector $\mathbf{x}$ within the specified range.

$$\mathrm{RMSE}(\mathbf{x}) = \sqrt{\frac{1}{N}\sum_{k=1}^{N} f_k(V_L,I_L,\mathbf{x})^2} \tag{9}$$

where$\mathbf{x}$ is the solution vector consists of unknown parameters, N is the number of experimental data.

3. JAYA algorithm

JAYA algorithm is a new population-based optimization algorithm developed by Rao for solving constrained and unconstrained optimization problems. The conceptual background of JAYA is that one solution obtained for a specific problem should approach to the optimal solution and evade the inferior solution simultaneously [24]. Unlike most other population-based algorithms, JAYA is free from algorithm-specific parameters, and involves only two common parameters like population size and the number of generation.

For an objective function $f(\mathbf{x})$ with D dimensional variables ($j = 1,2,...,D$), $x_{i,j}$ is the value of the jth variable for the ith candidate solution, thus $\mathbf{x}_i = (x_{i,1},x_{i,2},...,x_{i,D})$ is the position of ith candidate solution. The best candidate solution $\mathbf{x}_{best} = (x_{best,1},x_{best,2},...,x_{best,D})$ has the best value of $f(\mathbf{x})$ in the current population, while the worst candidate solution $\mathbf{x}_{worst} = (x_{worst,1},x_{worst,2},...,x_{worst,D})$ has the worst value of $f(\mathbf{x})$ in the current population. Then, $x_{i,j}$ is updated using Eq. (10).

$$x'_{i,j} = x_{i,j} + rand_1\cdot(x_{best,j}-|x_{i,j}|)-rand_2\cdot(x_{worst,j}-|x_{i,j}|) \tag{10}$$

where $x_{best,j}$ and $x_{worst,j}$ are the values of the jth variable for the best and worst solutions, respectively. $x'_{i,j}$ is the updated value of $x_{i,j}$, and $|x_{i,j}|$ is the absolute value of $x_{i,j}$. $rand_1$ and $rand_2$ are two uniformly distributed random numbers within [0,1]. In Eq. (10), the term$rand_1\cdot(x_{best,j}-|x_{i,j}|)$ represents the tendency of the solution attracted by the best solution, and the term $-rand_2\cdot(x_{worst,j}-|x_{i,j}|)$ indicates the tendency of the solution to shun the worst solution. The updated solution $\mathbf{x}'_i = (x'_{i,1},x'_{i,2},...,x'_{i,D})$ is accepted if it gives a better function value.

In the searching process, one solution obtained by JAYA algorithm is moving closer to the best solution and moving away from the worst solution. JAYA algorithm strives to become victory by approaching the best solution and thus it is named as JAYA (a Sanskrit word meaning victory) [33].

4. Improved JAYA algorithm

The improved JAYA (IJAYA) algorithm is presented in this section. Three main improvements exist in IJAYA. First, a self-adaptive weight is introduced to adjust the tendency of approaching the best solution and avoiding the worst solution. Second, a learning strategy based on the experience of other individuals is developed and employed randomly to maintain the population diversity. Third, chaotic learning method is proposed to improve the quality of the best solution in each generation. The core idea behind IJAYA is elucidated as follows.

4.1. Self-adaptive weight

In the searching process of JAYA, it is expected that the population should approach the promising region of search space at the early stage, and at the later stage, the local search in promising area should be implemented to refine the quality of population. To this end, a weight presented in Eq. (11) is introduced to adjust the degree of approaching the best solution and avoiding the worst solution. Then, Eq. (10) is replaced by Eq. (12) by adding the weight.

$$w = \begin{cases} \left(\frac{f(\mathbf{x}_{best})}{f(\mathbf{x}_{worst})}\right)^2, & \text{if} f(\mathbf{x}_{worst}) \neq 0 \\ 1, & \text{otherwise} \end{cases} \tag{11}$$

$$x'_{i,j} = x_{i,j} + rand_1\cdot(x_{best,j}-|x_{i,j}|)-w\cdot rand_2\cdot(x_{worst,j}-|x_{i,j}|) \tag{12}$$

where $f(\mathbf{x}_{best})$ and $f(\mathbf{x}_{worst})$ are the objective function values of the best solution and worst solution, respectively.

It can be observed that the introduced weight is self-adaptive and its value increases gradually, since the difference of function values between the best and worst solutions is becoming smaller as the search process. Therefore, the promising region can be located at the early stage due to the degree of approaching the best solution is relatively larger, while at the later stage, the local search in promising region can be achieved since the degree of approaching the best solution and avoiding the worst solution are similar. In addition, the weight w is determined automatically, and thus no additional parameter need to be tuned is introduced.

4.2. Experience-based learning strategy

In JAYA algorithm, the population is updated by considering the best solution and worst solution simultaneously, this method can accelerate the convergence rate and increase the exploitation capability of the algorithm. However, the population diversity and the exploration capability of the algorithm may be deteriorated with the prompt convergence rate. Hence, a learning strategy based on the experience of other solutions is developed to enhance the population diversity and thus increase the exploration ability. To be specific, other two individuals $\mathbf{x}_k$ and $\mathbf{x}_l$ are randomly selected from the population, then the potential search direction determined by them is used to update the current individual $\mathbf{x}_i$, as shown in Eq. (13).

$$x'_{i,j} = \begin{cases} x_{i,j} + rand\cdot(x_{k,j}-x_{l,j}), & \text{if} f(\mathbf{x}_k) < f(\mathbf{x}_l) \\ x_{i,j} + rand\cdot(x_{l,j}-x_{k,j}), & \text{otherwise} \end{cases} \tag{13}$$

where$x_{k,j}$ and $x_{l,j}$ are the values of the jth variable for the k and l individuals ($k \neq l \neq i$), respectively. $rand$ is a random number in the range [0, 1].

In order to balance the exploration and exploitation abilities of search process, the above experience-based learning strategy Eq. (13) and the introduced weight Eq. (12) are employed randomly for each individual in this study.

4.3. Chaotic elite learning method

During the search process, the best solution plays an important role since it guides and draws other individuals to its own region. However, the best individual may be located in a local optimum when solving multimodal problem. In this case, other individuals may be easily attracted to the best individual region, leading to premature convergence. To alleviate the issue, the learning method based on chaotic sequence is introduced to refine the quality of the best solution. Chaotic sequence features randomicity and ergodicity, and this very helpful for further improving the quality of one solution by generating new solution around it [13,14,38]. The chaotic sequence used in this study is the well-known logistic map defined by Eq. (14). Then, the best solution is updated using Eq. (15).

$$z_{m+1} = 4\cdot z_m\cdot(1-z_m) \tag{14}$$

$$x'_{best,j} = x_{best,j} + rand\cdot(2\cdot z_m-1) \tag{15}$$

where m is the iteration number, z_m is the value of mth chaotic iteration, and the initial value z_0 is randomly generated within [0, 1]. $x'_{best,j}$ is the updated value of jth variable for the best solution. The updated best solution is accepted if it gives a better function value.

4.4. Framework of IJAYA

Based on abovementioned descriptions, the pseudo code of IJAYA algorithm can be summarized in Algorithm 1. Moreover, the flow chart of IJAYA is shown in Fig. 2. It can be seen that the structure of IJAYA is simple as that of original JAYA, and no any additional parameter needs to be tuned is introduced in the IJAYA. That is, IJAYA is also free from algorithm-specific parameter. In addition, IJAYA and JAYA have the same complexity$O(G_{\max}\cdot NP\cdot D)$, where$G_{\max}$ is the maximal number of generation

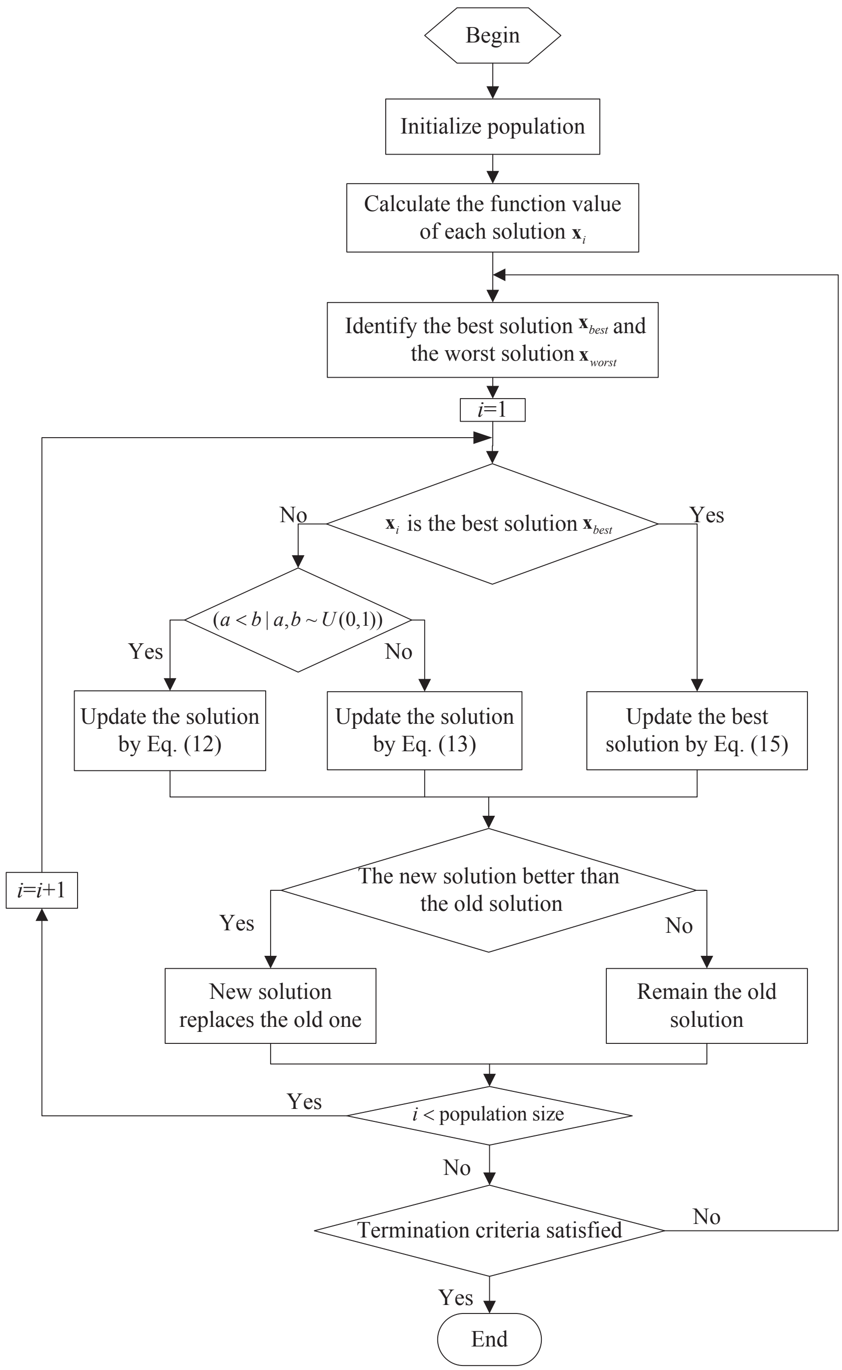

Fig. 2. The flow chart of IJAYA algorithm.

Table 1
Parameters range for the single and double diode models, and PV module model.

Parameter	Single diode/double diode		PV module	
	Lower bound	Upper bound	Lower bound	Upper bound
I_{ph} (A)	0	1	0	2
I_{sd},I_{sd1},I_{sd2} (μA)	0	1	0	50
R_S (Ω)	0	0.5	0	2
R_{sh} (Ω)	0	100	0	2000
n,n_1,n_2	1	2	1	50

Table 2
Parameter settings for the involved algorithms.

Algorithm	Parameters
IJAYA	NP = 20.
JAYA	NP = 20.
GOTLBO [21]	NP = 50, jumping rate Jr = 0.3.
LETLBO [40]	NP = 50.
LBSA [41]	NP = 50, mix rate = 1.
CLPSO [42]	NP = 40, inertia weight w:0.9–0.2, acceleration coefficient c = 1.49445, refreshing gap m = 5.
BLPSO [43]	NP = 40, inertia weight w:0.9–0.2, acceleration coefficient c = 1.49445, I = E=1.
DE/BBO [44]	NP = 100, I = E=1, $\pi_{\max}$ = 0.005, K = 2, F = rand (0.1,1), CR = 0.9.
CMM-DE/BBO [45]	NP = 100, I = E=1, $\pi_{\max}$ = 0.005, K = 2, F = rand (0.1,1), CR = 0.9, P_e = 0.5.

Algorithm 1. Pseudo code of IJAYA algorithm

Initialize population size (NP) and maximum number of function evaluations (Max_FES). Generate the initial population randomly;
Evaluate the objective function value for each individual;
$FES = NP$;
While $FES < Max\_FES$ **do**
  Choose the best individual $\mathbf{x}_{best}$ and the worst individual $\mathbf{x}_{worst}$ from population;
  For i = 1 to NP **do**
    If $\mathbf{x}_i$ is not the best individual $\mathbf{x}_{best}$ **then**
      If $(a < b | a,b \sim U(0,1))$ **then** //∗ *Self-adaptive weight* ∗//
        Calculate the weight w using Eq. (11);
        Update the jth (j = 1,2,...,D) variable value of $\mathbf{x}_i$ using Eq. (12);
      Else //∗*Experience-based learning strategy*∗//
        Select the other two individuals $\mathbf{x}_{r1}$ and $\mathbf{x}_{r2}$ from population randomly ($r1 \neq r2 \neq i$);
        Update the jth (j = 1,2,...,D) variable value of $\mathbf{x}_i$ using Eq. (13);
      End if
    Else //∗ *Chaotic elite learning method* ∗//
      Update the jth (j = 1,2,...,D) variable value of $\mathbf{x}_{best}$ using Eq. (15);
    End if
    Calculate the function value for the updated individual;
    $FES = FES + 1$;
    Accept the new solution if it is better than the old one
  End for
End while

Table 3
Comparison among different algorithms on single diode model.

Algorithm	I_{ph} (A)	I_{sd} (μA)	R_S (Ω)	R_{sh} (Ω)	n	RMSE
IJAYA	0.7608	0.3228	0.0364	53.7595	1.4811	**9.8603E-04**
JAYA	0.7608	0.3281	0.0364	54.9298	1.4828	9.8946E-04
GOTLBO	0.7608	0.3297	0.0363	53.3664	1.4833	9.8856E-04
LETLBO	0.7608	0.32597	0.0363	53.7429	1.4821	9.8738E-04
LBSA	0.7609	0.32583	0.0364	54.1083	1.4820	9.9125E-04
CLPSO	0.7608	0.34302	0.0361	54.1965	1.4873	9.9633E-04
BLPSO	0.7607	0.36620	0.0359	60.2845	1.4939	1.0272E-03
DE/BBO	0.7605	0.32477	0.0364	55.2627	1.4817	9.9922E-04
CMM-DE/BBO	0.7608	0.32384	0.0364	53.8753	1.4814	**9.8605E-04**
IADE	0.7607	0.33613	0.03621	54.7643	1.4852	9.8900E-04
IGHS	0.7608	0.3435	0.0361	53.2845	1.4874	9.9306E-04
ABSO	0.7608	0.30623	0.03659	52.2903	1.47878	9.9124E-04

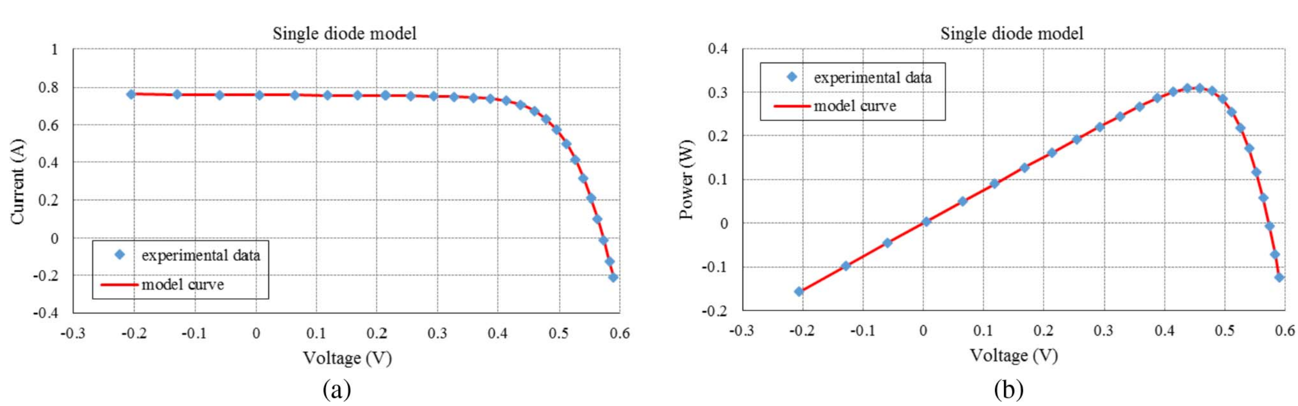

Fig. 3. Comparisons between experimental data and simulated data obtained by IJAYA for single diode model (a) *I-V* characteristics; (b) *P-V* characteristics.

Table 4
Absolute error of IJAYA for each measurement on single diode model.

Item	Vmeasured (V)	Imeasured (A)	Icalculated (A)	IAE
1	−0.2057	0.7640	0.76408300	0.00008300
2	−0.1291	0.7620	0.76265947	0.00065947
3	−0.0588	0.7605	0.76135269	0.00085269
4	0.0057	0.7605	0.76015229	0.00034771
5	0.0646	0.7600	0.75905435	0.00094565
6	0.1185	0.7590	0.75804225	0.00095775
7	0.1678	0.7570	0.75709227	0.00009227
8	0.2132	0.7570	0.75614266	0.00085734
9	0.2545	0.7555	0.75508882	0.00041118
10	0.2924	0.7540	0.75366651	0.00033349
11	0.3269	0.7505	0.75139433	0.00089433
12	0.3585	0.7465	0.74735805	0.00085805
13	0.3873	0.7385	0.74012235	0.00162235
14	0.4137	0.7280	0.72738829	0.00061171
15	0.4373	0.7065	0.70697944	0.00047944
16	0.4590	0.6755	0.67528720	0.00021280
17	0.4784	0.6320	0.63076483	0.00123517
18	0.4960	0.5730	0.57193362	0.00106638
19	0.5119	0.4990	0.49961038	0.00061038
20	0.5265	0.4130	0.41364992	0.00064992
21	0.5398	0.3165	0.31750930	0.00100930
22	0.5521	0.2120	0.21215297	0.00015297
23	0.5633	0.1035	0.10224948	0.00125052
24	0.5736	−0.0100	−0.00871730	0.00128270
25	0.5833	−0.1230	−0.12550357	0.00250357
26	0.5900	−0.2100	−0.20846403	0.00153597

5. Experimental results and analysis

In this section, the effectiveness of IJAYA is evaluated on parameters identification of different PV models, i.e., single diode, double diode, and PV module. To this end, the benchmark experimental current-voltage data of a solar cell and a solar module are used. The data are acquired from [39], where a 57 mm diameter commercial RTC France silicon solar cell (under 1000 W/m^2 at 33 °C) and a solar module named Photowatt-PWP201(under 1000 W/m^2 at 45 °C) that consists of 36 polycrystalline silicon cells in series. This data set has been widely used to test the techniques developed for parameters extraction [2,13,14,21]. To ensure a fair comparison, the lower and upper bounds for each parameter are shown in Table 1, which are the same as used in previous literatures.

To validate the superior performance of the proposed IJAYA algorithm, comparisons are carried out with other well-established algorithms. These algorithms are the basic JAYA [24], generalized oppositional TLBO (GOTLBO) [21], TLBO with learning experience of other learners (LETLBO) [40], learning backtracking search algorithm (LBSA) [41], comprehensive learning PSO (CLPSO) [42], biogeography-based learning PSO (BLPSO) [43], hybrid DE with BBO (DE/BBO) [44], and DE/BBO with covariance matrix based migration (CMM-DE/BBO) [45]. For fair comparison, all of the algorithms use the same maximum number of function evaluations (*Max_FES*) 50000 in each run for each problem. Besides, each algorithm is tested 30 times independently for every problem to minimize statistical errors. The parameter configurations for all compared algorithms are based on the suggestions in the corresponding literature and listed in Table 2. It is notable that the population size of IJAYA and JAYA are both set to be 20 after running a few trials [24,33].

Firstly, the comparisons are conducted on the best results represented by the RMSE values to illustrate the accuracy of each algorithm. And then, the statistical results and convergence curves are analyzed and presented to evaluate the robustness and convergence rate of each algorithm.

5.1. Results on the single diode model

For the single diode model, the comparison results involving the

Table 5
Comparison among different algorithms on double diode model.

Algorithm	I_{ph}(A)	I_{sd1}(μA)	R_S(Ω)	R_{sh}(Ω)	n_1	I_{sd2}(μA)	n_2	RMSE
IJAYA	0.7601	0.0050445	0.0376	77.8519	1.2186	0.75094	1.6247	**9.8293E-04**
JAYA	0.7607	0.0060763	0.0364	52.6575	1.8436	0.31507	1.4788	9.8934E-04
GOTLBO	0.7608	0.13894	0.0365	53.4058	1.7254	0.26209	1.4658	9.8742E-04
LETLBO	0.7608	0.17390	0.0365	54.3021	1.6585	0.22664	1.4578	9.8565E-04
LBSA	0.7607	0.24877	0.0365	56.0524	1.8817	0.27436	1.4682	9.8751E-04
CLPSO	0.7607	0.25843	0.0367	57.9422	1.4625	0.38615	1.9435	9.9894E-04
BLPSO	0.7608	0.27189	0.0366	61.1345	1.4674	0.43505	1.9662	1.0628E-03
DE/BBO	0.7606	0.0012237	0.0358	58.4018	1.8791	0.37220	1.4956	1.0255E-03
CMM-DE/BBO	0.7607	0.35366	0.0360	57.9882	1.4907	0.025623	1.8835	1.0088E-03
IGHS	0.7608	0.9731	0.0369	53.8368	1.9213	0.1679	1.4281	9.8635E-04
ABSO	0.76077	0.26713	0.03657	54.6219	1.46512	0.38191	1.98152	**9.8344E-04**

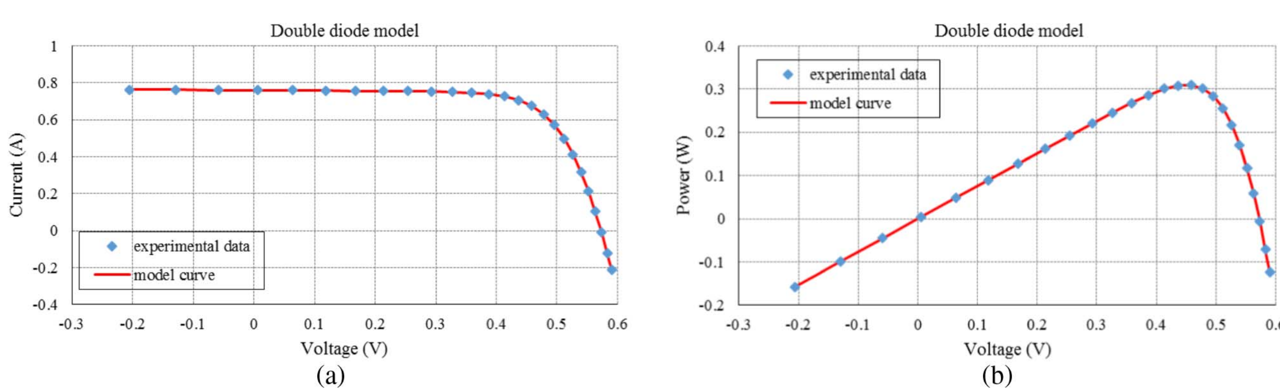

Fig. 4. Comparisons between experimental data and simulated data obtained by IJAYA for double diode model (a) *I-V* characteristics; (b) *P-V* characteristics.

Table 6
Absolute error of IJAYA for each measurement on double diode model.

Item	Vmeasured (V)	Imeasured (A)	Icalculated (A)	IAE
1	−0.2057	0.7640	0.76403108	0.00003108
2	−0.1291	0.7620	0.76264510	0.00064510
3	−0.0588	0.7605	0.76137259	0.00087259
4	0.0057	0.7605	0.76020309	0.00029691
5	0.0646	0.7600	0.75913193	0.00086807
6	0.1185	0.7590	0.75814115	0.00085885
7	0.1678	0.7570	0.75720437	0.00020437
8	0.2132	0.7570	0.75625597	0.00074403
9	0.2545	0.7555	0.75518696	0.00031304
10	0.2924	0.7540	0.75373008	0.00026992
11	0.3269	0.7505	0.75140585	0.00090585
12	0.3585	0.7465	0.74730817	0.00080817
13	0.3873	0.7385	0.74001849	0.00151849
14	0.4137	0.7280	0.72725674	0.00074326
15	0.4373	0.7065	0.70686230	0.00036230
16	0.4590	0.6755	0.67522394	0.00027606
17	0.4784	0.6320	0.63077352	0.00122648
18	0.4960	0.5730	0.57200430	0.00099570
19	0.5119	0.4990	0.49971050	0.00071050
20	0.5265	0.4130	0.41373174	0.00073174
21	0.5398	0.3165	0.31753942	0.00103942
22	0.5521	0.2120	0.21211485	0.00011485
23	0.5633	0.1035	0.10215958	0.00134042
24	0.5736	−0.0100	−0.00878197	0.00121803
25	0.5833	−0.1230	−0.12551336	0.00251336
26	0.5900	−0.2100	−0.20831777	0.00168223

estimated parameters and RMSE are presented in Table 3. Note that the results of IADE [10], IGHS [46],and ABSO [11] from literature are also presented for comparison. The overall best and the second best RMSE values among all compared algorithms are highlighted in **gray boldface** and **boldface**, respectively. From Table 3, It can be seen that IJAYA provides the least RMSE value (9.8603E-04) among all the chosen algorithms, followed by CMM-DE/BBO, LETLBO, GOTLBO, IADE, JAYA, ABSO, LBSA, IGHS, CLPSO, DE/BBO, and BLPSO. Due to the information on the accurate values of parameters is unavailable, the RMSE is employed to represent the accuracy. Although the RMSE values of other algorithms except BLPSO are very close to that of IJAYA, any reduction in the objective function is significant since it leads to improvement in the knowledge on the actual values of parameters. To further confirm the quality of the results, the best estimated parameters of IJAYA are used to reconstruct the *I-V* and *P-V* curves as shown in Fig. 3. It is obvious that the calculated data obtained by IJAYA are highly in coincidence with the measured data over the whole voltage range. Besides, the individual absolute error (IAE) between the experimental data and simulated data are presented in Table 4. All the IAE values are smaller than 2.5E-03, which validates the accuracy of the estimated parameters.

5.2. Results on the double diode model

For the double diode model, there are seven parameters need to be identified. The estimated parameters and the RMSE of different algorithms are listed in Table 5. The results of IGHS [46] and ABSO [11] from literature are also used to compare. It is clear that IJAYA also provides the best RMSE value (9.8293E-04) among all compared algorithms, and ABSO obtains the second best RMSE value. The *I-V* and *P-V* characteristics of the best model estimated by IJAYA and the experimental data are given in Fig. 4, and the IAE values are shown in Table 6. From Fig. 4, it can be clearly seen that the calculated data of IJAYA are in good agreement with the measured data. From Table 6, all the IAE values are smaller than 2.5E-03, indicating that the high-accurately identified parameters are provided.

Table 7
Comparison among different algorithms on PV module model.

Algorithm	$I_{ph}(A)$	$I_{sd}(\mu A)$	$R_S(\Omega)$	$R_{sh}(\Omega)$	n	RMSE
IJAYA	1.0305	3.4703	1.2016	977.3752	48.6298	**2.4251E-03**
JAYA	1.0302	3.4931	1.2014	1022.5	48.6531	2.4278E-03
GOTLBO	1.0307	3.5124	1.1995	969.9313	48.6766	2.4266E-03
LETLBO	1.0306	3.4705	1.2015	974.6190	48.6301	**2.4251E-03**
LBSA	1.0305	3.4901	1.2010	987.7807	48.6513	**2.4252E-03**
CLPSO	1.0304	3.6131	1.1978	1017.0	48.7847	2.4281E-03
BLPSO	1.0305	3.5176	1.2002	992.7901	48.6815	**2.4252E-03**
DE/BBO	1.0303	3.6172	1.1969	1015.1	48.7894	2.4283E-03
CMM-DE/BBO	1.0305	3.4823	1.2013	981.9823	48.6428	**2.4251E-03**
PS	1.0313	3.1756	1.2053	714.2857	48.2889	1.1800E-02
SA	1.0331	3.6642	1.1989	833.3333	48.8211	2.7000E-03

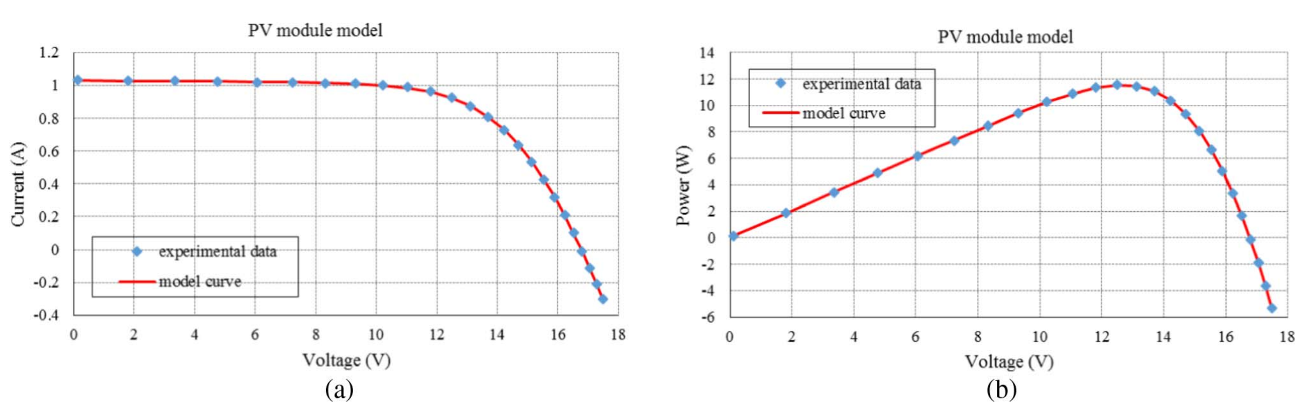

Fig. 5. Comparisons between experimental data and simulated data obtained by IJAYA for PV module model (a) *I-V* characteristics; (b) *P-V* characteristics.

Table 8
Absolute error of IJAYA for each measurement on PV module model.

Item	Vmeasured (V)	Imeasured (A)	Icalculated (A)	IAE
1	0.1248	1.0315	1.02912228	0.00237772
2	1.8093	1.0300	1.02737617	0.00262383
3	3.3511	1.0260	1.02572968	0.00027032
4	4.7622	1.0220	1.02408866	0.00208866
5	6.0538	1.0180	1.02226793	0.00426793
6	7.2364	1.0155	1.01990268	0.00440268
7	8.3189	1.0140	1.01633264	0.00233264
8	9.3097	1.0100	1.01046533	0.00046533
9	10.2163	1.0035	1.00060024	0.00289976
10	11.0449	0.9880	0.98452419	0.00347581
11	11.8018	0.9630	0.95950393	0.00349607
12	12.4929	0.9255	0.92282835	0.00267165
13	13.1231	0.8725	0.87259590	0.00009590
14	13.6983	0.8075	0.80727526	0.00022474
15	14.2221	0.7265	0.72833977	0.00183977
16	14.6995	0.6345	0.63714108	0.00264108
17	15.1346	0.5345	0.53621404	0.00171404
18	15.5311	0.4275	0.42950971	0.00200971
19	15.8929	0.3185	0.31877043	0.00027043
20	16.2229	0.2085	0.20738439	0.00111561
21	16.5241	0.1010	0.09616244	0.00483756
22	16.7987	−0.0080	−0.00832566	0.00032566
23	17.0499	−0.1110	−0.11093079	0.00006921
24	17.2793	−0.2090	−0.20923354	0.00023354
25	17.4885	−0.3030	−0.30083914	0.00216086

5.3. Results on the PV module model

For the PV module model, five parameters need to be identified. The determined parameters and RMSE values are presented in Table 7. The results of PS [47] and SA [48] from literature are also shown for comparison. It can be seen that IJAYA, together with the LETLBO, and CMM-DE/BBO, obtain the best RMSE value (2.4251E-03) among all the involved algorithms. LBSA and BLPSO both achieve the second best RMSE value. Moreover, the calculated data obtained by IJAYA and experimental data are compared in Fig. 5 and Table 8. The *I-V* and *P-V* characteristics of the estimated model are also in quite good agreement with the experimental data, and all the IAE values are smaller than 4.8E-03. The high accuracy parameters are achieved again by IJAYA algorithm.

5.4. Statistical results and convergence curve

The superior performance of IJAYA in terms of accuracy is demonstrated in the preceding subsections. In this subsection, the reliability and convergence rate of different algorithms are further tested through the statistical results and convergence curves. The statistical results for all compared algorithms over 30 independent runs are shown in Table 9. The Mean RMSE quantifies the average accuracy, and SD is the standard deviation of RMSE and indicates the reliability of the parameters estimation. For each model, the overall best and the second best results among the nine algorithms are highlighted in **gray boldface** and **boldface**, respectively.

In terms of the average accuracy and reliability, from Table 9, it can be observed that IJAYA performs much better than all other algorithms for single and double diode models. For PV module model, CMM-DE/BBO features the best average accuracy and reliability, and IJAYA also exhibits the competitive performance since it achieves the second best values in terms of the mean RMSE and the standard deviation. In addition, box-plots are used to show the distribution of results obtained by different algorithms over 30 independent runs, as shown in Fig. 6. The span of the solution distributions also shows the superior performance of the proposed IJAYA algorithm.

The convergence curves shown in Fig. 7 indicate the average RMSE performance of the 30 independent runs. It is clear that IJAYA has the faster convergence rate than other algorithms, especially for single and double diode models.

The aforementioned comparisons demonstrate that the proposed IJAYA has better searching accuracy, reliability, and faster convergence rate for solving the parameters identification problems of different PV

Table 9
Statistical results of RMSE of different algorithms for three models.

Model	Algorithm	RMSE			
		Min	Mean	Max	SD
Single diode model	IJAYA	**9.8603E-04**	**9.9204E-04**	**1.0622E-03**	**1.4033E-05**
	JAYA	9.8946E-04	1.1617E-03	1.4783E-03	1.8796E-04
	GOTLBO	9.8856E-04	1.0450E-03	1.2067E-03	5.0218E-05
	LETLBO	9.8738E-04	**1.0333E-03**	**1.1593E-03**	**4.6946E-05**
	LBSA	9.9125E-04	1.1466E-03	1.4862E-03	1.3482E-04
	CLPSO	9.9633E-04	1.0581E-03	1.3196E-03	7.4854E-05
	BLPSO	1.0272E-03	1.3139E-03	1.7928E-03	2.1166E-04
	DE/BBO	9.9922E-04	1.2948E-03	2.2258E-03	2.5074E-04
	CMM-DE/BBO	**9.8605E-04**	1.0486E-03	1.3475E-03	8.1679E-05
Double diode model	IJAYA	**9.8293E-04**	**1.0269E-03**	**1.4055E-03**	**9.8325E-05**
	JAYA	9.8934E-04	1.1767E-03	1.4793E-03	1.9356E-04
	GOTLBO	9.8742E-04	1.1475E-03	**1.3947E-03**	**1.1330E-04**
	LETLBO	**9.8565E-04**	**1.0869E-03**	1.4870E-03	1.5360E-04
	LBSA	9.8751E-04	1.2545E-03	1.7343E-03	2.2236E-04
	CLPSO	9.9894E-04	1.1458E-03	1.5494E-03	1.4367E-04
	BLPSO	1.0628E-03	1.4821E-03	1.7411E-03	1.7789E-04
	DE/BBO	1.0255E-03	1.5571E-03	2.4042E-03	3.6297E-04
	CMM-DE/BBO	1.0088E-03	1.5487E-03	2.0589E-03	2.9413E-04
PV module model	IJAYA	**2.4251E-03**	**2.4289E-03**	**2.4393E-03**	**3.7755E-06**
	JAYA	2.4278E-03	2.4537E-03	2.5959E-03	3.4563E-05
	GOTLBO	2.4266E-03	2.4754E-03	2.5638E-03	2.9388E-05
	LETLBO	**2.4251E-03**	2.4407E-03	2.5821E-03	2.9490E-05
	LBSA	**2.4252E-03**	2.4674E-03	2.5344E-03	2.9109E-05
	CLPSO	2.4281E-03	2.4549E-03	2.5433E-03	2.5810E-05
	BLPSO	**2.4252E-03**	2.4379E-03	2.4883E-03	1.3724E-05
	DE/BBO	2.4283E-03	2.4616E-03	2.5256E-03	2.9251E-05
	CMM-DE/BBO	**2.4251E-03**	**2.4252E-03**	**2.4268E-03**	**3.5548E-07**

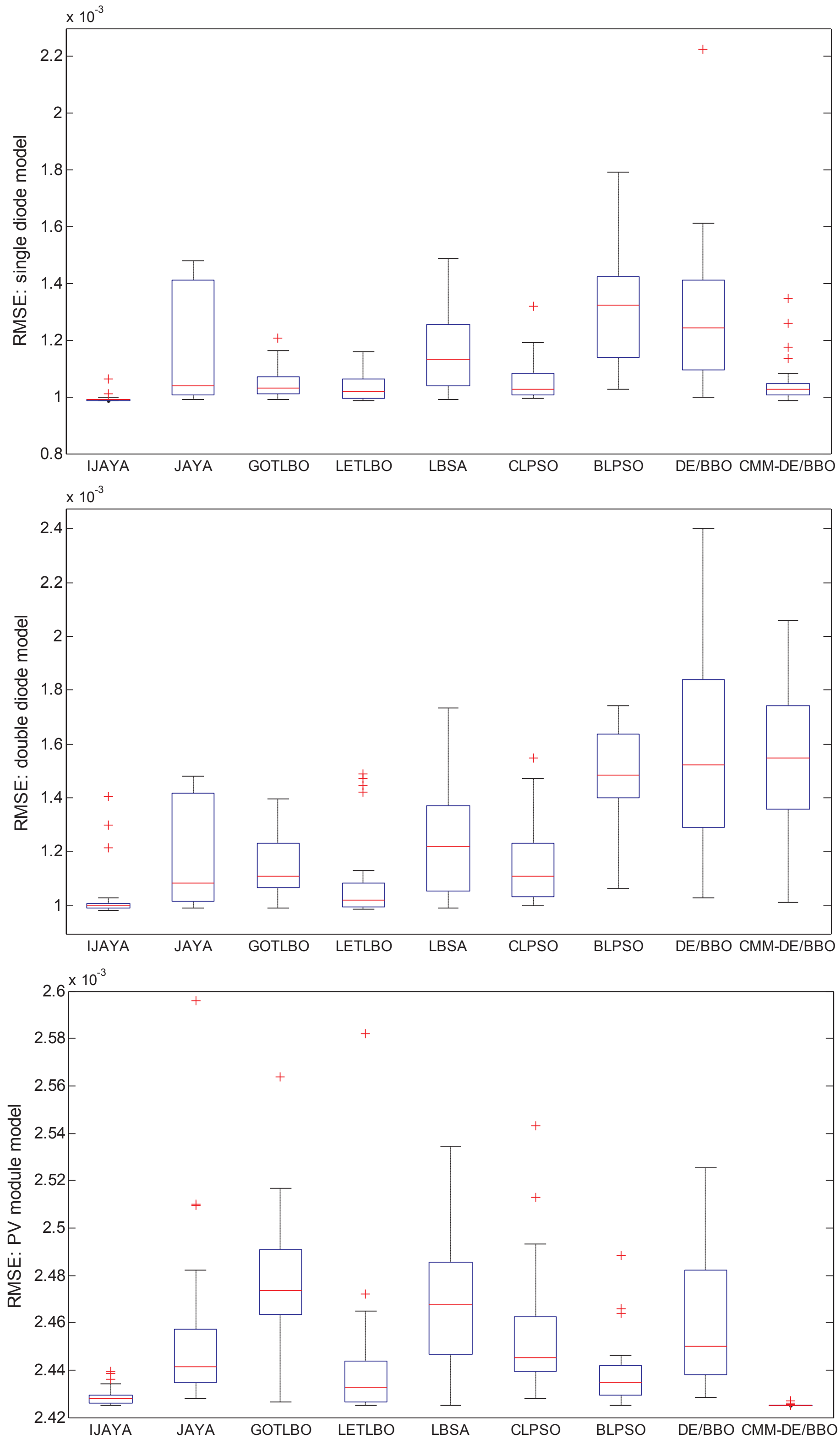

Fig. 6. Best RMSE boxplot over 30 runs of different algorithms for three models.

models, and its performance is superior or competitive in contrast with all compared algorithms.

5.5. Effectiveness of different strategies

In order to verify the effectiveness of different introduced strategies in proposed IJAYA, this subsection performs the experiments for IJAYA without the self-adaptive weight (denoted as IJAYA-1), IJAYA without the experience-based learning (denoted as IJAYA-2), and IJAYA without the chaotic elite learning (denoted as IJAYA-3), respectively. The statistical results of different IJAYA variants are summarized in Table 10. For each model, the overall best and the second best results among the four algorithms are highlighted in **gray boldface** and **boldface**, respectively. In Table 10, IJAYA can be seen to outperform all other variants in terms of the best and average RMSE values for each model. IJAYA-3 achieves the second best results in terms of average

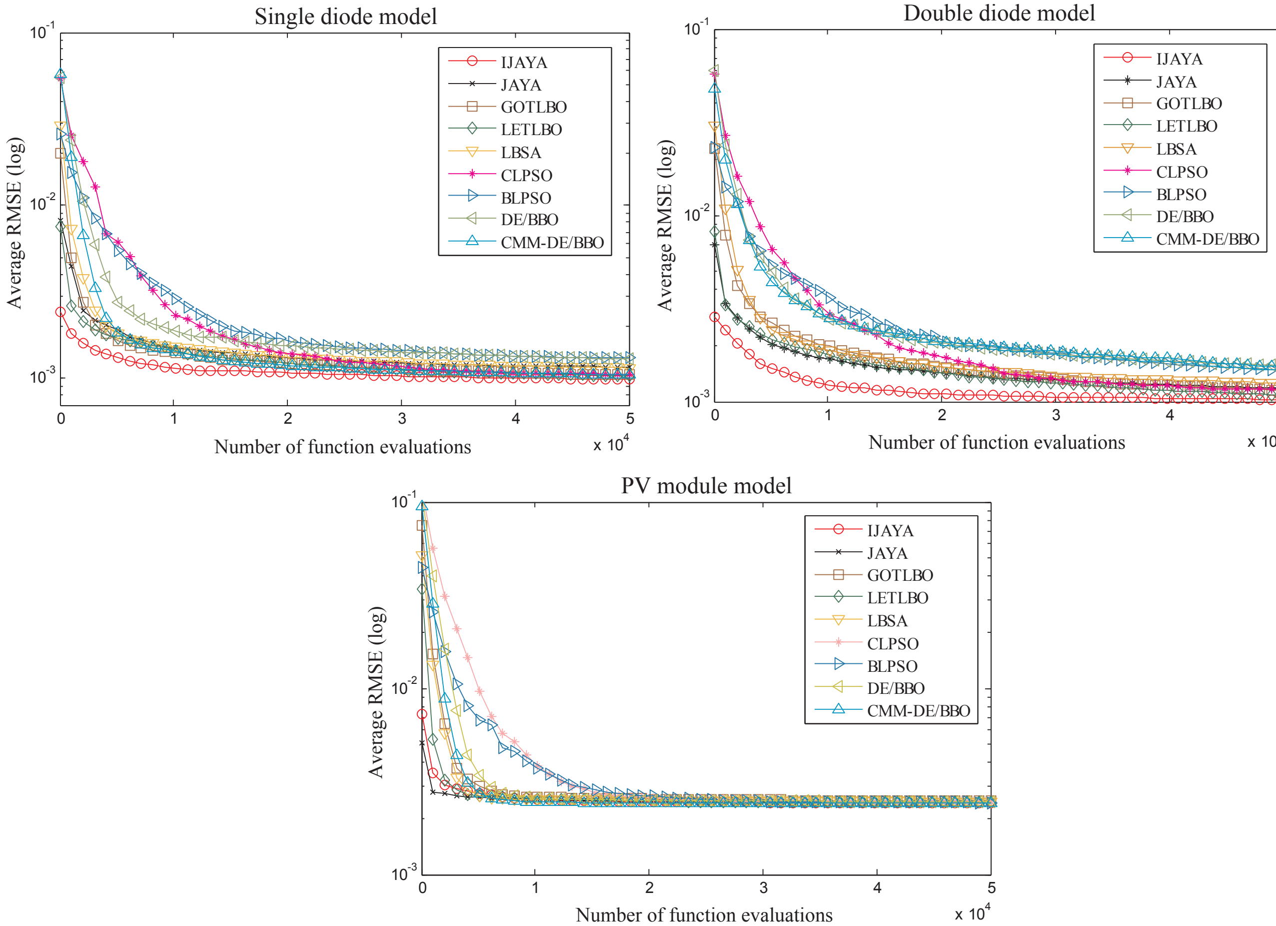

Fig. 7. Convergence curves of different algorithms for three models.

Table 10
Statistical results of RMSE of different IJAYA variants for three models.

Model	Algorithm	RMSE			
		Min	Mean	Max	SD
Single diode model	IJAYA	**9.8603E-04**	**9.9204E-04**	**1.0622E-03**	**1.4033E-05**
	IJAYA-1	9.9207E-04	1.0127E-03	1.0655E-03	1.5414E-05
	IJAYA-2	**9.8606E-04**	1.1223E-03	1.6623E-03	1.8498E-04
	IJAYA-3	9.8607E-04	**9.9297E-04**	**1.0272E-03**	**9.3113E-06**
Double diode model	IJAYA	**9.8293E-04**	**1.0269E-03**	**1.4055E-03**	**9.8325E-05**
	IJAYA-1	9.9729E-04	1.1282E-03	1.4767E-03	1.2264E-04
	IJAYA-2	**9.8315E-04**	1.0859E-03	1.4385E-03	1.4474E-04
	IJAYA-3	9.8432E-04	**1.0271E-03**	**1.2829E-03**	**6.0821E-05**
PV module model	IJAYA	**2.4251E-03**	**2.4289E-03**	**2.4393E-03**	**3.7755E-06**
	IJAYA-1	2.4253E-03	2.4315E-03	2.4446E-03	4.3379E-06
	IJAYA-2	2.4259E-03	2.4719E-03	2.6254E-03	4.8604E-05
	IJAYA-3	**2.4252E-03**	**2.4291E-03**	**2.4392E-03**	**3.3300E-06**

RMSE values, and obtains the best results in terms of the worst and the standard deviation for three models. The difference between the results of IJAYA and IJAYA-3 show that the chaotic elite learning is beneficial to enhance the quality of the final solutions. In summary, removing any strategy is insufficient to achieve the desired results, but integrating them lead to excellent performance. This superior performance of IJAYA verifies its appropriate balance between exploitation and exploration indeed benefit from the proposed strategies in this study.

6. Conclusions

In this paper, an improved JAYA (IJAYA) algorithm is proposed to accurately and steadily estimate the parameters of different PV models. In IJAYA, a self-adaptive weight is introduced to adjust the tendency of approaching the best solution and avoiding the worst solution during the search process. This weight aims to assist the algorithm to approach the potential search region at the early stage and implement the local search at the later stage. In addition, a learning strategy based on other individuals' experience is developed and employed randomly to improve the population diversity, and chaotic learning method is proposed to enhance the quality of the best solution in each generation. The proposed IJAYA algorithm does not introduce any parameter need to be tuned and thus easy to implementation. IJAYA is evaluated through parameters identification problems of single diode, double diode, and PV module models. Experiment results illustrate that IJAYA has the superior performance in terms of accuracy and reliability when compared with other well-established algorithms. Thus, IJAYA can be a promising candidate method to solve the parameters identification problems of photovoltaic models.

In future work, IJAYA will be applied to solve the economic dispatch problem in power systems. Also, some other modification will be proposed, extending the utilization of optimization algorithms for complex renewable energy problems.

Acknowledgements

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