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Research article

Enhanced chaotic JAYA algorithm for parameter estimation of photovoltaic cell/modules

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Parameters for defining photovoltaic models using measured voltage–current characteristics are essential for simulation, control, and evaluation of photovoltaic-based systems. This paper proposes an enhanced chaotic JAYA algorithm to classify the parameters of various photovoltaic models, such as the single-diode and double-diode models, accurately and reliably. The proposed algorithm introduces a self-adaptive weight to regulate the trend to reach the optimal solution and avoid the worst solution in various phases of the search space. The self-adaptive weight capability also allows the proposed technique to reach the best solution at the earliest phase, and later, the local search process starts, which also increase the ability to explore. A three different chaotic process, including sine, logistics and tent map, is proposed to optimize the consistency of each generation's best solution. The proposed algorithm and its variants proposed are used to solve the parameter estimation problem of various PV models. To show the proficiency of the suggested algorithm and its variants, an extensive simulation is carried out using MATLAB/Simulink software. Two statistical tests are conducted and compared with the latest techniques for validating the performance of the suggested algorithm and its variants. Comprehensive analysis and experimental results display that the suggested algorithm can achieve highly competitive efficiency in terms of accuracy and reliability compared to other algorithms in the literature. This research will be backed up with extra online service and guidance for the paper's source code at https://premkumarmanoharan.wixsite.com/mysite.

1. Introduction

New alternate energy sources are urgently developed as a result of the shortage and overuse of fossil fuels. Renewable energy sources are the better alternative for fossil fuels, booms in energy generation in response to the energy crisis [1]. Amongst all renewable energy sources, solar photovoltaic (PV) energy is the commonly used energy producer for its characteristics, such as green, clean, sustainability, etc. [2,3]. The PV system, consisting primarily of PV cells, has received increasing attention in recent years. It can transform solar energy into electricity directly. Generally, the characteristics of the PV systems is simulated using the electrical circuit model in different environments. The most frequently used models are single-diode model (SDM), double-diode model (DDM), and three-diode model (TDM) models, and these models can be built through the parameter identification and the mathematical modelling [4]. The PV systems are, however, regularly exposed to external situations, so that PV systems are certainly vulnerable to weakening. The real behaviour of PV systems is subject to primarily on their unknown parameters, which are volatile and uneven as the PV model subjected to a variety of issues. However, the parameters are generally inaccessible and variation because of defects, volatile operating conditions and ageing.

The exact estimation of parameters in the evaluation, simulation, control, and optimization of photovoltaic systems is crucial, and different parameter estimation approaches have been established in recent years [5,6]. Many researchers have suggested other methods, including the numerical and analytical methods used to estimate the cells and modules parameters [7,8]. The analytical method estimates the parameters using the information

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in the datasheet supplied by the supplier, such as open-circuit voltage (V_{oc}), maximal power (P_{mpp}) and short-circuit current (I_{sc}) fit into some areas of the V–I characteristic curves, etc. However, all points in V–I curves are used in the mathematical approach, which finds parameters that diminish the error between estimated and experimental values. Metaheuristic algorithms are among the numerical extraction methods, and numerous approaches and their alternatives have already been used to resolve the problem of the PV model's parameter estimates [9,10]. A brief classification of swarm intelligence and evolutionary techniques utilized for the photovoltaic parameter estimation problem is depicted in Fig. 1. Metaheuristic techniques are typically motivated by real-world problems to mimic physical laws or biological patterns to find better solutions to optimization problems. There are two major groups, such as swam-based and evolutionary approaches. Swarm intelligence (SI) technique involves collective or social intelligence that artificially mimics the decentralization of the nature of biological groups or the social processes of systems of self-organization. The motivation typically comes from biological communities with intelligence and collective behaviour to accomplish a certain goal in this algorithm. The scientific contributions of various algorithms are presented in Table 1.

The most common approach to modelling PV cells and modules accurately is to use equivalent electrical models. SDM, DDM, and TDM are widely chosen and used by numerous PV cell modelling researchers [11]. The SDM PV model has five associated parameters, such as photocurrent, I_{ph}, diode ideality factor, a, the diode saturation current, I_{sd}, shunt resistance, R_{sh}, and series resistance, R_{se}, and for modelling single-diode cells and modules, these five parameters need to be appropriately estimated.

The DDM PV model has seven associated parameters, such as $I_{ph}, I_{sd1}, I_{sd2}, a_1, a_2, R_{se}$ and R_{sh}, in which, I_{sd1} is the reverse saturation current of diode-1, I_{sd2} is the reverse saturation current of diode-2, a_1 is the ideality factor of diode-1 and a_2 is the ideality factor of diode-2, and for modelling double-diode cells and modules, these seven parameters need to be appropriately estimated. The TDM PV model has nine associated parameters, such as $I_{ph}, I_{sd1}, I_{sd2}, I_{sd3}, a_1, a_2, a_3, R_{se}$ and R_{sh}, in which, I_{sd3} is the reverse saturation current of diode-3 and a_3 is the ideality factor of diode-3, and for modelling three-diode cells and modules, these seven parameters need to be appropriately estimated. The architecture of TDM is more complicated but more reliable than the SDM and DDM. The estimation of five parameters or seven parameters or nine parameters of the PV cell/module is must so the model obtained accurately emulates V–I characteristics of the physical model. The discrepancy in experimental and estimated currents should be minimum for the cell/module. Some efforts have been made to use deterministic techniques to identify parameters based on minimizing the objective function to solve such optimization problems [35,36]. Deterministic methods, however, impose several model constraints, such as convexity and differentiability. Furthermore, because the identification of parameters of photovoltaic models is a non-linear and multi-modal problem, it is highly probable that they fall in local optima when using deterministic methods. The author of [37] introduced a resilient multiscale coordination control for fault-tolerance problems to handle the problem within global bound threats.

1.1. Related works

Heuristic techniques stimulated by various natural phenomena have been commonly used as a alternative to deterministic techniques in estimating PV cell/module parameters. They may not place constraints on the problem and therefore can easily be generalized for numerous problems in the real world. The author of [38] presented a differential evolution (DE) algorithm is suggested for the evaluation of PV cell parameters under various operating conditions. The authors of [39] presented the innovative method for crossover rate, and the scaling factor was introduced to develop an enhanced adaptive DE based parameter estimate method. The authors of [40] presented the artificial bee colony (ABC) algorithm to identify the solar cell parameters. The authors of [41] presented the bacterial foraging optimization technique to accurately model the solar photovoltaic cell properties. The authors of [42] proposed a hybrid biogeographic optimization (BO) built by integrating the BO with the DE mutation and chaos theory (BO-DE). First, the BO-DE was tested for benchmarking functions and then used for the solar cell parameter estimation. An improved Teaching–Learning optimization (ITLO) was developed by [15] with a triple-phase strategy to identify the parameters of the solar cell. The authors of [43] performed an interactive numerical simulation based on TLO, and then the recorded V–I data of various solar cell types were applied. The enhanced lion optimizer was introduced by [44] to increase the accuracy of the estimation of the solar cell parameters. The authors of [45] developed the mutative parallel chaos optimization (MPCO) algorithm to solve the designed parameter estimation problem. The authors of [46] used the ABC algorithm to extract solar cell parameters accurately. The authors of [47] reported the bird optimizer (BO) to estimate the PV module parameters under different operating conditions. The authors of [48] presented a DE algorithm combined with the mutation per generation to find the unidentified variables of DDM of the PV module. The six nature-inspired algorithms' performance was discussed in [49] to define SDM parameters. The authors of [50] proposed harmony-based methodologies for the estimate of parameters of harmony. The authors of [45] built a moth-flame optimizer (MFO) for the parameter estimation of TDM. The authors of [51] proposed an improved TLO algorithm to identify the cell parameters based on the generalized opposition and generation jumping. The authors of [52] presented a bacterial foraging technique for identifying the parameters of SDM and DDM of the PV module. The PV module parameters have been extracted from nameplate data by different variants of the bacterial foraging algorithm (BFA) in [53]. The authors of [54] proposed an enhanced PSO algorithm for estimating model parameters from the PV module. The authors of [55] presented time-varying particle swarm optimization (TPSO) to estimate PV cells and module parameters. The authors of [17] presented new RAO algorithms to estimate the cell/module parameters for all PV models, such as SDM, DDM, and TDM. A new cat swarm optimization method was presented by [4] to identify the unknown SDM parameters. The authors of [25] proposed the whale optimization algorithm (WOA) to identify the best parameters for various PV models. The authors of [56] presented an improved WOA for the same optimization problems. The authors of [57] combined the cuckoo search algorithm (CS) with their different variants to address the PV model parameter estimation issue. The authors of [58] investigated the JAYA algorithm for identifying the parameter of the PV cell models. Though these attempts have achieved satisfactory results, their parameters tuning or algorithm specific affects the performance. Users find it difficult to determine the variables for a particular or new problem of optimization, and incorrect adjustment of variables either raises the computation complexity or finds an optimal local output.

The JAYA algorithm is an old but strong approach to unconstrained and constrained optimization problems proposed by Rao [16]. No algorithm-specific parameter is required, excluding two joint parameters, viz. the number of generation and population size. In addition to common parameters, various other algorithms require algorithms specific parameters, unlike the JAYA

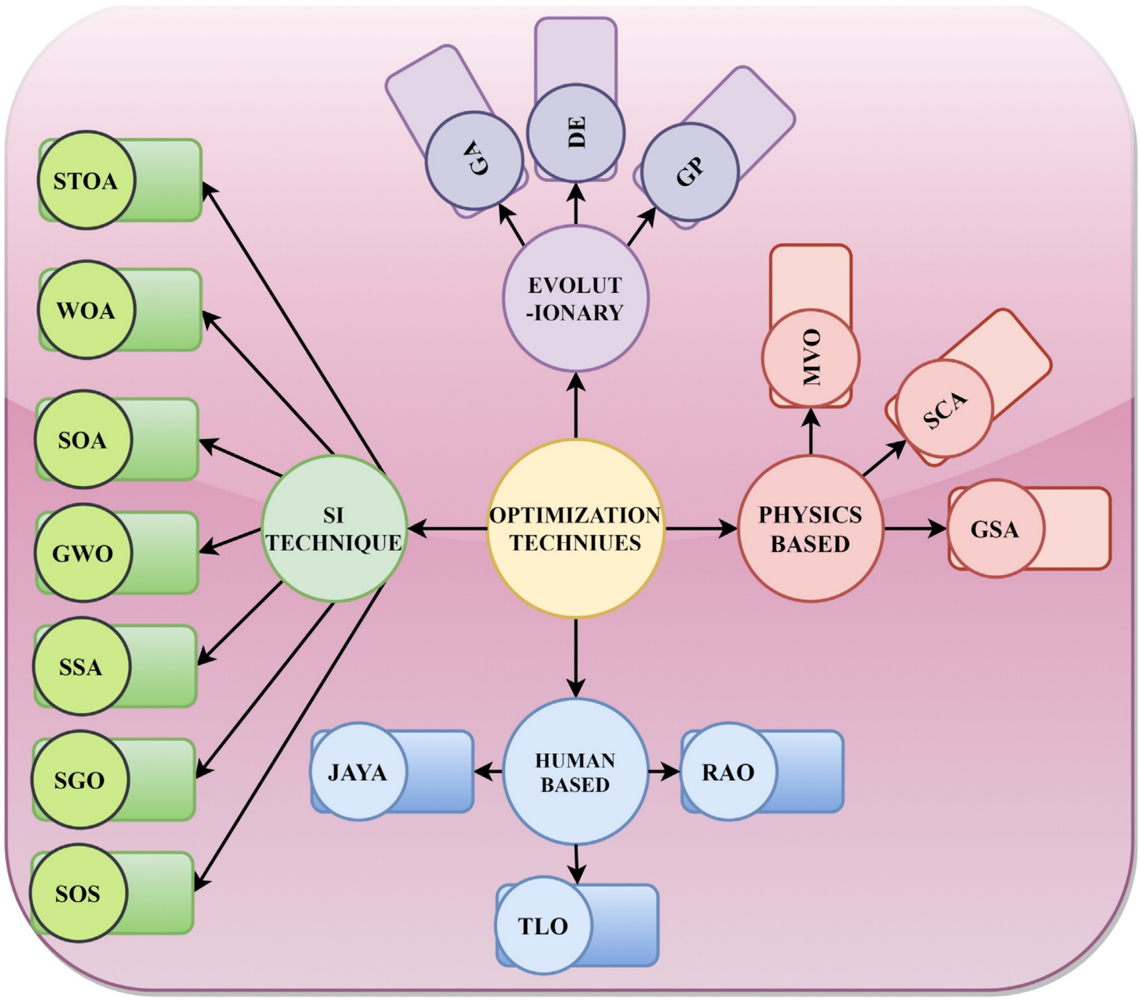

Fig. 1. A brief classification of optimization techniques.

algorithm. For example, DE needs the probability of crossover and scaling factor, and PSO requires the acceleration coefficient and inertia weights. Therefore, a major advantage of the JAYA algorithm can be achieved by avoiding the difficulty of adjusting parameters and reducing the time required to optimize the process. Although the TLO and RAO algorithms are free of specific algorithm parameters, two phases in TLO for each generation require two function evaluations. Therefore, TLO and RAO have high computation cost during a single generation than an algorithm with one function evaluation per generation. In contrast to TLO, JAYA technique only requires one phase, making the algorithm low computational time and low complexity in implementing it. The JAYA algorithm was improved and widely applied on different engineering optimization issues including controllers design [59], thermal equipment's [60], mechanical design [61], heat exchangers [62], electrical power systems [63], power flow [64], and other optimization issues. However, JAYA has some drawbacks, such as, firstly, the best solution is directed, and the worst solution avoided, even when the convergency speed is increased. The population diversity cannot be proficiently preserved, resulting in an optimum local solution. Secondly, no strategy is employed in order to increase the quality of the best solution through each function generation, and therefore, the final solution results in a non-optimal value. A revised JAYA algorithm is therefore introduced in [65] to better explore the search space without being stuck in a local minimum. But the disparity among exploration and exploitation is overlooked by the improved JAYA. Another modified JAYA algorithm is introduced in [66] to increase the search space capacity and balance between exploitation and exploration abilities. However, with the search iteration, it neglects the search capacity which constantly shifts. In addition, it is difficult enough to define design variables since there are many local solutions.

Though the features of the various modern optimization techniques available in the literature are distinct, these have been found that neither of these techniques can solve all types of optimization problems. This illustrates the importance of new optimization techniques in different areas because an algorithm's success in solving many optimization issues does not assure its performance in different groups of benchmark functions. Therefore, this paper proposes an enhanced chaotic JAYA (CJAYA) algorithm to reliably and accurately classify the various PV model parameters, such as SDM and DDM, due to its simple structure than the TDM. To mitigate the drawbacks of the JAYA algorithm, the idea of a chaotic and self-adaptive mechanism to escape from local minima was simultaneously integrated into the standard Jaya algorithm [67]. First of all, the whole population is sorted based on the solution quality. The population is then divided into fixed numbers of subpopulations, denoted as groups. The groups are generated through the process of chaotic and self-adaptive weight in the CJAYA algorithm. By discovering promising solutions based on the standard Jaya algorithm, each group is allowed to develop independently. This approach strengthens the solution by sharing the data that each group acquires independently. Therefore, in the CJAYA algorithm, the best solution is

Table 1
Scientific contributions of various algorithms.

S. No.	Algorithm	Ref.	Parameters	Test Benchmark	Remarks
1	Gravitational Search Algorithm (GSA)	[12]	$N = 50$, $IT_{max} = 500$	23 benchmark test functions	Not tested for RW problems
2	Multi-Verse Optimizer (MVO)	[13]	$N = 30$, $IT_{max} = 500$, WEP = [0.2,1], TDR=[0.6,0]	19 test functions with CEC2005 special session	Tested for conventional 6 RW constrained problems
3	Sine–Cosine Algorithm (SCA)	[14]	$N = 30$, $IT_{max} = 500$	19 test functions with CEC2005 special session	Tested for Airfoil design RW constrained problem
4	Teaching–Learning Optimization (TLO)	[15]	$N = 100$, FES_{max} =50,000	60 benchmark test functions (CEC2005)	Not tested for RW problems
5	JAYA	[16]	$N = 100$, FES_{max} =50,000	24 benchmark test functions (CEC2006)	Not tested for RW problems
6	RAO	[17]	$N = 100$, FES_{max} =30,000	50 benchmark test functions	Not tested for RW problems
7	Multi-Objective Modified Heat Transfer Search	[18]	$N = 100$, FES_{max} =50,000	Not tested	Tested for multi-objective truss design RW problems
8	Genetic Algorithm (GA)	[19]	N=50, $IT_{max} = 200$, $P_c = 0.95$, $P_m = 0.001$	Six unconstrained problems	First evolutionary computation algorithm
9	Differential Evolutionary (DE)	[20]	N=40, $IT_{max} = 200$, $P_{cr} = 0.2$	Eight unconstrained problems	Very popular due to its applications in various engineering fields
10	Genetic Programming (GP)	[21]	N=50, $IT_{max} = 200$, $P_c = 0.95$, $P_m = 0.001$	Two unconstrained problems	Tree based version of GA algorithm
11	Sooty Tern Optimization Algorithm (STOA)	[22]	$N = 100$, $IT_{max} = 1000$, $C_f = 2$, $S_A = [2, 0]$	CEC2005 & CEC2015	Tested for 7 constrained and unconstrained RW problems
12	Grey Wolf Optimizer (GWO)	[23]	$N = 30$, $IT_{max} = 500$, $a = 2$	29 test functions with CEC2005 special session	Tested for 3 constrained RW problems
13	Spotted Hyena Optimizer (SHO)	[24]	$N = 30$, $IT_{max} = 1000$, $h = [5, 0]$, $M = [0.5, 1]$	29 test functions with 5 unconstrained real-world problems	Not tested for constrained RW problems
14	Whale Optimization Algorithm (WOA)	[25]	$N = 30$, $IT_{max} = 500$, $a = [2, 0]$	29 test functions with 6 structural problems	Tested for 6 constrained RW problems
15	Equilibrium Optimizer (EO)	[26]	$N = 30$, $IT_{max} = 500$, $GP = 0.5$	58 test functions including CEC2017	Tested for 3 constrained RW problems
16	Emperor Penguin Optimizer	[27]	$N = 80$, $IT_{max} = 1000$, $l = [2, 3]$, $M = 2$, A=[−1.5,1.5]	44 test functions with 8 real-world problems	Tested for both unconstrained and constrained RW problems
17	Marine Predator Algorithm (MPA)	[28]	$N = 30$, $IT_{max} = 500$, $P = 0.5$, $v = 0.1$	58 test functions including CEC2017	Tested for 3 constrained RW problems
18	Modified Symbiotic Organisms Search (MSOS)	[29]	$N = 50$, FES_{max} =150,000	CEC2014	Tested for truss design RW problems
19	Salp Swarm Algorithm (SSA)	[30]	$N = 30$, $IT_{max} = 500$	42 test functions including CEC2017	Tested for single and multi-objective problems
20	Seagull Optimization Algorithm (SOA)	[31]	$N = 100$, $A = [2, 0]$, $f_c = 2$, $IT_{max} = 1000$	CEC2005 & CEC2015	Tested for 8 constrained and unconstrained RW problems
21	Multi-Objective Adaptive Symbiotic Organisms Search	[32]	$N = 50$, FES_{max} =150,000,	Not tested	Tested for multi-objective truss design RW problems
22	Cuckoo Search (CS)	[33]	$N = 15$, $IT_{max} = 500$, $\alpha = 1$, $m = 10$, $p_a = 0.25$	10 test functions	Not tested for RW problems
23	Intelligent Water-drop Optimization (IWO)	[34]	$N = 50$, $IT_{max} = 500$	Not tested	Tested for travelling salesman problem and Knapsack problem

achieved by the weight which is self-adaptive by evading the poor solution. This adaptive weight allows the algorithm to target the possible region early on and perform the local search later. Besides, a chaotic learning process is used to increase the quality of each generation's best solution. The CJAYA algorithm variants are tested by considering the sine map, logistics map, and the tent map. The performance of all versions of the CJAYA is verified on the PV models, such as SDM and DDM, for PV cells, and the same is applied to the SDM model of the PV modules and compared with various competitive optimization algorithms. The analysis and the simulation results display that CJAYA and its variants have superior accuracy and reliability performance. It is also stated that the proposed CJAYA algorithm can, therefore, be an efficient alternative to other PV structures. The major contributions of this paper are as follows.

- A new CJAYA algorithm for identifying the unknown PV cell/module parameters is proposed, and the proposed CJAYA has a self-adaptive weight capability that gives the best solution by evading the worst solution in search phases.
- A three chaotic learning process is suggested to improve the solution quality.
- The performance of the proposed CJAYA algorithm and its variants are validated on 23 standard benchmark functions.
- To validate the proposed algorithm in solving a real-world problem, three different PV cell/modules are considered: (1) RTC France Si solar cell, (2) STP6 -120/36 PV module and (3) STM6-40/36 PV module.
- Extensive experimentation and comparisons on benchmark functions and parameter estimation problem for the PV

models, such as SDM and DDM, demonstrate the effectiveness of the proposed algorithm.
- Experimental results and statistical data analysis were compared with other state-of-the-art algorithms to demonstrate the effectiveness of the proposed algorithm.
- In order to assess the ranking of the suggested CJAYA variants, statistical tests, such as Wilcoxon signed-rank test and Friedman's rank test, have been carried out.

The rest of this paper is planned accordingly. Section 2 discusses detail on the electrical equivalent of various PV models and the problem formulation of PV models. Section 3 presents the traditional JAYA algorithm, the suggested CJAYA algorithm, and its application for the parameter estimation problem. Section 4 analyzes and shows the results on various standard benchmark functions and PV models of the cell and module. In addition, the statistical test results are provided to validate the performance of the proposed CJAYA variants. Lastly, Section 5 includes conclusions.

2. Solar photovoltaic models and problem formulation

Numerous PV mathematical models described the V–I curves of the PV cell, and PV module is available in the literature [1,2]. The most frequently utilized model in practice is SDM and DDM. In this section, the equivalent circuit of the PV cell for both SDM and DDM and PV module, along with their objective functions, are presented.

2.1. Modelling of the solar photovoltaic cell and module

2.1.1. SDM of the PV cell

The SDM has famously been used in different fields, especially when describing the PV cell characteristics [68,69]. Fig. 2 shows the SDM structure, including photocurrent (I_{ph}), diode current (I_d), and the current through the shunt resistor (I_{sh}). In addition, the SDM output current (I_{pv}) is presented in Eq. (1).

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

The diode current (I_d) is presented in Eq. (2) as per the Shockley equation, and the current through the shunt resistor is given in Eq. (3).

$$I_d = I_{sd}\left[\exp\left(\frac{q(V_{pv} + I_{pv}R_{se})}{akT}\right) - 1\right] \tag{2}$$

$$I_{sh} = \frac{V_{pv} + I_{pv}R_{se}}{R_{sh}} \tag{3}$$

Where, the diode saturation current is denoted as I_{sd}, q denoted the electron charge which is equal to 1.602*10^{-19} C, V_{pv} denotes the PV output voltage, a represents the diode ideality factor, T denoted the absolute temperature in Kelvin, k denotes the Boltzmann constant which is equal to 1.3806*10^{-23}J/K, R_{se} denotes the series resistance, and R_{sh} denotes the shunt resistance of the cell.

By considering the above equations, Eq. (1) is modified as follows.

$$I_{pv} = I_{ph} - I_{sd}\left[\exp\left(\frac{q(V_{pv} + I_{pv}R_{se})}{akT}\right) - 1\right] + \frac{V_{pv} + I_{pv}R_{se}}{R_{sh}} \tag{4}$$

From Eq. (4), it is stated that the parameters required to model the PV cell based on SDM are I_{ph}, I_{sd}, a, R_{se} and R_{sh}.

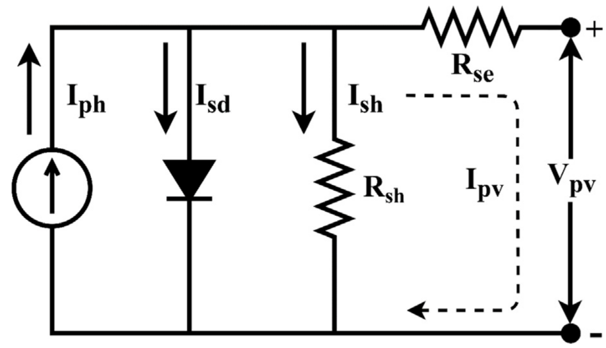

Fig. 2. Equivalent circuit of the PV cell based on SDM [17].

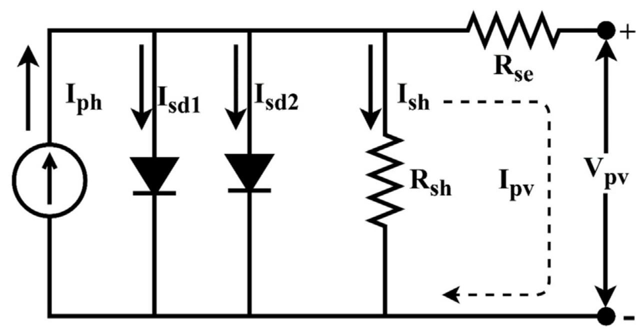

Fig. 3. Equivalent circuit of the PV cell based on DDM [17].

2.1.2. DDM of the PV cell

Considering the effect of the recombination loss in the depletion region, the DDM is developed [1]. There are two parallel-connected diodes with the controlled current source, and a parallel resistance is present in the DDM. The equivalent circuit is illustrated in Fig. 3. The total output PV current (I_{pv}) is given in Eq. (5).

$$\begin{aligned} I_{pv} &= I_{ph} - I_d + I_{sh} = I_{ph} - I_{sd1}\left[\exp\left(\frac{q\left(V_{pv} + I_{pv}R_{se}\right)}{a_1kT}\right) - 1\right] \\ &\quad - I_{sd2}\left[\exp\left(\frac{q(V_{pv} + I_{pv}R_{se})}{a_2kT}\right) - 1\right] + \frac{V_{pv} + I_{pv}R_{se}}{R_{sh}} \end{aligned} \tag{5}$$

Where, a_1 and a_2 denotes the diffusion and recombination ideality factors of the diode, and I_{sd1} and I_{sd2} denote the diffusion and saturation current of the diodes.

From Eq. (5), it is stated that the parameters required to model the PV cell based on DDM are I_{ph}, I_{sd1}, $I_{sd2}a_1$, a_2, R_{se} and R_{sh}.

2.1.3. Model of the solar PV module

As similar to PV cells, the output current equation of the PV module must be derived. As the PV module is made up of several cells in series or parallel, a number of series-connected and parallel-connected cells are considered while deriving the current equation of the photovoltaic module [1,70]. The equivalent circuit of the PV panel is illustrated in Fig. 4. The SDM and DDM based PV module may be respectively presented by Eqs. (6) and (7).

$$\begin{aligned} I_{pv} &= I_{ph}N_p - I_{sd}N_p\left[\exp\left(\frac{q(V_{pv} + I_{pv}R_{se}\left(N_{se}/N_p\right))}{N_{se}akT}\right) - 1\right] \\ &\quad + \frac{V_{pv} + I_{pv}R_{se}\left(N_{se}/N_p\right)}{R_{sh}\left(N_{se}/N_p\right)} \end{aligned} \tag{6}$$

$$I_{pv} = I_{ph}N_p - I_{sd1}N_p\left[\exp\left(\frac{\mathrm{q}\left(\mathrm{V_{pv}} + \mathrm{I_{pv}R_{se}}\left(\mathrm{N_{se}/N_p}\right)\right)}{\mathrm{N_{se}a_1kT}}\right) - 1\right]$$

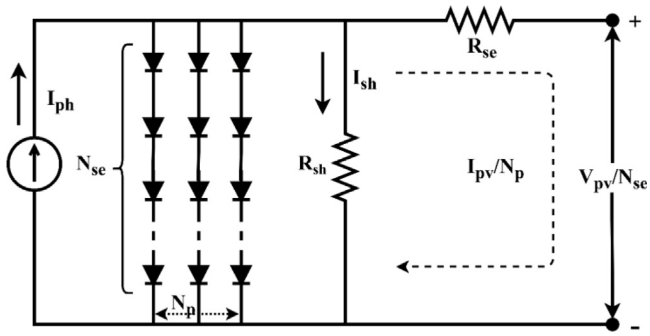

Fig. 4. Equivalent circuit of the PV module [17].

$$- I_{sd2}N_p \left[\exp\left(\frac{q\left(V_{pv} + I_{pv}R_{se}\left(N_{se}/N_p\right)\right)}{N_{se}a_2kT} \right) - 1 \right] + \frac{V_{pv} + I_{pv}R_{se}\left(N_{se}/N_p\right)}{R_{sh}\left(N_{se}/N_p\right)} \tag{7}$$

Where, N_{se} refers to the number of cells in series, N_p refers to the number of parallel solar cells, I_{pv} and V_{pv} represent the PV module current and voltage, respectively. In this paper, the SDM of the PV module is considered for simulation and analysis.

2.2. Problem formulation

The estimation of the PV cell parameters for different models is generally transformed into an optimization problem to mini-

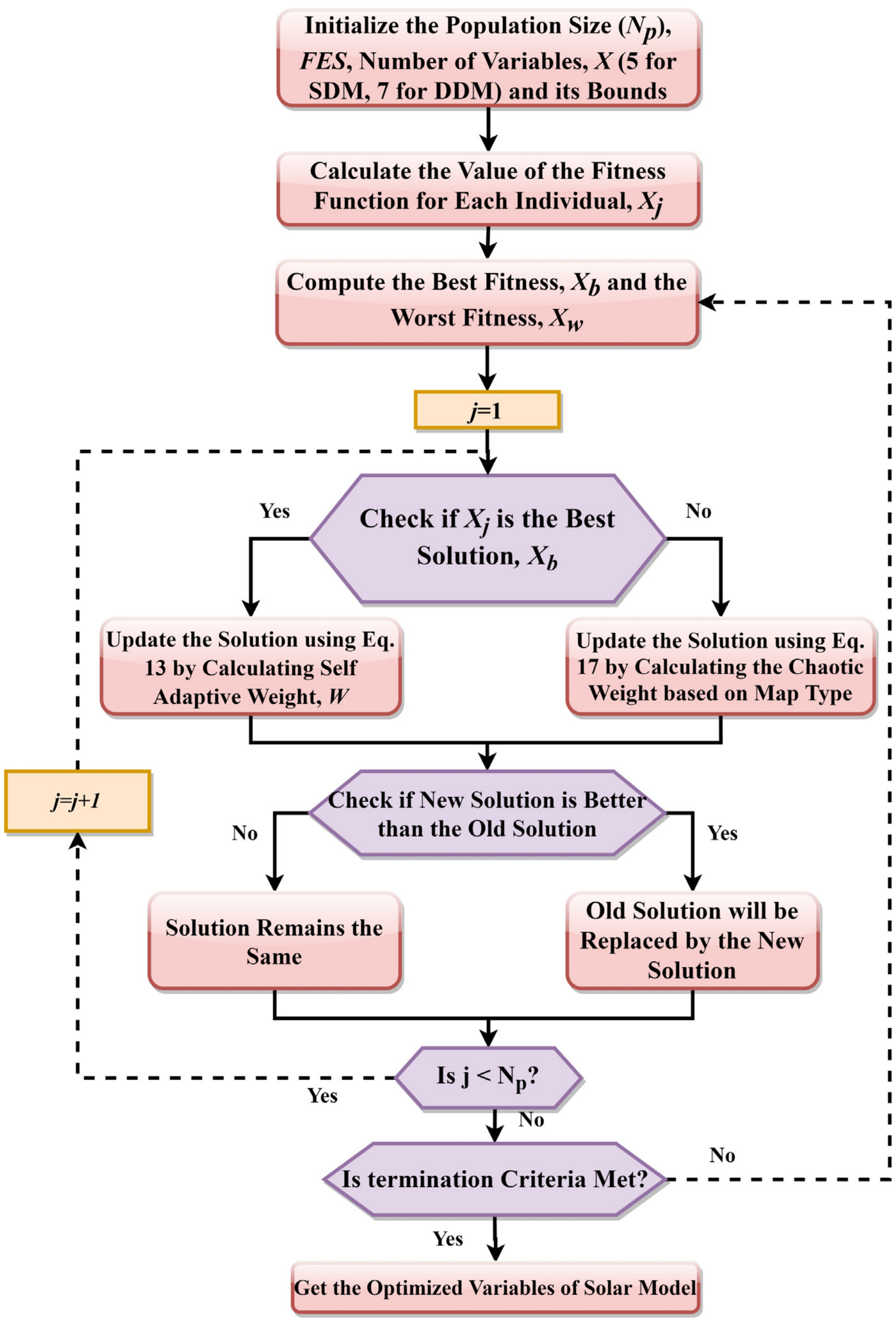

Fig. 5. Flowchart of the CJAYA algorithm for the identification of PV parameters.

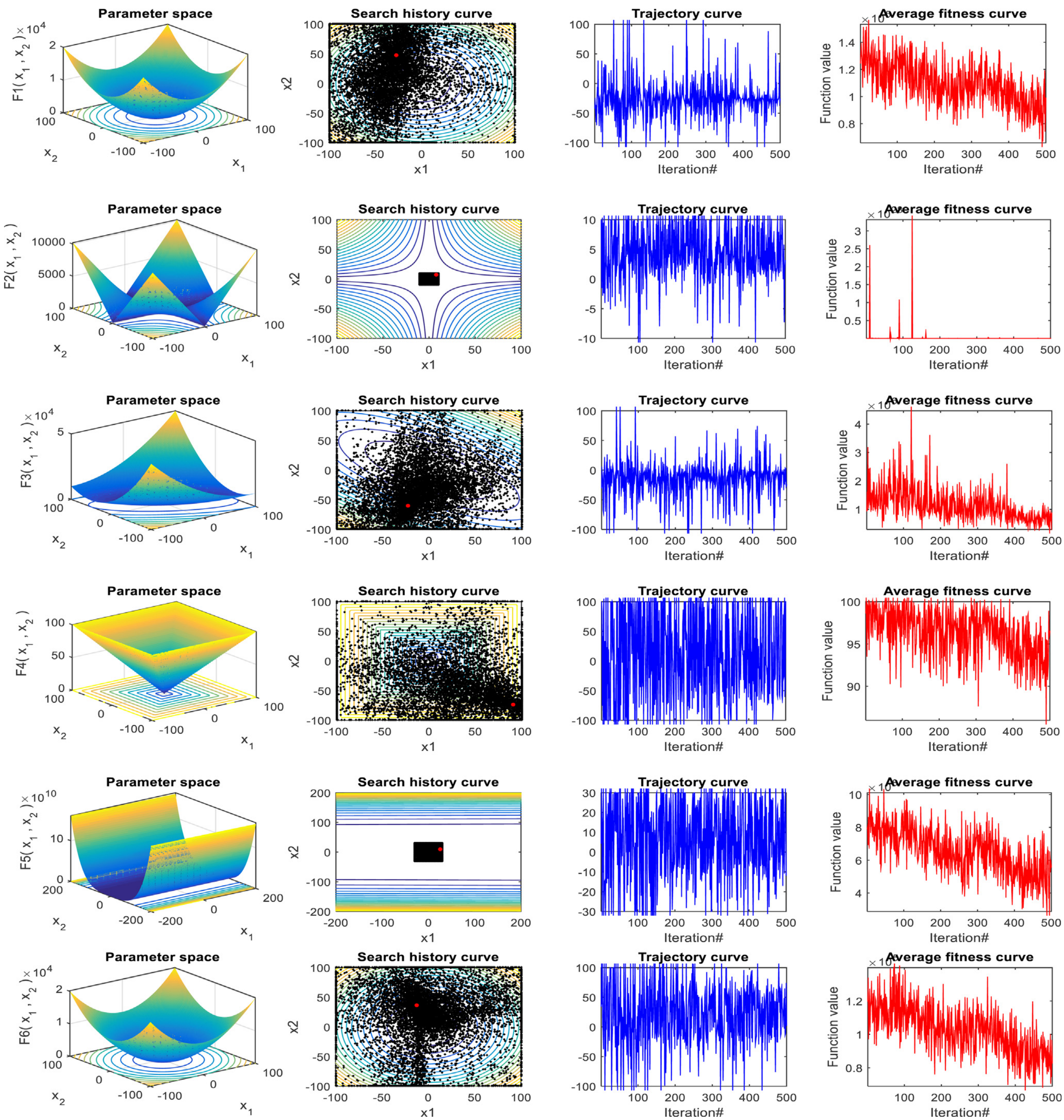

Fig. 6. Location distribution, search history curve, trajectory curve and average fitness curve of the first population in the first dimension using proposed CJAYA Algorithm.

mize the simulated parameters from estimated parameters and the difference between experimental data. In an optimization process, the output voltage, $V_{pv,}$ and the output current, I_{pv} is the actual data obtained from the experiments. As discussed earlier, find the optimal value of unidentified variables so that the error is as small as possible between calculated current and the measured current. Eq. (8) presents the objective function of the optimization problem, which is called the root mean square of the error (RMSE) [37]. The objective function can be solved using many optimization algorithms due to its non-linear transcendental structure. The primary purpose is to search the vector, X, which enables the value of $RMSE(X)$ to reach the least value.

$$RMSE\,(X) = \sqrt{\frac{1}{M}\sum_{l=1}^{M} f^{l}\left(V_{pv}^{l}, I_{pv}^{l}, X\right)^{2}} \tag{8}$$

Where M is the number of experimental data, and X is the set of unidentified variables. The SDM and DDM objective function can also be expressed respectively as Eqs. (9)–(10).

$$\begin{cases} f\left(V_{pv}, I_{pv}, X\right) = I_{ph} - I_{sd}\left[\exp\left(\dfrac{q\left(V_{pv} + I_{pv}R_{se}\right)}{akT}\right) - 1\right] \\ \quad + \dfrac{V_{pv} + I_{pv}R_{se}}{R_{sh}} - I_{pv} \\ X = \left\{I_{ph}, I_{sd}, a, R_{se}, R_{sh}\right\} \end{cases} \tag{9}$$

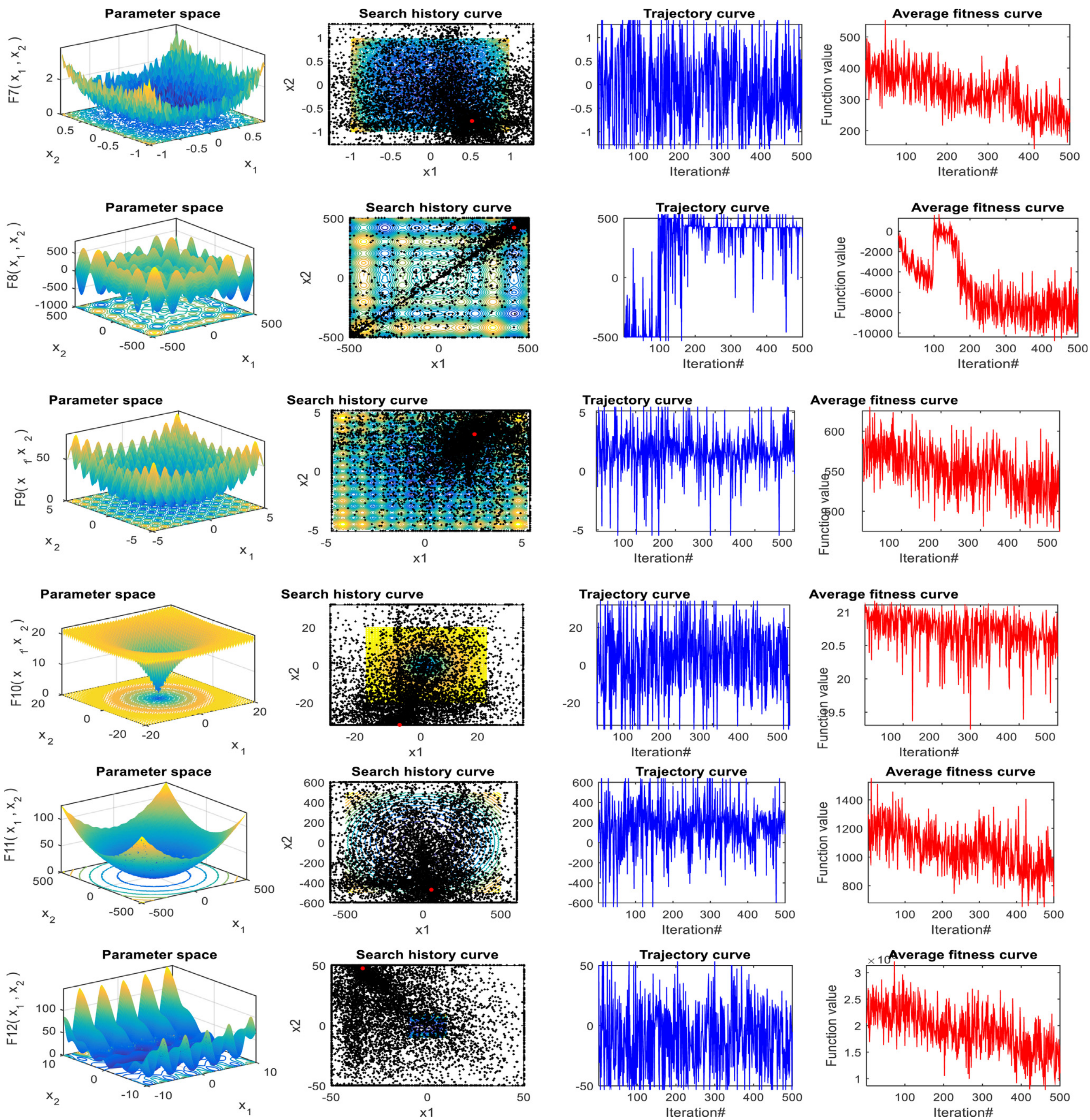

Fig. 6. (*continued*).

$$
\begin{cases} f\left(V_{pv}, I_{pv}, X\right) = I_{ph} - I_d + I_{sh} \\ \quad = I_{ph} - I_{sd1}\left[\exp\left(\dfrac{q\left(V_{pv} + I_{pv}R_{se}\right)}{a_1 kT}\right) - 1\right] \\ \qquad - I_{sd2}\left[\exp\left(\dfrac{q(V_{pv} + I_{pv}R_{se})}{a_2 kT}\right) - 1\right] + \dfrac{V_{pv} + I_{pv}R_{se}}{R_{sh}} - I_{pv} \\ X = \left\{I_{ph}, I_{sd1}, I_{sd2} a_1, a_2, R_{se}, R_{sh}\right\} \end{cases} \tag{10}
$$

3. Proposed Chaotic JAYA (CJAYA) algorithm

3.1. Conventional JAYA algorithm

The population-based JAYA algorithm is discovered by Rao to optimize the unconstrained and constrained problems. JAYA's conceptual background is that a single solution for a particular issue must tackle the optimum result and simultaneously avoid the worst result [16]. Unlike other algorithms, it does not require any algorithm-specific constraints, and it has two general parameters, including the number of generation and population size, N_p. For the objective function, *f(x)*, with variable dimension, *D*, $X_{j,i}$ is *i*th variable value for the *j*th candidate solution, therefore, $X_{j,i}$ = $(X_{j,1}, X_{j,2}, \ldots, X_{j,D})$ is *j*th candidate position. The candidate's best solution, $X_{b,i} = (X_{b,1}, X_{b,2}, \ldots, X_{b,D})$ has best solution in the present population, whereas the candidate's worst solution, $X_{w,i} = (X_{w,1}, X_{w,2}, \ldots, X_{w,D})$ has worst solution in the current population. Using Eq. (11), $X_{j,i}$ is updated.

$$
X_{j,i}^{\text{update}} = X_{j,i} + r_1\left(X_{b,i} - \left|X_{j,i}\right|\right) - r_2\left(X_{w,i} - \left|X_{j,i}\right|\right) \tag{11}
$$

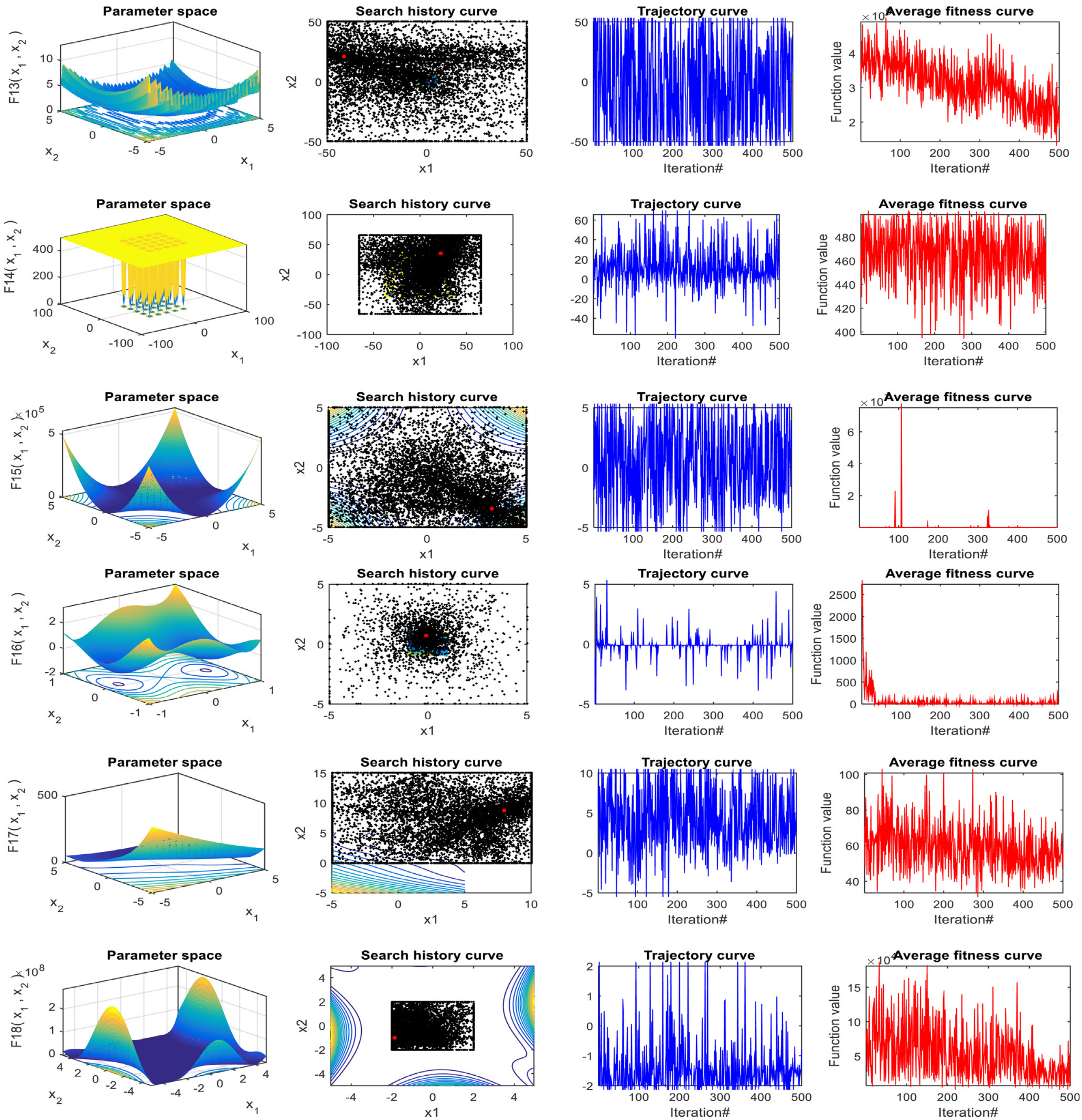

Fig. 6. (*continued*).

Where, r_1 and r_2 are the random variables distributed uniformly within [0, 1], $X_{j,i}^{\text{update}}$ denotes the updated value of the $X_{j,i}$, $X_{w,i}$ and $X_{b,i}$ are the worst and best solutions of the ith variable, respectively, and $\left|X_{j,i}\right|$ is the absolute value of the $X_{j,i}$. The term $-r_2\left(X_{w,i}-\left|X_{j,i}\right|\right)$ denotes the ability to reject the worst solution and the term, $+r_1\left(X_{b,i}-\left|X_{j,i}\right|\right)$ denotes the ability of the solution attracts towards the best output. The updated value is accepted only when the function value is better. The single solution attained by the algorithm moves quicker to the best solution, and during search process, one solution moves towards the worst solution. The introduction of a bound that is, the only substantial change would be taken into account, would be a potential improvement. Therefore, the solution accuracy can be improved by modifying the update mechanism in existing version.

3.2. *Chaotic JAYA (CJAYA) algorithm*

This section presents an enhanced chaotic JAYA (CJAYA) algorithm and its application to solve the parameter estimation optimization problem. In this paper, there two improvements are carried out with the conventional JAYA algorithm. A self-adaptive weight strategy is primarily presented to regulate the trend towards the optimum result and avoid the worst result. Next, it is proposed that the three chaotic learning methods, such as sine map, logistics map, and tent map that improves the best solution quality for every generation.

3.2.1. *Strategy-I (self adaptive weight)*

During the search procedure of the algorithm, the population must reach the promising area of the search region at an early

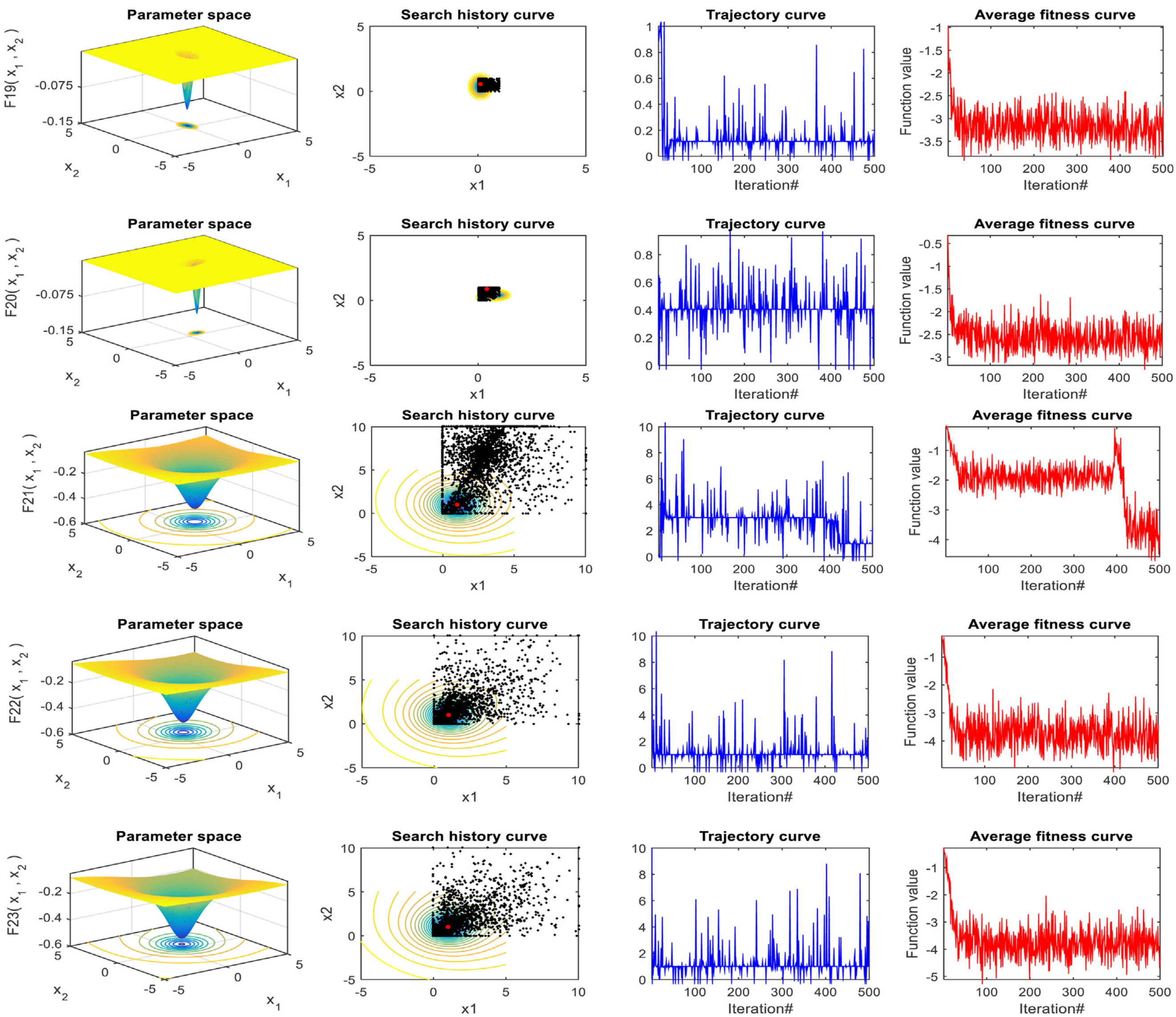

Fig. 6. (*continued*).

phase, and local search should be implemented in a promising way to increase the population quality. Considering that the self-adaptive weight strategy is dedicated to increasing the ability of exploitation, as presented in Eq. (13), the improved update equation reported in [62,71] is utilized in this paper. By comparing the update equation, as shown in Eq. (11), the new equation is introduced with a self-adaptive weight presented in Eq. (12). The theory is that the possible area can be detected at a preliminary phase because the level of approach to the best solution is comparatively greater, whereas, at a later phase, the detailed search can be accomplished in the potential area. After all, the level of approach to the best solution and avoidance of the worst solution is identical. The weight, W is presented in Eq. (12), and the degree of approach and avoidance of the worst solution is adjusted. This paper proposes a new self-adaptive inertia weight that is neither fixed to a constant value nor fixed as a time-varying function that decreases linearly. So, adopting Eq. (13) in place of Eq. (11) to update the candidate solution by weight addition.

$$W = \begin{cases} \left| \dfrac{f\ (X_b)}{f\ (X_w)} \right|^2, & if\ f\ (X_w \neq 0) \quad (\text{Variant} - \text{I}) \\ 1, & \text{Otherwise} \end{cases} \tag{12}$$

Where, $f\ (X_w)$ is the worst solution and $f\ (X_b)$ is the best solution values of the objective function in each iteration.

$$X_{j,i}^{\text{update}} = X_{j,i} + r_1 \left(X_{b,i} - \left| X_{j,i} \right| \right) - W * r_2 \left(X_{w,i} - \left| X_{j,i} \right| \right) \tag{13}$$

The added weight can be observed to adjust itself, and its value gradually increases as the difference in value between the worst and best results decreases as the search process progresses. Thus, due to the extent to which the best solution can be approached, the optimum area can be situated at the beginning, whereas local exploration in promising regions can be attained later because the step to which the best result is approachable and the worst result avoided is the same. Furthermore, the weight, W, is repeatedly calculated, and no extra parameter must be set.

3.2.2. Strategy-II (chaotic learning weight)

The best solution plays a major role during the search process because it leads and draws other populations to its individual area. Nevertheless, when resolving a multimodal issue, the individual best can be found in a local optimum. Other populations can quickly be drawn into the best region in this case, resulting in early convergence. The chaotic learning strategy is presented to increase the best solution quality by mitigating the problem. The chaotic arrangement has randomness and roughness, which is

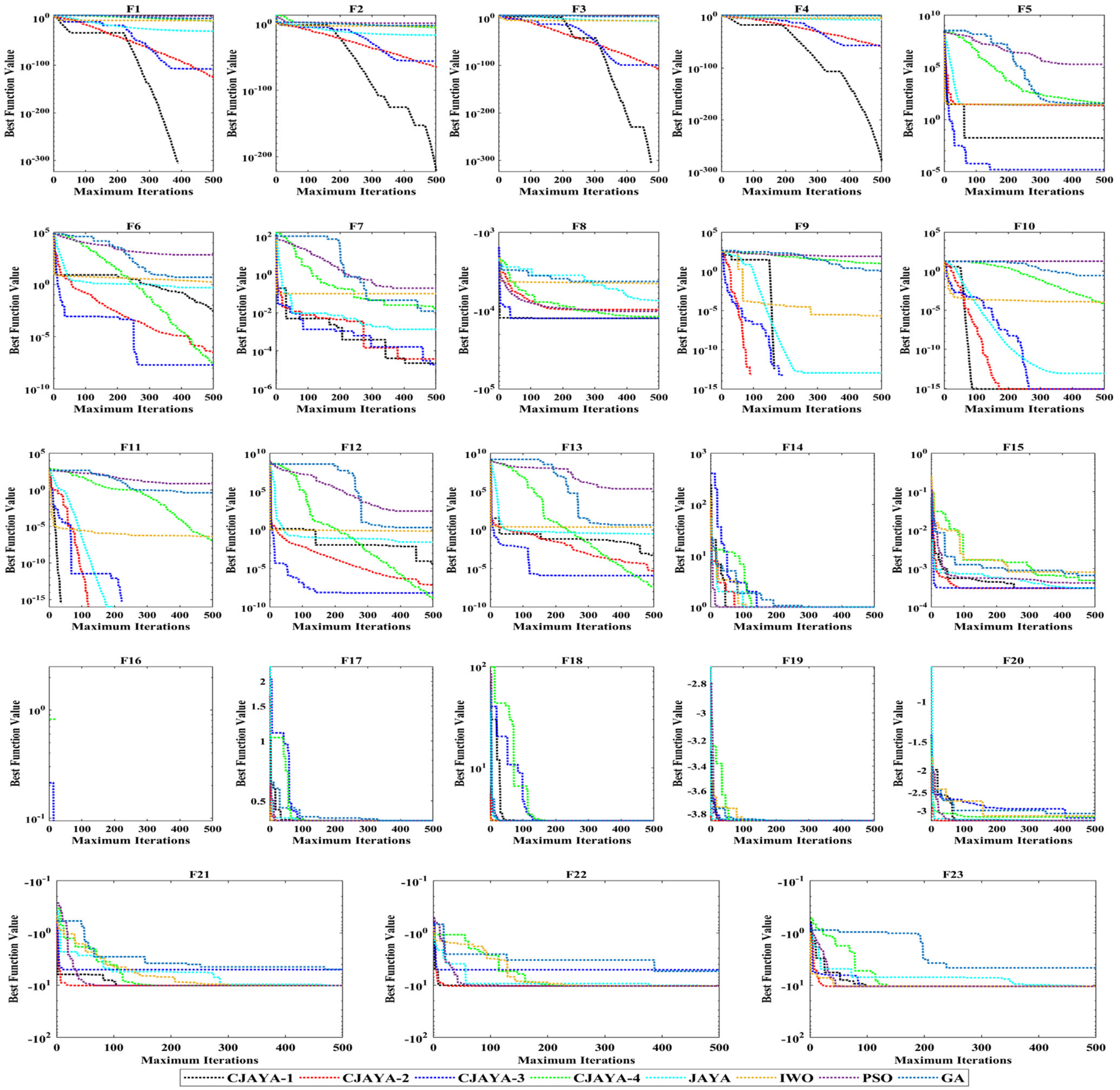

Fig. 7. Convergence curves of all algorithms on various benchmark functions.

very supportive when creating new solutions to further increase the solution quality [72]. The chaotic sequence used is the well-known sine map, logistic map and tent map, and well-defined by Eqs. (14)–(16), respectively. Now, the updated best solution is obtained by Eq. (17).

$$C_{m+1} = 2.3 * C_j^2 * sin\left(pi * C_m\right) \;\; (\text{Variant} - \text{II}) \tag{14}$$

$$C_{m+1} = \begin{cases} \dfrac{C_m}{0.7}, & if\ C_m < 0.7 \\ \dfrac{10}{3}\left(1 - C_m\right), & \text{Otherwise} \end{cases} \;\; (\text{Variant} - \text{III}) \tag{15}$$

$$C_{m+1} = 4 * C_m * \left(1 - C_m\right) \;\; (\text{Variant} - \text{IV}) \tag{16}$$

Based on the chaotic learning map type, two chaotic random numbers, such as $C_{m1,i}$ and $C_{m2,i}$ guide the movement of the solution as per Eq. (17) [73].

$$X_{j,i}^{\text{update}} = X_{j,i} + C_{m1,i}\left(X_{b,i} - \left|X_{j,i}\right|\right) - C_{m2,i}\left(X_{w,i} - \left|X_{j,i}\right|\right) \tag{17}$$

Where the iteration number is denoted by m and C_m denotes the chaotic value of mth iteration. If it provides a better solution, the best-modified solution is appropriate. The pseudocode of the proposed algorithm is presented in *Algorithm 1*, and the flowchart is illustrated in Fig. 5.

3.3. Computation complexity (CC) of CJAYA and its variants

Computation Complexity (CC) is the best metric for determining its run time by each optimizer. As similar to the traditional JAYA algorithm, the proposed CJAYA and its variants do not require any additional tuning parameters. The CC for CJAYA involves

Algorithm 1. CJAYA Algorithm Pseudocode

Initialize maximum number of function evaluation (FES_{max}) and population size (N_p).
Random initial population generation;
Estimate the value of $f(x)$ for every individual;
$FES = N_p$;
While $FES < FES_{max}$ **do**
  From the population, select the worst individual, X_w and best individual, X_b;
  For j=1 to N_p **do**
    If X_j is not the global solution **then** //∗ *Update the weight by strategy-1*∗//
      Compute the weight, w by Eq. 12;
      Update the value of i^{th} (i = 1, 2, …, D) variable of X_j by Eq. 13;
    Else //∗ *Weight update based on chaotic learning (Select any of the map type)* ∗//
      Calculate the weights, $C_{m1,i}$ and $C_{m2,i}$ using Eq. 14-16;
      Update the value of i^{th} (i = 1, 2, …, D) variable of X_b by Eq. 17;
    End if
  Compute the fitness for the updated best individual;
  $FES = FES+1$;
  Replace the worst solution by the new solution if it is better
  End for
End while

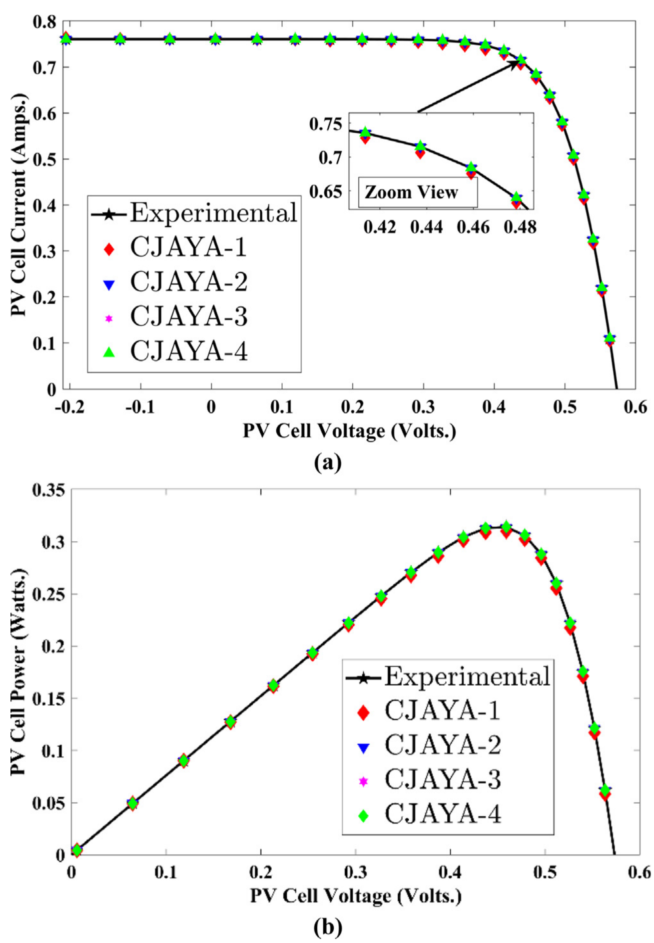

Fig. 8. Comparisons of simulated data with experimental data attained by CJAYA and its variants for the SDM; (a) V–I characteristics; (b) V–P characteristics.

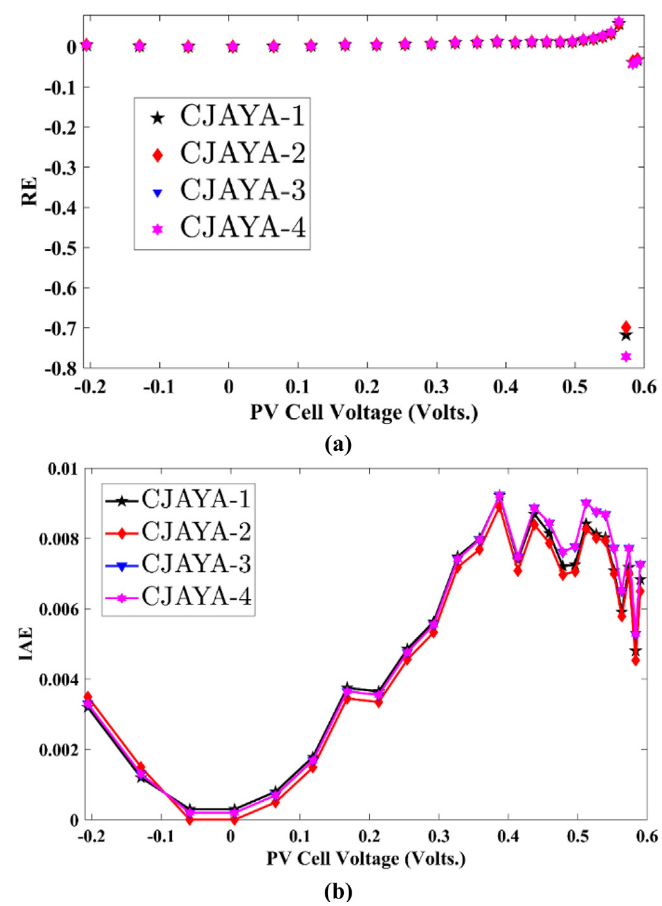

Fig. 9. Error-values of the simulated data and experimental data for the SDM; (a) RE values, (b) IAE values.

the time of comparison and modification of position, which is dependent on the number of populations is set as N_p, the maximum number of generations is set as G_m, and the number of variables is set as D. The proposed CJAYA requires three loops while updating the solution in each iteration. The outer loop indicates that the solution of each individual in the population is crisscrossed to confirm that the solutions are updated in the population. Another two-loop is utilized to minimize the unfeasible solutions during the update process, and it helps to increase the convergence speed of the CJAYA. Individuals must change their positions in each iteration, and analyses are carried out. The extra complexity of the CJAYA from the individual output quantitative approach (i.e., probability computation and population sorting) and the

Table 2
Statistical analysis of all algorithms on various benchmark functions.

	Algorithm	Min.	Max.	Mean	Median	STD	FRRT		Algorithm	Min.	Max.	Mean	Median	STD	FRRT
	CJAYA-1	**0**	**0**	**0**	**0**	**0**	**1**		CJAYA-1	0.0004461	0.0189488	0.0061889	0.0039896	0.0061276	3.2
	CJAYA-2	2.59E−126	6.99E−116	1.96E−116	2.22E−121	3.16E−116	2		CJAYA-2	4.993E−06	0.098895	0.0175914	0.0109897	0.0289305	3.4
	CJAYA-3	1.33E−108	9.759E−92	9.76E−93	1.88E−100	3.086E−92	3		CJAYA-3	1.216E−06	0.0001765	6.209E−05	3.483E−05	7.196E−05	1.9
F1	CJAYA-4	2.354E−08	3.242E−06	7.402E−07	2.408E−07	1.003E−06	5.4	F13	**CJAYA-4**	**3.525E−08**	**0.0109947**	**0.0022002**	**7.525E−07**	**0.0046332**	**1.5**
	JAYA	5.027E−29	3.257E−27	9.544E−28	3.645E−28	1.171E−27	4		JAYA	0.3103346	0.9349834	0.6656412	0.6963441	0.1853677	5
	IWO	2.294E−07	3.975E−07	3.133E−07	3.052E−07	5.927E−08	5.6		IWO	2.4600003	2.966078	2.915469	2.9660766	0.1600354	6
	PSO	863.09429	2490.2029	1586.9263	1413.5378	587.80619	8		PSO	233424.56	11727507	1880533.1	736550.12	3505775.5	7.9
	GA	0.0167235	97.478012	11.948322	1.239568	30.208434	7		GA	4.7548879	390122.73	54874.712	27.316819	121896.24	7.1
	CJAYA-1	**4.45E−223**	**4.98E−169**	**4.98E−170**	**2.34E−202**	**0**	**1**		CJAYA-1	0.9980038	0.9980038	0.9980038	0.9980038	1.42E−12	4.8
	CJAYA-2	1.725E−66	1.67E−60	2.576E−61	3.095E−62	5.215E−61	2		**CJAYA-2**	**0.9980038**	**0.9980038**	**0.9980038**	**0.9980038**	**0**	**2.25**
	CJAYA-3	7.207E−57	1.783E−50	4.361E−51	1.12E−53	6.736E−51	3		**CJAYA-3**	**0.9980038**	**0.9980038**	**0.9980038**	**0.9980038**	**0**	**2.25**
F2	CJAYA-4	1.099E−06	1.889E−05	4.746E−06	3.643E−06	5.168E−06	5	F14	**CJAYA-4**	**0.9980038**	**0.9980038**	**0.9980038**	**0.9980038**	**0**	**2.25**
	JAYA	9.577E−18	2.98E−16	9.345E−17	5.054E−17	1.072E−16	4		JAYA	0.9980038	10.763181	3.2635968	2.9821052	2.8389203	6.9
	IWO	0.0002065	0.0004175	0.000327	0.0003298	6.709E−05	6		IWO	0.9980038	3.0049884	1.3712763	0.998014	0.6575561	5.9
	PSO	7.4189574	32.720135	22.299882	23.860332	7.1480729	8		PSO	0.9980038	4.9574128	1.8903076	0.9981406	1.5066398	4.75
	GA	0.0012205	0.0480856	0.0124706	0.0054972	0.0165146	7		GA	0.9980122	2.9821052	1.9901737	1.9902695	1.0455876	6.9
	CJAYA-1	**0**	**5.93E−267**	**5.93E−268**	**0**	**0**	**1**		CJAYA-1	0.0003081	0.0007629	0.0004087	0.0003437	0.0001462	2.8
	CJAYA-2	1.41E−107	3.834E−91	4.027E−92	2.3E−100	1.207E−91	2.2		**CJAYA-2**	**0.0003075**	**0.0203633**	**0.0024046**	**0.0003075**	**0.0063166**	**2.4**
	CJAYA-3	9.69E−100	2.31E−72	2.31E−73	5.296E−92	7.305E−73	2.8		CJAYA-3	0.0003134	0.0004683	0.0003527	0.0003385	4.729E−05	2.6
F3	CJAYA-4	12379.064	40312.253	26912.202	26385.143	7709.7467	7.7	F15	CJAYA-4	0.0004608	0.0008241	0.0006849	0.0006937	0.0001247	4.8
	JAYA	1.133E−07	0.0004474	5.379E−05	8.589E−07	0.0001406	4.3		JAYA	0.0003091	0.0005974	0.000458	0.0004331	0.0001023	3.4
	IWO	7.072E−07	1.921E−06	1.405E−06	1.431E−06	3.494E−07	4.7		IWO	0.0008057	0.0016322	0.001093	0.000973	0.0003275	6.9
	PSO	15673.818	42129.468	23736.856	19861.598	9381.52	7		PSO	0.0004253	0.0022519	0.0013135	0.001572	0.0005786	6.7
	GA	681.71287	23363.496	8820.1628	6982.8555	7386.0495	6.3		GA	0.0006632	0.0015398	0.0009401	0.0008298	0.0003105	6.4
	CJAYA-1	**9.27E−280**	**1.21E−158**	**1.25E−159**	**2.37E−209**	**3.82E−159**	**1**		CJAYA-1	−1.0316285	−1.0316285	−1.0316285	−1.0316285	9.021E−10	6
	CJAYA-2	6.379E−59	5.576E−52	5.68E−53	3.298E−56	1.76E−52	2.1		**CJAYA-2**	**−1.0316285**	**−1.0316285**	**−1.0316285**	**−1.0316285**	**0**	**2.85**
	CJAYA-3	7.398E−57	7.468E−47	7.503E−48	3.417E−51	2.36E−47	2.9		CJAYA-3	−1.0316285	−1.0316285	−1.0316285	−1.0316285	7.401E−17	3.1
F4	CJAYA-4	7.5083815	16.92745	12.397037	11.820667	2.9750767	6	F16	**CJAYA-4**	**−1.0316285**	**−1.0316285**	**−1.0316285**	**−1.0316285**	**0**	**2.85**
	JAYA	1.431E−07	1.924E−06	8.769E−07	7.578E−07	6.064E−07	4		JAYA	−1.0316285	−1.0316284	−1.0316284	−1.0316284	1.983E−08	7
	IWO	0.000213	0.000411	0.0003167	0.000301	6.301E−05	5		IWO	−1.0316285	−1.0316285	−1.0316285	−1.0316285	7.401E−17	3.1
	PSO	56.421415	76.871334	67.581504	68.68775	7.2912544	8		PSO	−1.0316285	−1.0316285	−1.0316285	−1.0316285	7.401E−17	3.1
	GA	22.207801	56.347582	37.216958	40.552233	11.583885	7		GA	−1.0316233	−1.0315051	−1.0315809	−1.0315861	3.784E−05	8
	CJAYA-1	0.0168245	28.411366	12.042197	2.5494945	13.898834	3		CJAYA-1	0.3978874	0.3978875	0.3978874	0.3978874	4.632E−08	6.2
	CJAYA-2	21.846124	25.054065	23.292792	23.116798	1.0726415	2.6		**CJAYA-2**	**0.3978874**	**0.3978874**	**0.3978874**	**0.3978874**	**0**	**3**
	CJAYA-3	**1.523E−05**	**0.031778**	**0.0081625**	**0.0042781**	**0.0105722**	**1**		**CJAYA-3**	**0.3978874**	**0.3978874**	**0.3978874**	**0.3978874**	**0**	**3**
F5	CJAYA-4	36.116323	145.76672	87.062354	82.763069	27.985125	6.1	F17	**CJAYA-4**	**0.3978874**	**0.3978874**	**0.3978874**	**0.3978874**	**0**	**3**
	JAYA	26.079621	28.540024	27.157541	27.11803	0.7838911	3.7		JAYA	0.3978874	0.3979112	0.3978904	0.3978876	7.365E−06	6.8
	IWO	27.92924	28.228239	28.095381	28.168843	0.1248567	4.7		IWO	0.3978874	0.3978874	0.3978874	0.3978874	0	3
	PSO	197690.53	3197569.9	961661.27	760597.07	882005.93	8		PSO	0.3978874	0.3978874	0.3978874	0.3978874	0	3
	GA	34.959109	59232.224	13516.636	6861.9773	19326.599	6.9		GA	0.3980041	0.4005327	0.399295	0.3992052	0.0008813	8
	CJAYA-1	0.0028093	0.0109587	0.0064099	0.005365	0.0028876	4		CJAYA-1	3	3	3	3	2.04E−10	6
	CJAYA-2	3.107E−07	2.071E−05	9.837E−06	7.617E−06	6.543E−06	2.4		CJAYA-2	3	3	3	3	5.539E−16	3.35
	CJAYA-3	1.989E−08	0.0001803	6.631E−05	2.63E−05	7.678E−05	2.3		CJAYA-3	3	3	3	3	2.093E−16	2.55
F6	**CJAYA-4**	**3.042E−08**	**1.693E−06**	**3.315E−07**	**1.529E−07**	**4.995E−07**	**1.3**	F18	**CJAYA-4**	**3**	**3**	**3**	**3**	**7.972E−16**	**1.85**
	JAYA	0.4826879	0.9909065	0.7247368	0.7525656	0.1824027	5		JAYA	3.0000001	3.0001206	3.0000293	3.0000147	3.822E−05	7.5
	IWO	1.7035919	2.1273565	1.8676123	1.7868207	0.1755289	6		IWO	3	3	3	3	5.128E−16	2.95
	PSO	696.50087	10457.999	3378.7358	2258.6609	3422.0291	8		PSO	3	3	3	3	1.726E−15	4.3
	GA	4.9374594	29.659671	14.39786	13.266826	8.7448635	7		GA	3.0000021	3.0000828	3.0000229	3.000013	2.482E−05	7.5

(*continued on next page*)

Table 2 (*continued*).

	Algorithm	Min.	Max.	Mean	Median	STD	FRRT
F7	**CJAYA-1**	**2.286E−05**	**0.0006983**	**0.0001677**	**0.0001233**	**0.0001988**	**1.8**
	CJAYA-2	3.739E−05	0.0013228	0.0005518	0.0005411	0.000403	2.6
	CJAYA-3	1.924E−05	0.0002774	0.0001071	5.439E−05	0.0001068	1.6
	CJAYA-4	0.0169023	0.0507963	0.0307535	0.0261435	0.012249	5.1
	JAYA	0.0013512	0.0029475	0.0017609	0.0015394	0.0005072	4
	IWO	0.1008758	1.1639775	0.8139284	0.893636	0.3511329	7.6
	PSO	0.1967251	7.2586967	2.0691206	0.5827497	2.6744584	7.4
	GA	0.0122494	0.297205	0.103347	0.0660164	0.0864044	5.9
F8	**CJAYA-1**	**−12569.484**	**−12568.282**	**−12569.241**	**−12569.393**	**0.3877996**	**1.2**
	CJAYA-2	−9702.4527	−7921.5674	−8727.7659	−8878.1511	625.37255	4.5
	CJAYA-3	−12569.475	−11985.94	−12510.167	−12568.477	184.19747	1.8
	CJAYA-4	−11972.888	−10576.748	−11573.658	−11689.639	447.02595	3
	JAYA	−7478.9567	−5093.2327	−6301.8171	−6214.6699	742.05489	6
	IWO	−4500.2397	−3503.7174	−3946.6499	−3888.6259	381.74241	7.4
	PSO	−10213.075	−7313.7231	−8503.7046	−8385.4407	1038.2869	4.5
	GA	−4261.0468	−3485.1295	−3722.2085	−3615.9415	249.60148	7.6
F9	**CJAYA-1**	**0**	**0**	**0**	**0**	**0**	**2**
	CJAYA-2	**0**	**0**	**0**	**0**	**0**	**2**
	CJAYA-3	**0**	**0**	**0**	**0**	**0**	**2**
	CJAYA-4	10.439791	16.916522	13.809299	13.982244	2.0727258	6.3
	JAYA	1.137E−13	5.5382983	1.1361928	4.832E−13	1.9920114	4.3
	IWO	2.164E−06	9.17E−06	4.795E−06	4.146E−06	2.142E−06	4.7
	PSO	86.439101	187.10555	139.21016	137.71817	26.292905	8
	GA	1.3626611	105.38733	39.565285	35.705252	32.458519	6.7
F10	**CJAYA-1**	**8.882E−16**	**8.882E−16**	**8.882E−16**	**8.882E−16**	**0**	**2**
	CJAYA-2	**8.882E−16**	**8.882E−16**	**8.882E−16**	**8.882E−16**	**0**	**2**
	CJAYA-3	**8.882E−16**	**8.882E−16**	**8.882E−16**	**8.882E−16**	**0**	**2**
	CJAYA-4	7.276E−05	0.0003657	0.0001667	0.0001446	9.551E−05	5.5
	JAYA	8.615E−14	1.501E−13	1.124E−13	1.021E−13	2.552E−14	4
	IWO	0.0001115	0.0001609	0.0001348	0.0001349	1.716E−05	5.5
	PSO	19.95737	19.963186	19.961545	19.962999	0.002078	7.4
	GA	0.2921915	20.274642	17.750243	20.201448	6.1933094	7.6
F11	**CJAYA-1**	**0**	**0**	**0**	**0**	**0**	**2.4**
	CJAYA-2	**0**	**0**	**0**	**0**	**0**	**2.4**
	CJAYA-3	**0**	**0**	**0**	**0**	**0**	**2.4**
	CJAYA-4	1.501E−07	0.0076735	0.0015077	1.047E−06	0.0031773	5.4
	JAYA	0	0.023232	0.0036827	0	0.0080892	3.2
	IWO	4.372E−07	1.164E−06	7.998E−07	7.353E−07	2.234E−07	5.2
	PSO	7.0837547	97.986502	32.247685	16.616909	30.260549	8
	GA	0.4159288	1.0383205	0.783448	0.7346482	0.1917179	7
F12	CJAYA-1	3.867E−05	0.0129827	0.0064562	0.006077	0.0052123	3.9
	CJAYA-2	6.941E−08	5.298E−06	9.077E−07	2.175E−07	1.624E−06	2.3
	CJAYA-3	6.787E−09	6.329E−05	9.937E−06	1.013E−06	1.995E−05	2.4
	CJAYA-4	**1.388E−09**	**0.103669**	**0.0103669**	**1.945E−08**	**0.032783**	**1.5**
	JAYA	0.0266929	0.1186274	0.0503202	0.0386261	0.0291197	4.9
	IWO	0.7053668	1.016417	0.7960205	0.746646	0.111683	6
	PSO	300.57475	2533983.3	512956.25	137371.15	899439.76	7.9
	GA	2.1229998	47632.757	5232.4188	12.198293	14966.231	7.1

	Algorithm	Min.	Max.	Mean	Median	STD	FRRT
F19	CJAYA-1	−3.8627821	−3.8627817	−3.862782	−3.862782	1.708E−07	3.8
	CJAYA-2	−3.8627821	−3.8627821	−3.8627821	−3.8627821	9.004E−16	1.95
	CJAYA-3	−3.8627627	−3.8574093	−3.860863	−3.8609267	0.0017021	5.8
	CJAYA-4	**−3.8627821**	**−3.8627821**	**−3.8627821**	**−3.8627821**	**9.362E−16**	**1.8**
	JAYA	−3.8627747	−3.8552812	−3.8605732	−3.8619291	0.0028522	5.5
	IWO	−3.8621571	−3.8510594	−3.8561789	−3.856183	0.0036088	6.8
	PSO	−3.8627821	−3.8549006	−3.8612058	−3.8627821	0.0033231	3.15
	GA	−3.8620861	−3.8520816	−3.8555379	−3.8543922	0.0034369	7.2
F20	CJAYA-1	−3.3219792	−3.1997191	−3.2143838	−3.2030446	0.0378198	3.1
	CJAYA-2	**−3.3219952**	**−3.2031021**	**−3.2506593**	**−3.2031021**	**0.0613961**	**1.5**
	CJAYA-3	−3.2277933	−2.9581366	−3.1111464	−3.117192	0.0838802	5.1
	CJAYA-4	−3.1992948	−2.9039126	−3.059897	−3.0524786	0.0931059	5.9
	JAYA	−3.3219887	−2.4317731	−3.178328	−3.2623374	0.2715483	3
	IWO	−3.1658706	−2.8301663	−2.9856896	−2.9408145	0.1351738	7.1
	PSO	−3.3219952	−2.8103389	−3.1782167	−3.1987672	0.1507305	3.5
	GA	−3.0878159	−1.9076101	−2.9044935	−3.00292	0.3518618	6.8
F21	CJAYA-1	−10.153162	−10.152221	−10.152809	−10.152912	0.0003113	3.1
	CJAYA-2	−10.1532	−5.0551977	−8.1139989	−10.1532	2.6325969	2.9
	CJAYA-3	−5.054704	−5.0475154	−5.0523447	−5.0529861	0.0025001	6.1
	CJAYA-4	**−10.1532**	**−10.1532**	**−10.1532**	**−10.1532**	**1.518E−13**	**1.5**
	JAYA	−10.152255	−2.6826626	−8.1784989	−10.149872	3.2368614	4.6
	IWO	−10.152895	−2.6290012	−6.8740271	−7.5801815	3.5414217	5.8
	PSO	−10.1532	−2.6304717	−6.376777	−5.0779849	3.397408	4.5
	GA	−4.9838067	−0.4972784	−2.6603644	−2.6986517	1.8835012	7.5
F22	CJAYA-1	−10.402776	−10.402494	−10.402654	−10.402695	0.0001018	3
	CJAYA-2	−10.402941	−3.7243003	−8.2351186	−10.402941	2.8519468	2.95
	CJAYA-3	−5.0875255	−5.0773779	−5.0839511	−5.0852784	0.0036443	5.8
	CJAYA-4	**−10.402941**	**−3.7243003**	**−9.7350765**	**−10.402941**	**2.1119715**	**2.1**
	JAYA	−10.402079	−10.399208	−10.400663	−10.400707	0.001063	4
	IWO	−10.392475	−3.7231508	−5.892954	−4.4047106	2.9304228	6.3
	PSO	−10.402941	−1.837593	−6.6818727	−7.0636205	3.9577284	4.65
	GA	−5.4261157	−0.9074052	−3.1533992	−3.4235055	1.8631791	7.2
F23	CJAYA-1	−10.536392	−10.535346	−10.536059	−10.53606	0.0003033	3.6
	CJAYA-2	−10.53641	−5.1284808	−9.454824	−10.53641	2.2801831	2.65
	CJAYA-3	−10.522322	−5.0966028	−5.663024	−5.1274871	1.7074114	6.3
	CJAYA-4	**−10.53641**	**−10.53641**	**−10.53641**	**−10.53641**	**2.777E−15**	**1.5**
	JAYA	−10.536333	−2.42157	−9.723631	−10.535032	2.5656829	4.6
	IWO	−10.527984	−3.8350947	−8.4248137	−9.8201586	2.6860331	5.7
	PSO	−10.53641	−1.8594803	−7.5481951	−10.53641	3.9486997	3.85
	GA	−4.6700827	−0.9463041	−2.7154233	−2.5931344	1.3068104	7.8
-							

The bold letter indicates the best results in terms of Min, Max, Mean, Median, STD, and FRRT

Table 3
Computation time complexity in sec. of all algorithms.

Benchmark type	CJAYA-1	CJAYA-2	CJAYA-3	CJAYA-4	JAYA	IWO	PSO	GA
F1	**0.265625**	0.3125	0.640625	1.625	1.671875	22.1875	0.4245	9.1875
F2	**0.296875**	0.328125	0.6875	1.640625	1.703125	18.67188	0.5478	9.09375
F3	**1.40625**	1.4375	3.390625	2.71875	2.859375	23.34375	1.6543	10.26563
F4	**0.375**	0.40625	0.984375	1.6875	1.765625	22.26563	0.4134	9.1875
F5	**0.40625**	0.46875	1.203125	1.75	1.796875	22.01563	0.4648	9.296875
F6	**0.390625**	0.453125	1.09375	1.71875	1.78125	22.25	0.4583	9.265625
F7	0.53125	0.59375	1.28125	1.84375	1.921875	34.46875	**0.515625**	9.390625
F8	**0.4375**	0.515625	1.28125	1.765625	1.84375	21.23438	0.4967	9.34375
F9	**0.4375**	0.5	1.234375	1.78125	1.828125	12.40625	0.5654	9.28125
F10	**0.46875**	0.515625	1.28125	1.828125	1.859375	21.90625	0.5323	9.296875
F11	**0.5**	0.546875	1.375	1.859375	1.890625	22.3125	0.6544	9.296875
F12	**0.953125**	1.015625	2.484375	2.328125	2.390625	22.70313	0.9862	9.828125
F13	0.9375	1	2.46875	2.3125	2.375	22.75	**0.8762**	9.8125
F14	**2**	**2**	2.484375	2.484375	3.390625	21.79688	2.2761	3.359375
F15	**0.265625**	0.28125	1.046875	0.875	1.625	11.4375	0.5484	2.140625
F16	**0.1875**	**0.1875**	0.6875	0.703125	1.515625	5.875	0.3143	1.546875
F17	**0.171875**	**0.171875**	0.671875	0.671875	1.5	5.96875	0.2649	1.53125
F18	**0.1875**	**0.1875**	0.703125	0.6875	1.515625	5.96875	0.4373	1.546875
F19	**0.34375**	0.359375	1.265625	0.921875	1.71875	33.89063	0.4592	1.984375
F20	**0.359375**	**0.359375**	1.265625	1.265625	1.75	34.125	0.4974	2.84375
F21	**0.53125**	**0.53125**	1.640625	1.09375	1.90625	11.78125	0.5851	2.484375
F22	**0.625**	**0.625**	1.859375	1.171875	1.984375	11.90625	0.7556	2.53125
F23	**0.75**	**0.75**	2.140625	1.296875	2.078125	12.04688	0.8201	2.671875
CC = (Total time/23)	**0.557745**	0.588995	1.442255	1.566576	1.942255	19.27446	0.676014	6.3125

The bold letter indicates the best CC

Table 4
Test cases of the PV models considered.

Test cases	Type of PV	Number of series cells	Temperature (°C)	Irradiance (W/m^2)	PV model
1/2	RTC Si France cell	1	33	1000	SDM/DDM
3	STP6-120/36 module	36	55	1000	SDM
4	STM6-40/36 module	36	51	1000	SDM

Table 5
Parameter ranges of PV models.

Parameters	RTC France Si Cell		STP6-120/36 Module		STM6-40/36 Module	
	LB	UB	LB	UB	LB	UB
I_{ph} (A)	0	1	0	8	0	2
a (SDM)	1	2	1	50	1	60
a_1, a_2 (DDM)	1	2	–	–	–	–
I_{sd}, I_{sd1}, I_{sd2} (μA)	0	1	0	50	1	50
R_{se} (Ω)	0	0.5	0	0.4	0	0.4
R_{sh} (Ω)	0	100	0	1500	0	1000

perturbation based on self-adaptive chaotic for the CC relative to the basic version of the JAYA algorithm. The population sorting complexity is O($N_p.log(N_p)$), the probability computation complexity is O(N_p), and O(D) is for self-adaptive chaotic perturbation. Meanwhile the traditional JAYA complexity is O($G_m \cdot N_p \cdot D$), the total complexity of CJAYA and its all variants is equals to O($G_m \cdot (N_p \cdot D + N_p \cdot log(N_p) + N_p + D)$). Generally, the population size N_p is proportional to the dimension of the given problem. Hence, as per the computation rules, the overall complexity of CJAYA and its variants is O($G_m \cdot N_p \cdot D$). Differently, using the benchmark suite, the algorithmic complexity of all selected optimizers is also determined. In determining the algorithmic CC, the following expression is adopted [74].

$$CC = \frac{\sum_{i=1}^{N} t_{1i}}{N} \tag{18}$$

where t_{1i} is the computation time required to perform 500 iterations for the problem i and N denote the number of selected benchmark problems.

4. Simulation results and discussions

4.1. Results on benchmark functions

Firstly, the performance of the proposed CJAYA algorithm and its variants are validated by considering 23 various types of benchmark functions [23]. The details of benchmark functions are provided in Appendix-I for better understanding. Despite the simplicity, to be able to equate the results to those of the various optimizers, these test functions are considered. In general, minimization benchmark functions are used and can be split into three groups: unimodal, multimodal and multimodal fixed-dimension. On each benchmark function, the CJAYA algorithm and all other selected algorithms were run 10 times. The statistical findings are listed in Table 2 (Min, Max, Median, Mean, and Standard deviation (STD)) and non-parametric Friedman ranking test (FRRT) is also performed. All the benchmark functions are optimized with the population size of 50 and the maximum number of iterations of 500 for all selected algorithms, such as JAYA [16], IWO [34], PSO [75], and GA [19]. The findings from Table 2 are summarized as follows. The computation complexity of all selected algorithms is listed in Table 3. The convergence

Table 6
Parameter settings of various algorithms for parameter estimation problems.

Algorithms	Parameters	Values			
		Case-I	Case-II	Case-III	Case-IV
CJAYA and its Variants	Number of fitness evaluations, FES_{max}	50,000	50,000	50,000	50000
	Population size, N_p	30	50	80	80
JAYA [58]	Number of fitness evaluations, FES_{max}	50,000	60,000	80,000	80,000
	Population size, N_p	30	50	80	80
RAO [17]	Number of fitness evaluations, FES_{max}	50,000	60,000	80,000	80,000
	Population size, N_p	30	50	80	80
BO-DE [42]	Number of fitness evaluations, FES_{max}	50,000	60,000	80,000	80,000
	Population size, N_p	30	50	80	80
	K	2	2	2	2
	$\pi_{\max}$	0.005	0.005	0.005	0.005
	CR	0.9	0.9	0.9	0.9
TPSO [54]	Weights, w_1 and w_2	0.9, 0.2	0.9, 0.2	0.9, 0.4	0.9, 0.4
	Constants, c_1 and c_2	2	2	2	2
	Population size, N_p	30	50	50	50
	Maximum number of iterations, IT_{max}	1000	1200	1500	1500
ITLO [15]	Population size, N_p	30	50	50	50
	Maximum number of iterations, IT_{max}	1000	1200	1500	1500
IWO [34]	Population size, N_p	30	50	50	50
	Maximum number of iterations, IT_{max}	1000	1200	1500	1500
GA [19]	Population size, N_p	30	50	50	50
	Maximum number of iterations, IT_{max}	1000	1200	1500	1500
	Crossover and Mutation probability	0.5 and 0.02			
	Number of bits per chromosome	16			

Table 7
IAE of CJAYA and its variants on SDM.

V_{pv} (V)	I_{pv} (A)	Simulated value				I	II	III	IV
		I	II	III	IV				
		I_{pv} (A)	I_{pv} (A)	I_{pv} (A)	I_{pv} (A)	IAE_i	IAE_i	IAE_i	IAE_i
−0.2057	0.7640	0.7608	0.7605	0.7607	0.7607	0.0032	0.0035	0.0033	0.0033
−0.1291	0.7620	0.7608	0.7605	0.7607	0.7607	0.0012	0.0015	0.0013	0.0013
−0.0588	0.7605	0.7608	0.7605	0.7607	0.7607	0.0003	0.0000	0.0002	0.0002
0.0057	0.7605	0.7608	0.7605	0.7607	0.7607	0.0003	0.0000	0.0002	0.0002
0.0646	0.7600	0.7608	0.7605	0.7607	0.7607	0.0008	0.0005	0.0007	0.0007
0.1185	0.7590	0.7608	0.7605	0.7607	0.7607	0.0018	0.0015	0.0017	0.0017
0.1678	0.7570	0.7608	0.7605	0.7607	0.7607	0.0038	0.0035	0.0037	0.0037
0.2132	0.7570	0.7606	0.7603	0.7605	0.7605	0.0036	0.0033	0.0035	0.0035
0.2545	0.7555	0.7604	0.7601	0.7603	0.7603	0.0049	0.0046	0.0048	0.0048
0.2924	0.7540	0.7596	0.7593	0.7595	0.7595	0.0056	0.0053	0.0055	0.0055
0.3269	0.7505	0.7580	0.7577	0.7579	0.7579	0.0075	0.0072	0.0074	0.0074
0.3585	0.7465	0.7545	0.7542	0.7545	0.7545	0.0080	0.0077	0.0080	0.0080
0.3873	0.7385	0.7477	0.7474	0.7477	0.7477	0.0090	0.0089	0.0092	0.0092
0.4137	0.7280	0.7354	0.7351	0.7355	0.7355	0.0074	0.0071	0.0075	0.0075
0.4373	0.7065	0.7152	0.7149	0.7154	0.7154	0.0087	0.0084	0.0089	0.0089
0.4590	0.6755	0.6836	0.6834	0.6839	0.6839	0.0081	0.0079	0.0084	0.0084
0.4784	0.6320	0.6392	0.6390	0.6396	0.6396	0.0072	0.0070	0.0076	0.0076
0.4960	0.5730	0.5803	0.5801	0.5808	0.5808	0.0073	0.0071	0.0078	0.0078
0.5119	0.4990	0.5074	0.5073	0.5080	0.5080	0.0084	0.0083	0.0090	0.0090
0.5265	0.4130	0.4211	0.4210	0.4218	0.4218	0.0081	0.0080	0.0088	0.0088
0.5398	0.3165	0.3245	0.3244	0.3252	0.3252	0.0080	0.0079	0.0087	0.0087
0.5521	0.2120	0.2191	0.2190	0.2197	0.2197	0.0071	0.0070	0.0077	0.0077
0.5633	0.1035	0.1094	0.1093	0.1100	0.1100	0.0059	0.0058	0.0065	0.0065
0.5736	−0.0100	−0.0028	−0.0030	−0.0023	−0.0023	0.0072	0.0070	0.0077	0.0077
0.5833	−0.1230	−0.1182	−0.1185	−0.1177	−0.1177	0.0048	0.0045	0.0053	0.0053
0.5900	−0.2100	−0.2032	−0.2035	−0.2027	−0.2027	0.0068	0.0065	0.0073	0.0073

I-CJAYA-1, II-CJAYA-2, III-CJAYA-3, IV-CJAYA-4

curve allows a metaheuristic to extensively explore the search space. These modifications should be decreased at the end of optimization to highlight exploitation. To observe the behaviour of the proposed CJAYA algorithm, the parameter search space, search history curve, trajectory curve, and average fitness curves for all 23 benchmark functions are illustrated in Fig. 6. To observe the CJAYA variants convergence behaviour and box plot shown in Fig. 7 and Fig. 8, respectively.

- According to Table 2 and Fig. 6(F1–F7), the CJAYA algorithm variants can produce very competitive results. It should be noted that for benchmarking exploitation, the unimodal functions are appropriate. Therefore, these findings illustrate the superior performance of CJAYA algorithm variants in terms of optimal utilization.
- Compared to the unimodal functions, there are many local optima with multimodal functions, with the number increasing exponentially with dimension. This makes them perfect for benchmarking an algorithm's exploration ability. CJAYA algorithm variants can also provide very competitive results on the multimodal benchmark functions, based on the results of Table 2 and Fig. 6 (F8–F16). For most of the

Table 8
RE of CJAYA and its variants on SDM.

V_{pv} (V)	I_{pv} (A)	Simulated value				I	II	III	IV
		I	II	III	IV				
		I_{pv} (A)	I_{pv} (A)	I_{pv} (A)	I_{pv} (A)	RE_i	RE_i	RE_i	RE_i
−0.2057	0.7640	0.7608	0.7605	0.7607	0.7607	0.0042	0.0046	0.0043	0.0043
−0.1291	0.7620	0.7608	0.7605	0.7607	0.7607	0.0016	0.0020	0.0017	0.0017
−0.0588	0.7605	0.7608	0.7605	0.7607	0.7607	0.0004	0.0000	0.0003	0.0003
0.0057	0.7605	0.7608	0.7605	0.7607	0.7607	0.0004	0.0000	0.0003	0.0003
0.0646	0.7600	0.7608	0.7605	0.7607	0.7607	0.0010	0.0007	0.0009	0.0009
0.1185	0.7590	0.7608	0.7605	0.7607	0.7607	0.0024	0.0020	0.0022	0.0022
0.1678	0.7570	0.7608	0.7605	0.7607	0.7607	0.0050	0.0046	0.0048	0.0048
0.2132	0.7570	0.7606	0.7603	0.7605	0.7605	0.0048	0.0044	0.0047	0.0047
0.2545	0.7555	0.7604	0.7601	0.7603	0.7603	0.0064	0.0060	0.0063	0.0063
0.2924	0.7540	0.7596	0.7593	0.7595	0.7595	0.0075	0.0071	0.0074	0.0074
0.3269	0.7505	0.7580	0.7577	0.7579	0.7579	0.0100	0.0096	0.0099	0.0099
0.3585	0.7465	0.7545	0.7542	0.7545	0.7545	0.0107	0.0103	0.0107	0.0107
0.3873	0.7385	0.7477	0.7474	0.7477	0.7477	0.0125	0.0121	0.0125	0.0125
0.4137	0.7280	0.7354	0.7351	0.7355	0.7355	0.0101	0.0097	0.0103	0.0103
0.4373	0.7065	0.7152	0.7149	0.7154	0.7154	0.0123	0.0119	0.0126	0.0126
0.4590	0.6755	0.6836	0.6834	0.6839	0.6839	0.0121	0.0116	0.0125	0.0125
0.4784	0.6320	0.6392	0.6390	0.6396	0.6396	0.0114	0.0110	0.0121	0.0121
0.4960	0.5730	0.5803	0.5801	0.5808	0.5808	0.0127	0.0123	0.0136	0.0136
0.5119	0.4990	0.5074	0.5073	0.5080	0.5080	0.0169	0.0166	0.0181	0.0181
0.5265	0.4130	0.4211	0.4210	0.4218	0.4218	0.0197	0.0194	0.0212	0.0212
0.5398	0.3165	0.3245	0.3244	0.3252	0.3252	0.0254	0.0251	0.0274	0.0274
0.5521	0.2120	0.2191	0.2190	0.2197	0.2197	0.0334	0.0330	0.0364	0.0364
0.5633	0.1035	0.1094	0.1093	0.1100	0.1100	0.0571	0.0559	0.0629	0.0629
0.5736	−0.0100	−0.0028	−0.0030	−0.0023	−0.0023	−0.7174	−0.6988	−0.7719	−0.7719
0.5833	−0.1230	−0.1182	−0.1185	−0.1177	−0.1177	−0.0390	−0.0369	−0.0429	−0.0429
0.5900	−0.2100	−0.2032	−0.2035	−0.2027	−0.2027	−0.0326	−0.0309	−0.0346	−0.0346

I-CJAYA-1, II-CJAYA-2, III-CJAYA-3, IV-CJAYA-4

Table 9
Comparison between various algorithms on the SDM.

Algorithms	I_{ph} (A)	I_{sd} (A)	R_{se} (Ω)	R_{sh} (Ω)	a	RMSE (E-04)
CJAYA-1	0.7605	3.28E−07	0.0363	56.8876	1.4828	9.8745
CJAYA-2	**0.7608**	**3.38E−07**	**0.0359**	**52.7279**	**1.4857**	**9.8602**
CJAYA-3	0.7607	3.16E−07	0.0364	52.8166	1.4791	9.8625
CJAYA-4	0.7607	3.16E−07	0.0364	52.8166	1.4791	9.8769
JAYA	0.7605	3.62E−07	0.0357	62.6139	1.4926	9.8955
RAO	0.7603	3.64E−07	0.0359	55.1406	1.4933	9.8971
TPSO	0.7607	3.45E−07	0.0362	52.4569	1.4799	9.9741
ITLO	0.7608	3.70E−07	0.0359	58.6288	1.4950	9.8874
BO-DE	0.7608	3.42E−07	0.0360	49.8552	1.4870	9.9926
IWO	0.7608	3.39E−07	0.0361	50.4789	1.4902	9.9472
GA	0.7602	4.84E−07	0.0348	82.7492	1.5230	13.956

multimodal functions, the CJAYA outperforms and indicate that in terms of exploration, the CJAYA have merit.

- The multimodal benchmark functions in the fixed-dimension are very demanding testbeds for metaheuristic algorithms. The fixed-dimension multimodal functions can thus simultaneously target both exploration and exploitation. Moreover, due to a large number of local optima, the local optima avoidance of an algorithm can be investigated. Pursuant to Table 2 and Fig. 6 (F17–F23), The CJAYA algorithm variants include the composite benchmark functions with very competitive outcomes. This shows that variants of CJAYA demonstrate a good balance between exploration and exploitation that results in the avoidance of high local optima. This superior capability is due to the self-adaptive weight formula.

The complexity of all algorithms is reported in Table 3. It can be realized from Table 3 that CJAYA-1 has the lowest CC and IWO has the highest CC. From Fig. 7, it is observed that the convergence speed of the CJAYA and its variants are superior to other competitive algorithms.

4.2. Results on solar photovoltaic parameter estimation problem

In this section, CJAYA's effectiveness is assessed on the identification of parameters for various PV models, such as SDM, DDM, and PV module. To that end, experimental V–I data from the cell/module is used as a benchmark. The data acquired for a commercial RTC France Si solar cell with a diameter of 57 mm at 1000 W/m^2 and 33 °C operating condition and the PV modules of STP6-120/36 (at 1000 W/m^2 and 55 °C) and STM6-40/36 (at 1000 W/m^2 and 51 °C) both consisting of 36 series-connected cells [10,11,42,44,76]. The experimental data/samples are collected from the open-source environment, and these samples are free from any hidden errors [77]. There are four test cases considered in this paper, and the same is presented in Table 4. To ensure a fair contrast, Table 5 indicates the upper and lower limits for each variable, which are the same as those used in the literature.

Comparisons are being made with various competitive algorithms to validate the performance of the suggested CJAYA algorithm and its variants. The algorithms considered for the performance comparison is listed in Table 6. In addition, each algorithm is run independently for 30 times to reduce statistical errors for each problem. For all the algorithms, the parameter configurations are based on the recommendations in the respective literature and presented in Table 5. Based on the trial runs,

Table 10
IAE of CJAYA and its variants on DDM.

V_{pv} (V)	I_{pv} (A)	Simulated value				I	II	III	IV
		I	II	III	IV				
		I_{pv} (A)	I_{pv} (A)	I_{pv} (A)	I_{pv} (A)	IAE_i	IAE_i	IAE_i	IAE_i
−0.2057	0.7640	0.7642	0.7638	0.7636	0.7638	0.0002	0.0002	0.0004	0.0002
−0.1291	0.7620	0.7628	0.7625	0.7622	0.7625	0.0008	0.0005	0.0002	0.0005
−0.0588	0.7605	0.7615	0.7612	0.7610	0.7612	0.0010	0.0007	0.0005	0.0007
0.0057	0.7605	0.7603	0.7601	0.7599	0.7601	0.0002	0.0004	0.0006	0.0004
0.0646	0.7600	0.7592	0.7591	0.7589	0.7591	0.0008	0.0009	0.0011	0.0009
0.1185	0.7590	0.7582	0.7581	0.7580	0.7581	0.0008	0.0009	0.0010	0.0009
0.1678	0.7570	0.7572	0.7572	0.7571	0.7572	0.0002	0.0002	0.0001	0.0002
0.2132	0.7570	0.7563	0.7563	0.7562	0.7563	0.0007	0.0007	0.0008	0.0007
0.2545	0.7555	0.7552	0.7552	0.7552	0.7553	0.0003	0.0003	0.0003	0.0002
0.2924	0.7540	0.7537	0.7538	0.7538	0.7539	0.0003	0.0002	0.0002	0.0001
0.3269	0.7505	0.7514	0.7515	0.7515	0.7516	0.0009	0.0010	0.0010	0.0011
0.3585	0.7465	0.7473	0.7474	0.7474	0.7475	0.0008	0.0009	0.0009	0.0010
0.3873	0.7385	0.7400	0.7401	0.7401	0.7401	0.0015	0.0016	0.0016	0.0016
0.4137	0.7280	0.7273	0.7274	0.7273	0.7273	0.0007	0.0006	0.0007	0.0007
0.4373	0.7065	0.7069	0.7070	0.7068	0.7068	0.0004	0.0005	0.0003	0.0003
0.4590	0.6755	0.6753	0.6755	0.6751	0.6751	0.0002	0.0000	0.0004	0.0004
0.4784	0.6320	0.6309	0.6314	0.6308	0.6307	0.0011	0.0006	0.0012	0.0013
0.4960	0.5730	0.5722	0.5729	0.5721	0.5720	0.0008	0.0001	0.0009	0.0010
0.5119	0.4990	0.4997	0.5005	0.4996	0.4995	0.0007	0.0015	0.0006	0.0005
0.5265	0.4130	0.4138	0.4147	0.4138	0.4136	0.0008	0.0017	0.0008	0.0006
0.5398	0.3165	0.3176	0.3186	0.3177	0.3174	0.0011	0.0021	0.0012	0.0009
0.5521	0.2120	0.2125	0.2137	0.2127	0.2124	0.0005	0.0017	0.0007	0.0004
0.5633	0.1035	0.1031	0.1044	0.1033	0.1030	0.0004	0.0009	0.0002	0.0005
0.5736	−0.0100	−0.0089	−0.0074	−0.0088	−0.0090	0.0011	0.0026	0.0012	0.0010
0.5833	−0.1230	−0.1241	−0.1224	−0.1242	−0.1242	0.0011	0.0006	0.0012	0.0012
0.5900	−0.2100	−0.2090	−0.2071	−0.2092	−0.2091	0.0010	0.0029	0.0008	0.0009

I-CJAYA-1, II-CJAYA-2, III-CJAYA-3, IV-CJAYA-4

Table 11
RE of CJAYA and its variants on DDM.

V_{pv} (V)	I_{pv} (A)	Simulated value				I	II	III	IV
		I	II	III	IV				
		I_{pv} (A)	I_{pv} (A)	I_{pv} (A)	I_{pv} (A)	RE_i	RE_i	RE_i	RE_i
−0.2057	0.7640	0.7608	0.7605	0.7607	0.7607	0.0003	0.0003	0.0006	0.0002
−0.1291	0.7620	0.7608	0.7605	0.7607	0.7607	0.0010	0.0006	0.0003	0.0006
−0.0588	0.7605	0.7608	0.7605	0.7607	0.7607	0.0013	0.0010	0.0007	0.0010
0.0057	0.7605	0.7608	0.7605	0.7607	0.7607	0.0003	0.0005	0.0007	0.0005
0.0646	0.7600	0.7608	0.7605	0.7607	0.7607	0.0011	0.0012	0.0014	0.0012
0.1185	0.7590	0.7608	0.7605	0.7607	0.7607	0.0011	0.0011	0.0013	0.0012
0.1678	0.7570	0.7608	0.7605	0.7607	0.7607	0.0003	0.0003	0.0001	0.0003
0.2132	0.7570	0.7606	0.7603	0.7605	0.7605	0.0010	0.0009	0.0010	0.0009
0.2545	0.7555	0.7604	0.7601	0.7603	0.7603	0.0004	0.0003	0.0004	0.0003
0.2924	0.7540	0.7596	0.7593	0.7595	0.7595	0.0003	0.0003	0.0003	0.0002
0.3269	0.7505	0.7580	0.7577	0.7579	0.7579	0.0012	0.0013	0.0013	0.0014
0.3585	0.7465	0.7545	0.7542	0.7545	0.7545	0.0011	0.0012	0.0012	0.0013
0.3873	0.7385	0.7477	0.7474	0.7477	0.7477	0.0021	0.0021	0.0022	0.0022
0.4137	0.7280	0.7354	0.7351	0.7355	0.7355	0.0009	0.0009	0.0009	0.0009
0.4373	0.7065	0.7152	0.7149	0.7154	0.7154	0.0005	0.0007	0.0004	0.0004
0.4590	0.6755	0.6836	0.6834	0.6839	0.6839	0.0004	0.0001	0.0006	0.0006
0.4784	0.6320	0.6392	0.6390	0.6396	0.6396	0.0017	0.0010	0.0020	0.0021
0.4960	0.5730	0.5803	0.5801	0.5808	0.5808	0.0014	0.0003	0.0016	0.0018
0.5119	0.4990	0.5074	0.5073	0.5080	0.5080	0.0014	0.0030	0.0013	0.0010
0.5265	0.4130	0.4211	0.4210	0.4218	0.4218	0.0019	0.0042	0.0020	0.0014
0.5398	0.3165	0.3245	0.3244	0.3252	0.3252	0.0034	0.0067	0.0038	0.0029
0.5521	0.2120	0.2191	0.2190	0.2197	0.2197	0.0022	0.0078	0.0031	0.0018
0.5633	0.1035	0.1094	0.1093	0.1100	0.1100	0.0042	0.0088	0.0024	0.0047
0.5736	−0.0100	−0.0028	−0.0030	−0.0023	−0.0023	−0.0962	−0.0974	−0.0945	−0.0952
0.5833	−0.1230	−0.1182	−0.1185	−0.1177	−0.1177	−0.0091	−0.0049	−0.0094	−0.0097
0.5900	−0.2100	−0.2032	−0.2035	−0.2027	−0.2027	−0.0049	−0.0139	−0.0039	−0.0043

I-CJAYA-1, II-CJAYA-2, III-CJAYA-3, IV-CJAYA-4

the minimum population size, N_p, is selected as 30 for both the conventional JAYA and the proposed CJAYA algorithms.

First, to show the accuracy of each algorithm, the assessments are made on the best solutions characterized by the RMSE. And then, to evaluate each algorithm's convergence rate and the robustness, the statistical results are examined.

4.3. Results on SDM of the PV cell (Test Case-I)

Fig. 8 shows the V–I characteristics and V–P characteristics of estimated SDM found by the proposed CJAYA and its variants; it is clear that the simulated value of the current by the CJAYA is highly in accordance with the experimental data over the whole

Table 12
Comparison between various algorithms on the DDM.

Algorithms	I_{ph} (A)	I_{sd1} (A)	R_{se} (Ω)	R_{sh} (Ω)	$\mathbf{a}_1$	I_{sd2} (A)	a_2	RMSE (E-04)
CJAYA-1	0.7607	2.01E−07	0.0368	57.4673	1.4414	9.99E−07	2.0000	10.5897
CJAYA-2	0.7609	3.52E−07	0.0364	53.8749	1.9900	2.79E−07	1.4692	9.8945
CJAYA-3	0.7605	3.10E−07	0.0360	58.3289	1.4800	1.58E−07	1.8259	10.1458
CJAYA-4	**0.7607**	**3.03E−07**	**0.0362**	**57.0983**	**1.4769**	**3.16E−07**	**1.9965**	**9.8269**
JAYA	0.7607	2.36E−07	0.0379	47.8077	1.9655	2.09E−07	1.4404	10.6145
RAO	0.7604	1.77E−07	0.0365	70.5817	1.4348	1.00E−06	1.9029	10.7899
TPSO	0.7602	3.82E−07	0.0361	64.0265	1.4889	3.23E−07	1.8887	10.7898
ITLO	0.7605	3.10E−07	0.0360	58.3289	1.4800	1.58E−07	1.8259	10.6981
BO-DE	0.7599	4.01E−07	0.0356	78.5755	1.5041	1.25E−07	1.9791	10.4815
IWO	0.7601	3.78E−07	0.0358	62.0458	1.4744	2.45E−07	1.9458	10.7845
GA	0.7598	3.87E−07	0.0356	69.1549	1.4998	2.50E−08	1.9730	12.2679

Table 13
IAE of CJAYA and its variants on SDM of the STP6-120/36 PV module.

V_{pv} (V)	I_{pv} (A)	Simulated value				I	II	III	IV
		I	II	III	IV				
		I_{pv} (A)	I_{pv} (A)	I_{pv} (A)	I_{pv} (A)	IAE_i	IAE_i	IAE_i	IAE_i
19.2100	0.0000	0.0004	−0.0081	−0.0028	0.0066	0.0004	0.0081	0.0028	0.0066
17.6500	3.8300	3.8175	3.8205	3.8193	3.8172	0.0125	0.0095	0.0107	0.0128
17.4100	4.2900	4.2603	4.2632	4.2619	4.2606	0.0297	0.0268	0.0281	0.0294
17.2500	4.5600	4.5334	4.5362	4.5348	4.5341	0.0266	0.0238	0.0252	0.0259
17.1000	4.7900	4.7737	4.7764	4.7749	4.7747	0.0163	0.0136	0.0151	0.0153
16.9000	5.0700	5.0707	5.0733	5.0717	5.0721	0.0007	0.0033	0.0017	0.0021
16.7600	5.2700	5.2632	5.2657	5.2640	5.2648	0.0068	0.0043	0.0060	0.0052
16.3400	5.7500	5.7681	5.7704	5.7684	5.7703	0.0181	0.0204	0.0184	0.0203
16.0800	6.0000	6.0299	6.0321	6.0298	6.0323	0.0299	0.0321	0.0298	0.0323
15.7100	6.3600	6.3425	6.3447	6.3420	6.3451	0.0175	0.0153	0.0180	0.0149
15.3900	6.5800	6.5629	6.5649	6.5620	6.5655	0.0171	0.0151	0.0180	0.0145
14.9300	6.8300	6.8111	6.8133	6.8099	6.8136	0.0189	0.0167	0.0201	0.0164
14.5800	6.9700	6.9556	6.9578	6.9542	6.9579	0.0144	0.0122	0.0158	0.0121
14.1700	7.1000	7.0861	7.0885	7.0846	7.0881	0.0139	0.0115	0.0154	0.0119
13.5900	7.2300	7.2165	7.2192	7.2151	7.2182	0.0135	0.0108	0.0149	0.0118
13.1600	7.2900	7.2832	7.2862	7.2819	7.2847	0.0068	0.0038	0.0081	0.0053
12.7400	7.3400	7.3308	7.3340	7.3297	7.3321	0.0092	0.0060	0.0103	0.0079
12.3600	7.3700	7.3627	7.3661	7.3619	7.3638	0.0073	0.0039	0.0081	0.0062
11.8100	7.3800	7.3954	7.3991	7.3949	7.3962	0.0154	0.0191	0.0149	0.0162
11.1700	7.4100	7.4198	7.4237	7.4198	7.4204	0.0098	0.0137	0.0098	0.0104
10.3200	7.4400	7.4384	7.4427	7.4391	7.4388	0.0016	0.0027	0.0009	0.0012
9.7400	7.4200	7.4458	7.4503	7.4470	7.4461	0.0258	0.0303	0.0270	0.0261
9.0600	7.4500	7.4514	7.4560	7.4532	7.4515	0.0014	0.0060	0.0032	0.0015
0.0000	7.4800	7.4654	7.4724	7.4757	7.4647	0.0146	0.0076	0.0043	0.0153

I-CJAYA-1, II-CJAYA-2, III-CJAYA-3, IV-CJAYA-4

Table 14
RE of CJAYA and its variants on SDM of the STP6-120/36 PV module.

V_{pv} (V)	I_{pv} (A)	Simulated value				I	II	III	IV
		I	II	III	IV				
		I_{pv} (A)	I_{pv} (A)	I_{pv} (A)	I_{pv} (A)	RE_i	RE_i	RE_i	RE_i
17.6500	3.8300	3.8175	3.8205	3.8193	3.8172	0.0033	0.0025	0.0028	0.0033
17.4100	4.2900	4.2603	4.2632	4.2619	4.2606	0.0069	0.0062	0.0066	0.0069
17.2500	4.5600	4.5334	4.5362	4.5348	4.5341	0.0058	0.0052	0.0055	0.0057
17.1000	4.7900	4.7737	4.7764	4.7749	4.7747	0.0034	0.0028	0.0031	0.0032
16.9000	5.0700	5.0707	5.0733	5.0717	5.0721	0.0001	0.0007	0.0003	0.0004
16.7600	5.2700	5.2632	5.2657	5.2640	5.2648	0.0013	0.0008	0.0011	0.0010
16.3400	5.7500	5.7681	5.7704	5.7684	5.7703	0.0031	0.0036	0.0032	0.0035
16.0800	6.0000	6.0299	6.0321	6.0298	6.0323	0.0050	0.0053	0.0050	0.0054
15.7100	6.3600	6.3425	6.3447	6.3420	6.3451	0.0027	0.0024	0.0028	0.0023
15.3900	6.5800	6.5629	6.5649	6.5620	6.5655	0.0026	0.0023	0.0027	0.0022
14.9300	6.8300	6.8111	6.8133	6.8099	6.8136	0.0028	0.0024	0.0029	0.0024
14.5800	6.9700	6.9556	6.9578	6.9542	6.9579	0.0021	0.0017	0.0023	0.0017
14.1700	7.1000	7.0861	7.0885	7.0846	7.0881	0.0020	0.0016	0.0022	0.0017
13.5900	7.2300	7.2165	7.2192	7.2151	7.2182	0.0019	0.0015	0.0021	0.0016
13.1600	7.2900	7.2832	7.2862	7.2819	7.2847	0.0009	0.0005	0.0011	0.0007
12.7400	7.3400	7.3308	7.3340	7.3297	7.3321	0.0012	0.0008	0.0014	0.0011
12.3600	7.3700	7.3627	7.3661	7.3619	7.3638	0.0010	0.0005	0.0011	0.0008
11.8100	7.3800	7.3954	7.3991	7.3949	7.3962	0.0021	0.0026	0.0020	0.0022
11.1700	7.4100	7.4198	7.4237	7.4198	7.4204	0.0013	0.0019	0.0013	0.0014
10.3200	7.4400	7.4384	7.4427	7.4391	7.4388	0.0002	0.0004	0.0001	0.0002
9.7400	7.4200	7.4458	7.4503	7.4470	7.4461	0.0035	0.0041	0.0036	0.0035
9.0600	7.4500	7.4514	7.4560	7.4532	7.4515	0.0002	0.0008	0.0004	0.0002
0.0000	7.4800	7.4654	7.4724	7.4757	7.4647	0.0020	0.0010	0.0006	0.0020

I-CJAYA-1, II-CJAYA-2, III-CJAYA-3, IV-CJAYA-4

Table 15
Comparison between various algorithms on the SDM of the STP6-120/36 module.

Algorithms	I_{ph} (A)	I_{sd} (A)	R_{se} (Ω)	R_{sh} (Ω)	a	RMSE (E-02)
CJAYA-1	7.4736	2.48E−06	0.1646	1003.7706	45.5443	1.6693
CJAYA-2	7.4663	2.40E−06	0.1653	1337.9380	45.4499	1.6674
CJAYA-3	**7.4778**	**2.39E−06**	**0.1650**	**591.3058**	**45.4331**	**1.6285**
CJAYA-4	7.4655	2.32E−06	0.1655	1500	45.3393	1.6292
JAYA	7.4804	2.50E−06	0.1662	1373.3634	45.5640	1.6874
RAO	7.4842	6.29E−06	0.1468	1500	48.5712	1.6921
TPSO	7.4802	5.78E−06	0.1599	1146.2560	46.1236	1.8874
ITLO	7.4769	2.66E−06	0.1645	1497.5652	45.7629	1.6741
BO-DE	7.4669	2.75E−06	0.1609	1159.1504	45.8604	1.6789
IWO	7.4798	3.47E−06	0.1602	1044.2568	46.4453	1.8784
GA	7.4865	4.20E−06	0.1548	736.6680	47.2030	1.9963

Table 16
IAE of CJAYA and its variants on SDM of the STM6-40/36 PV module.

V_{pv} (V)	I_{pv} (A)	Simulated value				I	II	III	IV
		I	II	III	IV				
		I_{pv} (A)	I_{pv} (A)	I_{pv} (A)	I_{pv} (A)	IAE_i	IAE_i	IAE_i	IAE_i
0.0000	1.6630	1.6634	1.6637	1.6634	1.6633	0.0004	0.0007	0.0004	0.0003
0.1180	1.6630	1.6632	1.6635	1.6632	1.6631	0.0002	0.0005	0.0002	0.0001
2.2370	1.6610	1.6595	1.6597	1.6596	1.6595	0.0015	0.0013	0.0014	0.0015
5.4340	1.6530	1.6540	1.6540	1.6541	1.6539	0.0010	0.0010	0.0011	0.0009
7.2600	1.6500	1.6507	1.6506	1.6508	1.6505	0.0007	0.0006	0.0008	0.0005
9.6800	1.6450	1.6456	1.6454	1.6458	1.6454	0.0006	0.0004	0.0008	0.0004
11.5900	1.6400	1.6394	1.6392	1.6396	1.6393	0.0006	0.0008	0.0004	0.0007
12.6000	1.6360	1.6338	1.6336	1.6341	1.6338	0.0022	0.0024	0.0019	0.0022
13.3700	1.6290	1.6274	1.6271	1.6276	1.6274	0.0016	0.0019	0.0014	0.0016
14.0900	1.6190	1.6183	1.6180	1.6186	1.6184	0.0007	0.0010	0.0004	0.0006
14.8800	1.5970	1.6030	1.6026	1.6032	1.6032	0.0060	0.0056	0.0062	0.0062
15.5900	1.5810	1.5814	1.5810	1.5816	1.5817	0.0004	0.0000	0.0006	0.0007
16.4000	1.5420	1.5419	1.5415	1.5420	1.5423	0.0001	0.0005	0.0000	0.0003
16.7100	1.5240	1.5207	1.5203	1.5208	1.5211	0.0033	0.0037	0.0032	0.0029
16.9800	1.5000	1.4986	1.4982	1.4986	1.4990	0.0014	0.0018	0.0014	0.0010
17.1300	1.4850	1.4846	1.4842	1.4846	1.4850	0.0004	0.0008	0.0004	0.0000
17.3200	1.4650	1.4648	1.4645	1.4649	1.4652	0.0002	0.0005	0.0001	0.0002
17.9100	1.3880	1.3865	1.3863	1.3864	1.3867	0.0015	0.0017	0.0016	0.0013
19.0800	1.1180	1.1162	1.1164	1.1161	1.1158	0.0018	0.0016	0.0019	0.0022

Table 17
RE of CJAYA and its variants on SDM of the STM6-40/36 PV module.

V_{pv} (V)	I_{pv} (A)	Simulated value				I	II	III	IV
		I	II	III	IV				
		I_{pv} (A)	I_{pv} (A)	I_{pv} (A)	I_{pv} (A)	RE_i	RE_i	RE_i	RE_i
0.0000	1.6630	1.6634	1.6637	1.6634	1.6633	0.0002	0.0004	0.0002	0.0002
0.1180	1.6630	1.6632	1.6635	1.6632	1.6631	0.0001	0.0003	0.0001	0.0001
2.2370	1.6610	1.6595	1.6597	1.6596	1.6595	0.0009	0.0008	0.0009	0.0009
5.4340	1.6530	1.6540	1.6540	1.6541	1.6539	0.0006	0.0006	0.0007	0.0005
7.2600	1.6500	1.6507	1.6506	1.6508	1.6505	0.0004	0.0004	0.0005	0.0003
9.6800	1.6450	1.6456	1.6454	1.6458	1.6454	0.0003	0.0003	0.0005	0.0003
11.5900	1.6400	1.6394	1.6392	1.6396	1.6393	0.0004	0.0005	0.0002	0.0004
12.6000	1.6360	1.6338	1.6336	1.6341	1.6338	0.0013	0.0015	0.0012	0.0013
13.3700	1.6290	1.6274	1.6271	1.6276	1.6274	0.0010	0.0012	0.0008	0.0010
14.0900	1.6190	1.6183	1.6180	1.6186	1.6184	0.0004	0.0006	0.0002	0.0003
14.8800	1.5970	1.6030	1.6026	1.6032	1.6032	0.0038	0.0035	0.0039	0.0039
15.5900	1.5810	1.5814	1.5810	1.5816	1.5817	0.0002	0.0000	0.0004	0.0004
16.4000	1.5420	1.5419	1.5415	1.5420	1.5423	0.0001	0.0003	0.0000	0.0002
16.7100	1.5240	1.5207	1.5203	1.5208	1.5211	0.0022	0.0024	0.0021	0.0019
16.9800	1.5000	1.4986	1.4982	1.4986	1.4990	0.0010	0.0012	0.0009	0.0007
17.1300	1.4850	1.4846	1.4842	1.4846	1.4850	0.0003	0.0005	0.0003	0.0000
17.3200	1.4650	1.4648	1.4645	1.4649	1.4652	0.0001	0.0003	0.0001	0.0002
17.9100	1.3880	1.3865	1.3863	1.3864	1.3867	0.0011	0.0013	0.0011	0.0009
19.0800	1.1180	1.1162	1.1164	1.1161	1.1158	0.0016	0.0014	0.0017	0.0020

range of measured voltage. In the meantime, Fig. 9 illustrates the relative error (RE) and absolute error (IAE) of the current between the experimental and simulated data at each point of the measured voltage. Low values of RE and IAE indicates the superiority of the respective algorithm. Tables 7 and 8 show further the current values obtained from the simulation, in addition to the appropriate RE and IAE, the definitions of which are presented in Eqs. (17)–(18). In addition, the IAE values on SDM are below 9.02E−03, and the RE is within the range of [-0.055, 3.125E−04], demonstrating that CJAYA simulated SDM can accurately define the real characteristics of the PV cells.

$$RE_i = \frac{I_{experiment} - I_{simulated}}{I_{experiment}} \tag{19}$$

$$IAE_i = \left| I_{experiment} - I_{simulated} \right| \tag{20}$$

Table 18
Comparison between various algorithms on the SDM of the STM6-40/36 module.

Algorithms	I_{ph} (A)	I_{sd} (A)	R_{se} (Ω)	R_{sh} (Ω)	a	RMSE (E-03)
CJAYA-1	1.6641	1.85E−06	0.1449	567.6801	54.9755	1.7298
CJAYA-2	1.6638	1.81E−06	0.1489	581.9964	54.8986	1.7290
CJAYA-3	**1.6638**	**1.83E−06**	**0.1501**	**590.2574**	**54.9330**	**1.7242**
CJAYA-4	1.6638	1.66E−06	0.1602	577.3071	54.5580	1.7285
JAYA	1.6636	1.95E−06	0.1361	582.8000	55.1875	1.7536
RAO	1.6640	1.93E−06	0.1400	583.4846	55.1411	1.7855
TPSO	1.6632	2.01E−06	0.1456	625.2365	55.2489	1.8878
ITLO	1.6649	1.26E−06	0.1867	515.1326	53.4862	1.7345
BO-DE	1.6633	2.19E−06	0.1245	620.5499	55.6669	1.7441
IWO	1.6629	1.97E−06	0.1347	614.7896	55.0014	1.8713
GA	1.6627	1.93E−06	0.1432	623.5991	55.1354	1.9862

Table 19
Statistical results of various algorithms for different test cases.

Test case	Algorithm	RMSE values				Run time (s)
		Best	Worst	Mean	STD	
I	CJAYA-1	9.8745E−04	9.8958E−04	9.9782E−04	2.6991E−06	16.58
	CJAYA-2	**9.8602E−04**	**9.8723E−04**	**9.8975E−04**	**2.1231E−08**	**15.69**
	CJAYA-3	9.8625E−04	9.8878E−04	9.8991E−04	4.5584E−08	16.22
	CJAYA-4	9.8769E−04	9.8983E−04	9.9904E−04	2.8211E−06	17.02
	JAYA	9.8955E−04	1.2569E−03	1.3152E−03	4.2253E−04	18.95
	RAO	9.8971E−04	1.3356E−03	1.4781E−03	1.2257E−04	19.95
	TPSO	9.9741E−04	2.4587E−03	2.2167E−03	4.5812E−04	21.15
	ITLO	9.8874E−04	9.8973E−04	9.9955E−04	2.9568E−06	17.45
	BO-DE	9.9926E−04	1.0256E−03	1.1015E−03	1.4855E−05	22.54
	IWO	9.9472E−04	2.0014E−03	2.1458E−03	4.4475E−04	20.12
	GA	13.956E−04	1.5582E−03	1.6857E−03	1.9894E−04	34.25
II	CJAYA-1	10.5897E−04	1.0611E−03	1.1569E−03	8.6472E−05	17.11
	CJAYA-2	9.8945E−04	9.9013E−04	9.9274E−04	1.5695E−07	**16.42**
	CJAYA-3	10.1458E−04	1.0145E−03	1.0365E−03	7.5514E−05	17.35
	CJAYA-4	**9.8269E-04**	**9.8358E−04**	**9.9204E−04**	**1.4471E−07**	16.85
	JAYA	10.6145E−04	1.1859E−03	1.2014E−03	2.5586E−04	19.35
	RAO	10.7899E−04	1.2532E−03	1.3358E−03	1.0257E−04	20.56
	TPSO	10.7898E−04	1.5112E−03	1.4471E−03	8.4693E−04	21.98
	ITLO	10.6981E−04	1.0685E−03	1.0748E−03	2.4416E−05	18.47
	BO-DE	10.4815E−04	1.1247E−03	1.1355E−03	7.2258E−04	23.54
	IWO	10.7845E−04	1.4879E−03	1.4190E−03	8.0014E−04	21.12
	GA	12.2679E−04	1.3893E−03	1.4251E−03	1.0014E−04	36.58
III	CJAYA-1	1.6693E−02	1.7855E−02	1.6987E−02	6.8991E−06	16.12
	CJAYA-2	1.6674E−02	1.6685E−02	1.6374E−02	5.5884E−06	15.95
	CJAYA-3	**1.6285E-02**	**1.6299E−02**	**1.6202E−02**	**3.2565E−07**	**14.58**
	CJAYA-4	1.6292E−02	1.6325E−02	1.6355E−02	4.1121E−07	14.93
	JAYA	1.6874E−02	1.6879E−01	1.6845E−02	1.6958E−04	17.85
	RAO	1.6921E−02	1.7045E−01	1.6987E−02	1.4458E−04	19.58
	TPSO	1.8874E−02	7.1145E−01	7.6936E−02	4.7741E−04	21.11
	ITLO	1.6741E−02	1.6744E−02	1.6665E−02	4.3257E−06	17.45
	BO-DE	1.6789E−02	1.7012E−01	1.6989E−02	2.4169E−05	22.69
	IWO	1.8784E−02	6.5878E−01	7.4866E−02	4.6932E−04	20.14
	GA	1.9963E−02	0.1414E−00	9.8788E−02	3.5844E−04	32.47
IV	CJAYA-1	1.7298 E-03	1.7359E−03	1.7989E−03	4.5123E−06	16.65
	CJAYA-2	1.7290 E-03	1.7322E−03	1.7869E−03	2.6987E−06	16.69
	CJAYA-3	**1.7242 E-03**	**1.7289E−03**	**1.6845E−03**	**1.4751E−07**	**15.25**
	CJAYA-4	1.7285 E-03	1.7322E−03	1.6987E−03	2.1589E−07	15.89
	JAYA	1.7536 E-03	1.7925E−02	1.8592E−03	8.4759E−05	17.25
	RAO	1.7855 E-03	1.8525E−02	1.9582E−03	9.9154E−05	19.12
	TPSO	1.8878E−03	7.6482E−02	1.9254E−03	2.7489E−04	20.77
	ITLO	1.7345 E-03	1.7456E−03	1.7569E−03	9.8745E−07	17.02
	BO-DE	1.7441 E-03	1.7854E−02	1.9635E−03	1.6955E−05	21.45
	IWO	1.8713E−03	7.5633E−02	1.9852E−03	2.6969E−04	20.33
	GA	1.9862 E-03	1.5911E−01	3.2567E−03	2.5698E−04	31.41

The bold letter indicates the best result

The findings of the comparison relating the RMSE value and the parameters estimated for the SDM are presented in Table 9. The complete RMSE values of first best and second-best amongst various other algorithms, which are considered for the comparison, are highlighted with bold letters. Table 9 shows that CJAYA-2 provides the least RMSE value, i.e., 9.8602E−04, compared to other algorithms considered, followed by CJAYA-3, CJAYA-1, CJAYA-4, ITLO, JAYA, RAO, IWO, BO-DE, TPSO, and GA, respectively. Since information is unavailable on the exact values of the parameters, the RMSE is used to define the accuracy. It is observed that the value of RMSE of all algorithms excluding TPSO is close to the proposed algorithm; a little decrease in fitness function is important because it leads to better information about the real parameter values.

Table 20
Wilcoxon signed-rank test results of all algorithms for four cases with 30 individual runs.

Test case	CJAYA vs	Test results			Win
		p-value	R^-	R^+	
I	JAYA	1.69e−06	0	463	+
	RAO	1.69e−06	0	463	+
	TPSO	4.58e−06	0	432	+
	ITLO	1.69e−06	0	463	+
	BO-DE	1.69e−06	0	463	+
	IWO	1.69e−06	0	463	+
	GA	1.69e−06	0	463	+
II	JAYA	1.98e−06	0	463	+
	RAO	2.09e−06	0	463	+
	TPSO	3.58e−06	22	447	+
	ITLO	2.02e−06	0	463	+
	BO-DE	1.98e−06	0	463	+
	IWO	1.98e−06	0	463	+
	GA	1.98e−06	0	463	+
III	JAYA	3.56e−04	47	425	+
	RAO	4.25e−04	47	425	+
	TPSO	9.87e−04	66	407	+
	ITLO	3.69e−04	45	425	+
	BO-DE	4.22e−04	45	425	+
	IWO	5.12e−04	52	425	+
	GA	5.12e−04	52	425	+
IV	JAYA	3.96e−04	52	402	+
	RAO	4.36e−04	52	402	+
	TPSO	1.22e−03	59	398	+
	ITLO	3.77e−04	51	402	+
	BO-DE	4.39e−04	51	403	+
	IWO	5.33e−04	52	402	+
	GA	5.33e−04	52	402	

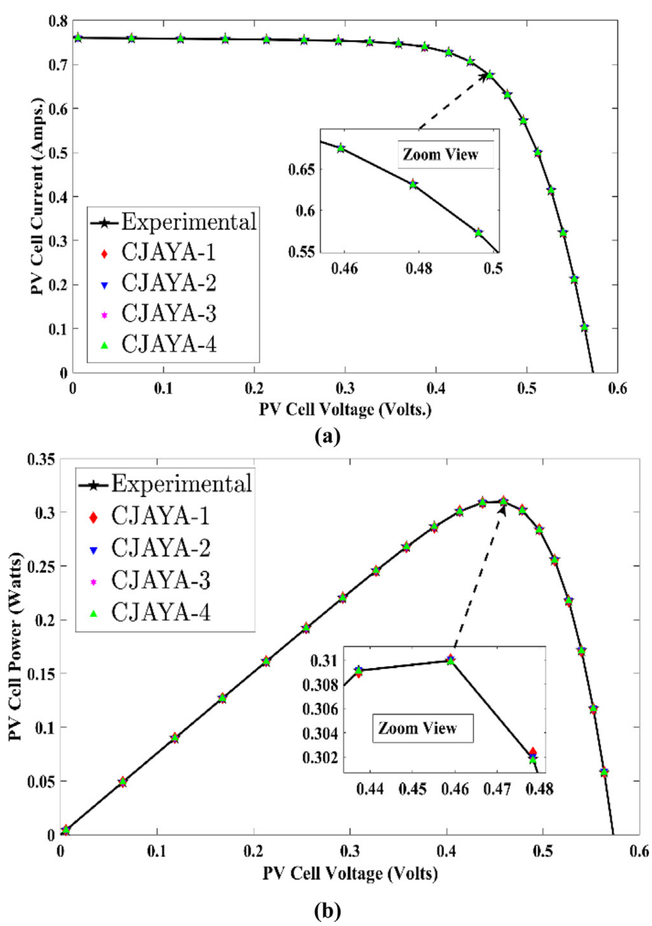

Fig. 10. Comparisons of simulated data with experimental data attained by CJAYA and its variants for the DDM; (a) V–I characteristics; (b) V–P characteristics.

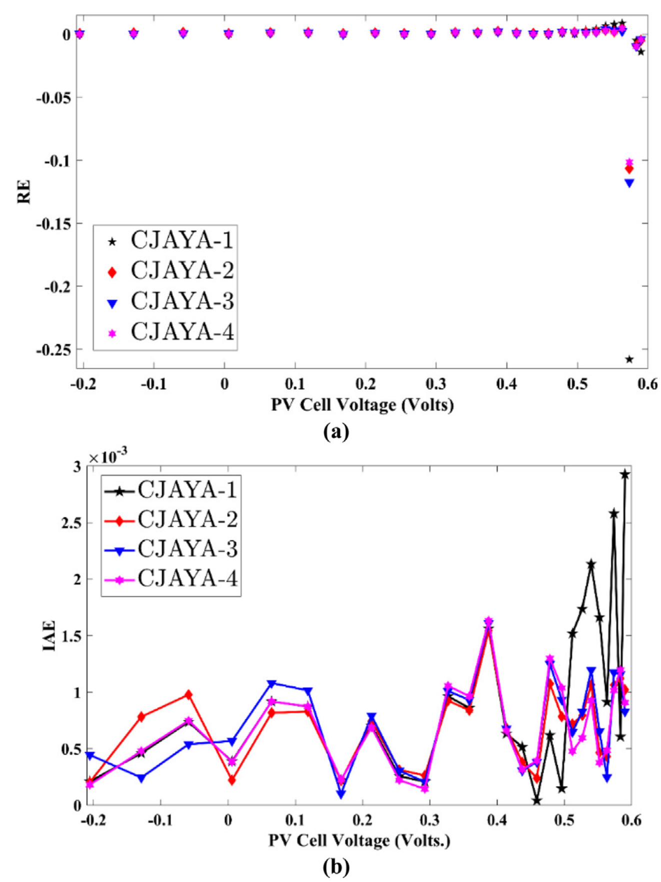

Fig. 11. Error-values of the simulated data and experimental data for the DDM; (a) RE values, (b) IAE values.

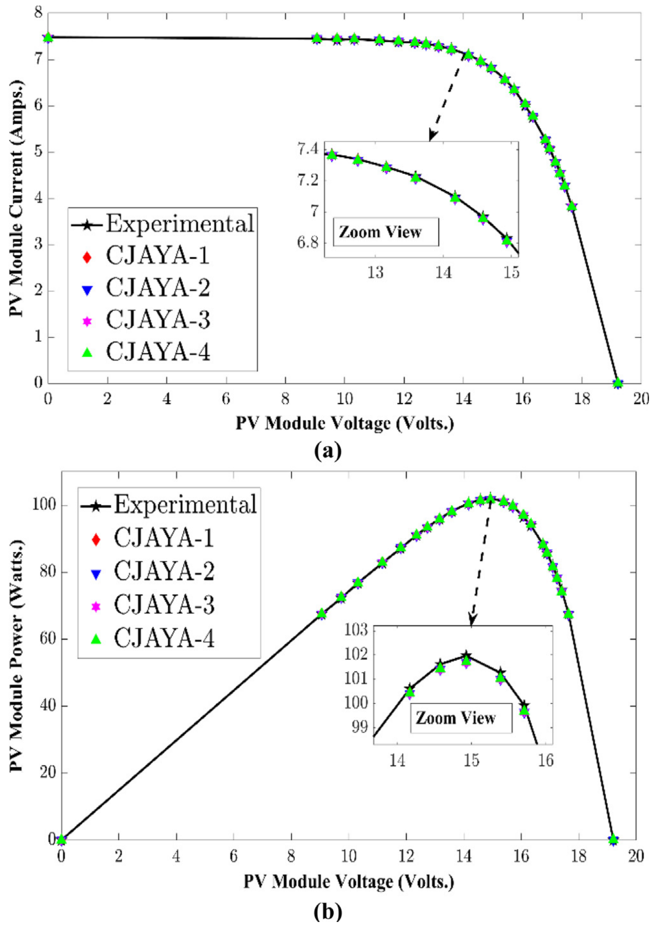

Fig. 12. Comparisons of simulated data with experimental data attained by CJAYA and its variants for the SDM of STP6-120/36; (a) V–I characteristics; (b) V–P characteristics.

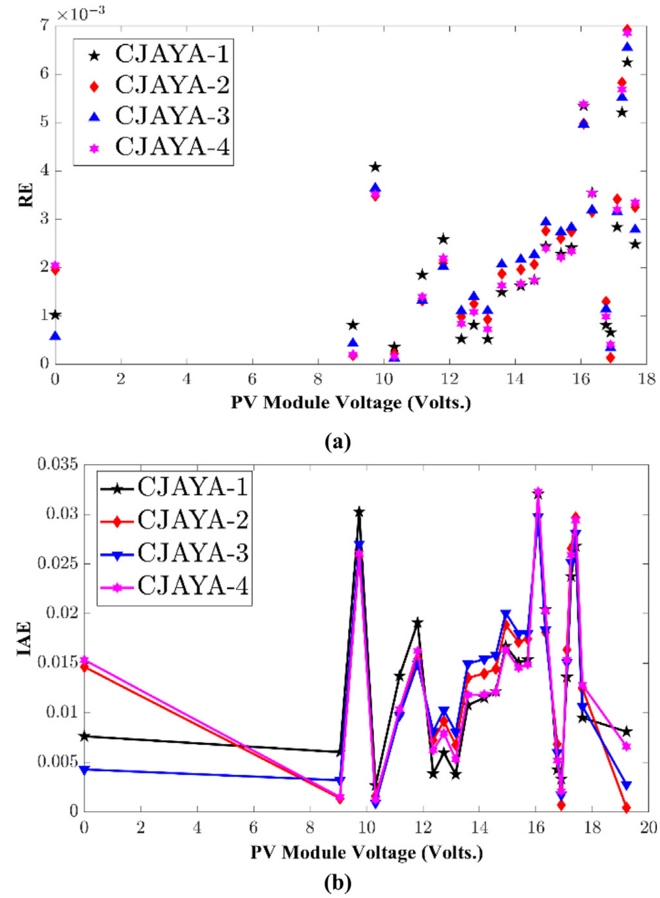

Fig. 13. Error-values of the simulated data and experimental data for the SDM of the STP6-120/36 PV module; (a) RE values, (b) IAE values.

4.4. Results on DDM of the PV cell (Test Case-II)

Fig. 10 shows the V–I characteristics and V–P characteristics of estimated DDM found by the proposed CJAYA and its variants; it is clear that the simulated value of the current by the CJAYA is highly in accordance with the experimental data over the whole range of measured voltage. In the meantime, Fig. 11 illustrates the relative error (RE) and absolute error (IAE) of the value. Tables 10 and 11 show further the current values obtained from the simulation, in addition to the appropriate RE and IAE. In addition, the IAE values on DDM are below 2.845E−03, and the RE is within the range of [-9.75E−2, 2.052E−04], demonstrating that CJAYA simulated DDM can accurately define the real characteristics of the PV cells.

The findings of the comparison relating RMSE and optimized parameters for the SDM are listed in Table 12. The overall RMSE values of first best and second-best amongst various other algorithms, which are considered for the comparison, are highlighted with bold letters. Table 12 shows that CJAYA-4 provides the least RMSE value, i.e., 9.8269E−04, compared to other algorithms considered, followed by CJAYA-2, CJAYA-3, BO-DE, CJAYA-1, JAYA, ITLO, RAO, IWO, TPSO, and GA, respectively. It is observed that the value of RMSE of all algorithms excluding TPSO is close to the proposed algorithm; a little decrease in fitness function is important because it leads to better information about the real parameter values.

4.5. Results on SDM of the PV module

4.5.1. STP6-120/36 PV module (Test Case-III)

Fig. 12 shows the V–I characteristics and V–P characteristics of estimated SDM of the STP6-120/36 PV module found by the proposed CJAYA and its variants; it is clear that the simulated value of the current by the CJAYA is highly in accordance with the experimental data over the whole range of measured voltage. In the meantime, Fig. 13 illustrates the relative error (RE) and absolute error (IAE) of the value. Tables 13 and 14 show further the current values obtained from the simulation, in addition to the appropriate RE and IAE. In addition, the IAE values on SDM of the module are below 3.192E−02, and the RE is within the range of [2.11E−4, 6.92E−03], demonstrating that CJAYA simulated SDM can accurately define the real characteristics of the PV module.

The findings of the comparison relating the estimated parameters and RMSE for the SDM of the STP6-120/36 PV module are presented in Table 15. The overall RMSE values of first best and second-best amongst various other algorithms, which are considered for the comparison, are highlighted with bold letters. Table 15 shows that CJAYA-3 provides the least RMSE value, i.e., 1.6285E−02, compared to other algorithms considered, followed by CJAYA-4, CJAYA-2, CJAYA-1, ITLO, BO-DE, JAYA, RAO, IWO, TPSO, and GA, respectively. It is observed that the value of RMSE of all algorithms is close to the proposed algorithm.

4.5.2. STM6-40/36 PV module (Test Case-IV)

Fig. 14 shows the V–I characteristics and V–P characteristics of estimated SDM of the STM6-40/36 PV module found by the

Table 21
The average ranks for all algorithms based on Friedman test.

Algorithm	Test results			
	Min rank	Mean rank	SD ank	Time rank
CJAYA-1	3.50	4.50	4.25	3.25
CJAYA-2	2.25	2.00	2.75	2.25
CJAYA-3	1.50	1.50	2.00	2.00
CJAYA-4	2.25	2.25	3.00	2.50
JAYA	6.25	6.00	8.00	6.00
RAO	7.00	7.00	7.00	7.00
TPSO	10.25	10.00	8.50	9.00
ITLO	6.00	5.25	4.50	5.00
BO-DE	6.25	5.75	5.75	10.00
IWO	9.00	9.00	8.00	8.00
GA	9.50	11.00	8.75	11.00

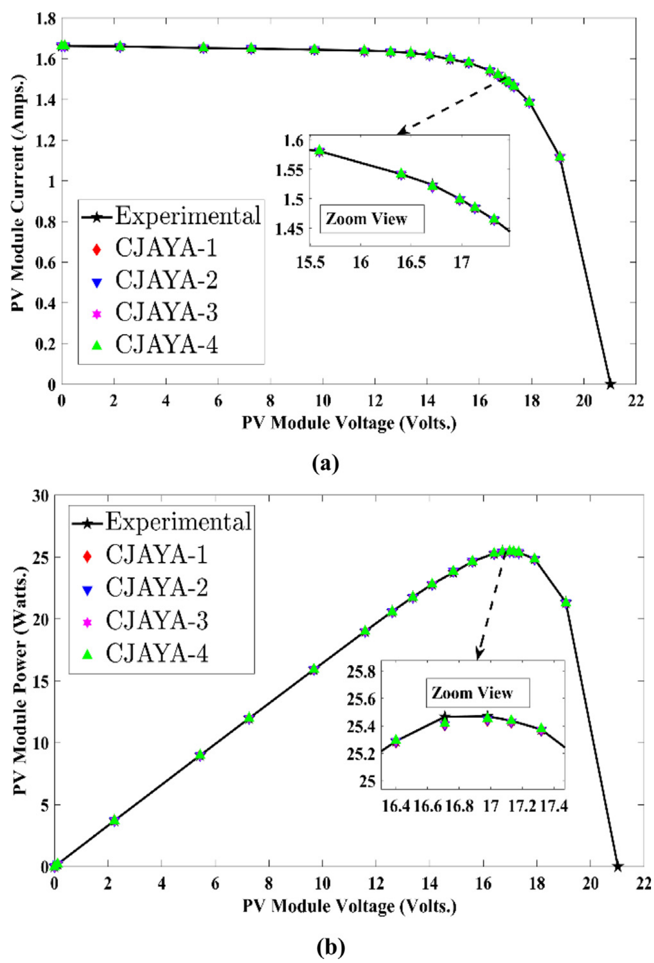

Fig. 14. Comparisons of simulated data with experimental data attained by CJAYA and its variants for the SDM of STM6-40/36; (a) V–I characteristics; (b) V–P characteristics.

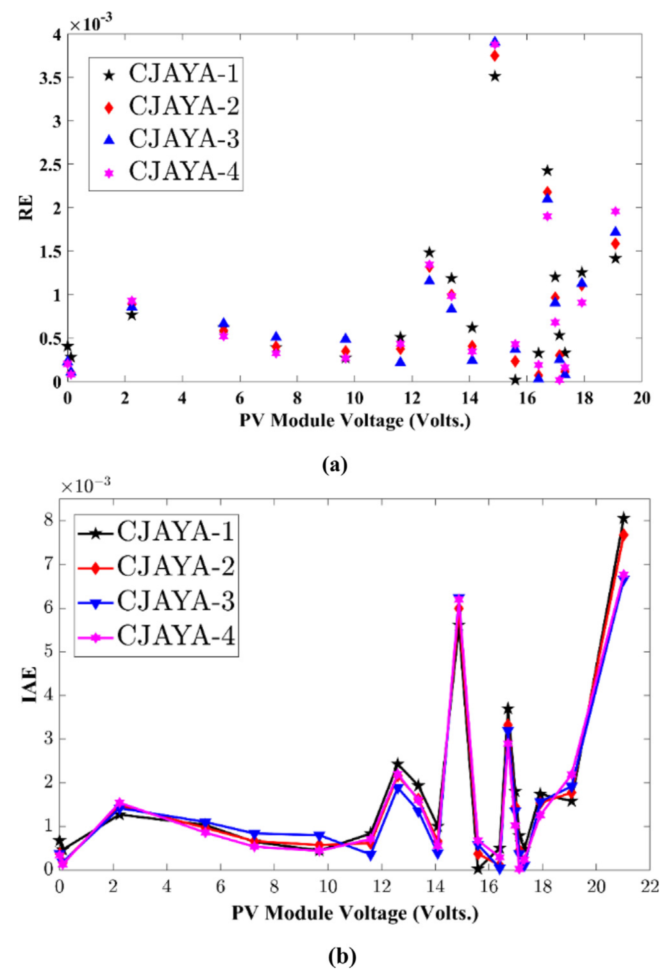

Fig. 15. Error-values of the simulated data and experimental data for the SDM of the STM6-40/36 PV module; (a) RE values, (b) IAE values.

proposed CJAYA and its variants; it is clear that the simulated value of the current by the CJAYA is highly in accordance with the experimental data over the whole range of measured voltage. In the meantime, Fig. 15 illustrates the relative error (RE) and absolute error (IAE) of the value. Tables 16 and 17 shows further the current values obtained from the simulation, in addition to the appropriate RE and IAE. In addition, the IAE values on SDM of the module are below 3.325E−02, and the RE is within the range of [1.22E−4, 3.858E−03], demonstrating that CJAYA simulated SDM can accurately define the real characteristics of the PV module.

The findings of the comparison relating the estimated parameters and RMSE for the SDM of the STM6-40/36 PV module are presented in Table 18. The overall RMSE values of first best and second-best amongst all techniques, which are considered for the comparison, are highlighted with bold letters. Table 18 shows that CJAYA-3 provides the least RMSE value, i.e., 1.7242E−03, compared to other algorithms considered, followed by CJAYA-4, CJAYA-2, CJAYA-1, ITLO, BO-DE, JAYA, RAO, IWO, TPSO, and GA, respectively. It is also observed that the RMSE of other techniques are close to the proposed algorithm.

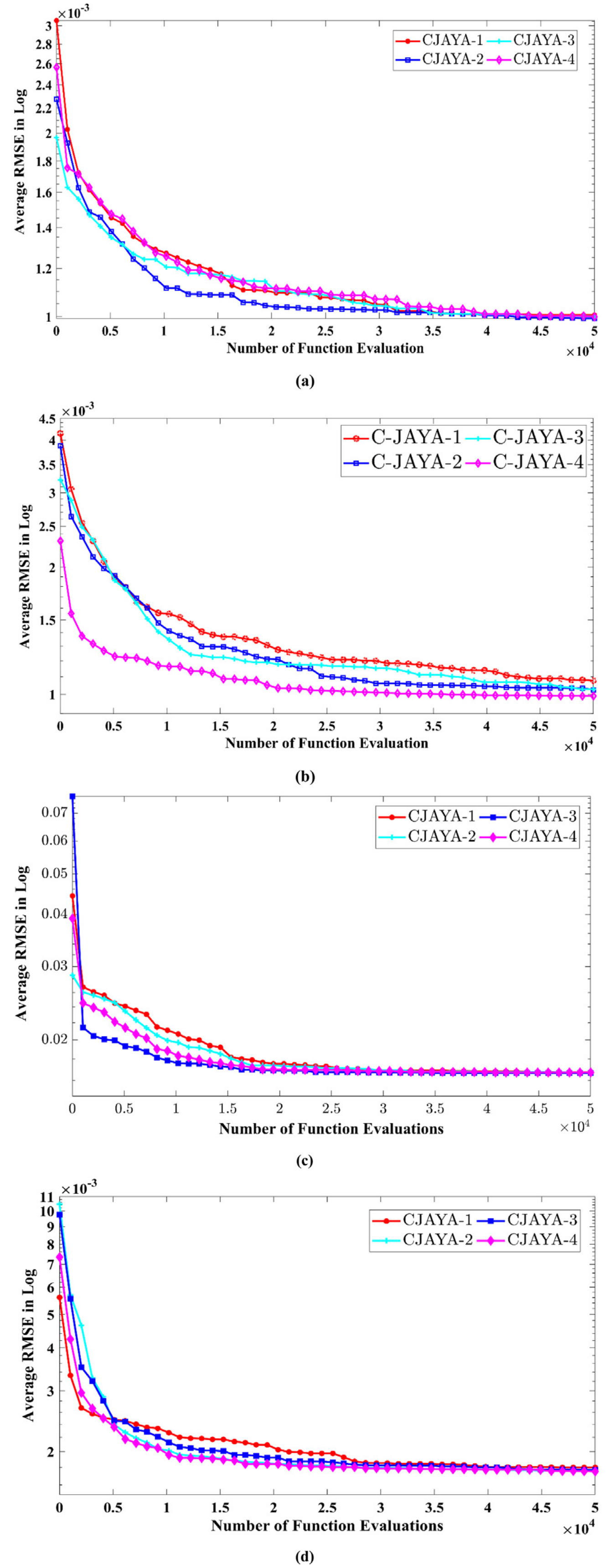

Fig. 16. Convergence curves of proposed algorithms; (a) SDM of the PV cell, (b) DDM of the PV cell, (c) SDM of the STP6-120/36 PV module, (c) SDM of the STM6-40/36 PV module.

4.6. Statistical data analysis of various algorithms

For the comparative analysis, JAYA, RAO, time-varying PSO (TPSO), improved Teaching–Learning optimization (ITLO), bio-geographic differential evolution (BO-DE), Intelligent water drop optimization (IWO), and GA are applied directly to minimize the value of RMSE for four different test cases. The control parameters of the various algorithm are listed in Table 3 after several trial runs of each algorithm. For the proposed algorithms, JAYA, RAO, and BO-DE, the number of function evaluations is selected as stopping criteria, and for algorithms, such as TPSO, ITLO, IWO [34], and GA [19], a number of iterations are kept as a stopping criterion. The best results for each algorithm are recorded in the above sub-sections over different runs. Because the 11 algorithms are stochastic approaches, the overall performance of these algorithms in terms of statistical results is necessary to be evaluated. Based on this analysis, Table 19 illustrates the best, worst, mean, standard deviation (STD), and the run time of the algorithms.

Table 19 shows that CJAYA performs better than other selected techniques in terms of average precision and reliability. Also, CJAYA and its variants get the best RMSE for all PV model types. Pertaining to the worst RMSE values, CJAYA and its variants attain the minimal worst values. With regard to the mean values of RMSE, it is clear that CJAYA and its variants perform best for all PV models. Considering the SD values, the ruggedness of the algorithms can be reflected. It is also observed that CJAYA and its variants have the smallest SD values for all models. The algorithms, such as CJAYA and its variants, ITLO, JAYA, RAO, take less computation time than the rest of the algorithms. The convergence curves between all variants for the four different test cases are shown in Fig. 16 to validate further and compare the convergence of all variants. Since the proposed CJAYA and its variants performing better than the other algorithms, the convergence curves of the four proposed algorithms only illustrated in Fig. 16. The curve indicates the average value of the RMSE of 30 runs. In addition, in Table 19, the run time of all algorithms for four test cases is presented. For all four test cases, the proposed CJAYA and its variants have less run time than the other compared algorithms, as shown in Table 19. Therefore, in terms of reliability and accuracy, CJAYA and its variants can achieve a superior result.

The Wilcoxon signed-rank test is deployed to illustrate the effectiveness of our proposed algorithm [78]. Table 20 describes the efficiency comparisons of all the algorithms. R^- and R^+ in Table 20 indicates the sum of ranks in which the proposed CJAYA performs worse and better than the other competitive algorithms. The last column indicates the superiority of the algorithms, and '+' indicates that CJAYA is superior to compared algorithms. From Table 20, it is observed that the proposed CJAYA algorithms obtain all '+'s. Therefore, it is concluded from the Wilcoxon signed-rank test that CJAYA and its variants perform better than the other algorithms with the level of significance, α is equal to 0.05.

The Friedman test is used further to examine the relationship between different algorithms [78]. Lower rank means a higher performance of the respective algorithm in the Friedman test. The average ratings measured by the Friedman test are shown in Table 21 for α is equal to 0.05. According to the FRRT analysis, the proposed CJAYA-3 whose scores are 1.5 (Min), 1.5 (Mean), 2 (SD) and 2 (Time) and stands in the top rank, followed by CJAYA-2, CJAYA-4, and CJAYA-1, respectively. All the variants of the proposed algorithms perform better than JAYA, RAO, TPSO, ITLO, BO-DE, IWO, and GA algorithms.

Table A.1
Unimodal benchmark functions.

Function	Dim	Limits	f_{min}
$f_1(x) = \sum_{i=1}^{n} x_i^2$	30	[−100, 100]	0
$f_2(x) = \sum_{i=1}^{n} \|x_i\| + \prod_{i=1}^{n} \|x_i\|$	30	[−10, 10]	0
$f_3(x) = \sum_{i=1}^{n} \left(\sum_{j-1}^{i} x_j\right)^2$	30	[−100, 100]	0
$f_4(x) = \max_i \{\|x_i\|, 1 \leqslant i \leqslant n\}$	30	[−100, 100]	0
$f_5(x) = \sum_{i=1}^{n-1} [100(x_{i+1} - x_i^2)^2 + (x_i - 1)^2]$	30	[−30, 30]	0
$f_6(x) = \sum_{i=1}^{n} ([x_i + 0.5])^2$	30	[−100, 100]	0
$f_7(x) = \sum_{i=1}^{n} ix_i^4 + random[0, 1)$	30	[−1.28, 1.28]	0

Table A.2
Multimodal benchmark functions.

Function	Dim	Limits	f_{min}
$F_8(x) = \sum_{i=1}^{n} -x_i \sin(\sqrt{\|x_i\|})$	30	[−500, 500]	−418.9829 × 5
$F_9(x) = \sum_{i=1}^{n} [x_i^2 - 10\cos(2\pi x_i) + 10]$	30	[−5.12, 5.12]	0
$F_{10}(x) = -20\exp\left(-0.2\sqrt{\frac{1}{n}\sum_{i=1}^{n} x_i^2}\right) - \exp\left(\frac{1}{n}\sum_{i=1}^{n}\cos(2\pi x_i)\right) + 20 + e$	30	[−32, 32]	0
$F_{11}(x) = \frac{1}{4000}\sum_{i=1}^{n} x_i^2 - \prod_{i=1}^{n}\cos\left(\frac{x_i}{\sqrt{i}}\right) + 1$	30	[−600, 600]	0
$F_{12}(x) = \frac{\pi}{n}\{10\sin(\pi y_1) + \sum_{i=1}^{n-1}(y_i - 1)^2[1 + 10\sin 2(\pi y_{i+1})] + (y_n - 1)^2\} + \sum_{i=1}^{n} u(x_i, 10, 100, 4)$ $y_i = 1 + \frac{x_i + 1}{4}, u(x_i, a, k, m) = \begin{cases} k(x_i - a)^m & x_i > a \\ 0 & -a < x_i < a \\ k(-x_i - a)^m & x_i < -a \end{cases}$	30	[−50, 50]	0
$F_{13}(x) = 0.1\{\sin_2(3\pi x_1) + \sum_{i=1}^{n}(x_i - 1)^2[1 + \sin_2(3\pi x_i + 1)] + (x_n - 1)^2[1 + \sin_2(2\pi x_n)]\} + \sum_{i=1}^{n} u(x_i, 5, 100, 4)$	30	[−50, 50]	0

Table A.3
Fixed-dimension multimodal benchmark functions.

Function	Dim	Limits	f_{min}
$F_{14}(x) = \left(\frac{1}{500} + \sum_{j=1}^{25}\frac{1}{j + \sum_{i=1}^{2}(x_i - a_{ij})^6}\right)^{-1}$	2	[−65, 65]	1
$F_{15}(x) = \sum_{i=1}^{11}\left[a_i - \frac{x_1(b_i^2 + b_i x_2)}{b_i^2 + b_i x_3 + x_4}\right]^2$	4	[−5, 5]	0.00030
$F_{16}(x) = 4x_1^2 - 2.1x_1^4 + \frac{1}{3}x_1^6 + x_1x_2 - 4x_2^2 + 4x_2^4$	2	[−5, 5]	−1.0316
$F_{17}(x) = \left(x_2 - \frac{5.1}{4\pi^2}x_1^2 + \frac{5}{\pi}x_1 - 6\right)^2 + 10\left(1 - \frac{1}{8\pi}\right)\cos x_1 + 10$	2	[−5, 5]	0.398
$F_{18}(x) = [1 + (x_1 + x_2 + 1)^2(19 - 14x_1 + 3x_1^2 - 14x_2 + 6x_1x_2 + 3x_2^2)] \times [30 + (2x_1 - 3x_2)^2 \times (18 - 32x_1 + 12x_1^2 + 48x_2 - 36x_1x_2 + 27x_2^2)]$	2	[−2, 2]	3
$F_{19}(x) = -\sum_{i=1}^{4} vc_i \exp(-\sum_{j=1}^{3} va_{ij}(x_j - p_{ij})^2)$	3	[1, 3]	−3.86
$F_{20}(x) = -\sum_{i=1}^{4} c_i \exp(-\sum_{j=1}^{6} a_{ij}(x_j - p_{ij})^2)$	6	[0, 1]	−3.32
$F_{21}(x) = -\sum_{i=1}^{5}[(X - a_i)(X - a_i)^T + c_i]^{-1}$	4	[0, 10]	−10.1532
$F_{22}(x) = -\sum_{i=1}^{7}[(X - a_i)(X - a_i)^T + c_i]^{-1}$	4	[0, 10]	−10.4028
$F_{23}(x) = -\sum_{i=1}^{10}[(X - a_i)(X - a_i)^T + c_i]^{-1}$	4	[0, 10]	−10.5363

5. Conclusions

This paper proposes an enhanced CJAYA algorithm to estimate the parameters of various PV models progressively and accurately. CJAYA introduces a self-adapting weight to adapt to the tendency to avoid the worst result and approach the best result over the search phases. This adaptive weight is intended to help the CJAYA to reach the promising search space early and carry out the local exploration later on. Furthermore, chaotic techniques are proposed, which increases the best solution quality for each generation. Since the proposed algorithm is not algorithm-specific, there is no parameter tuning required and, therefore, easy to implement in the proposed algorithm. The assessment of CJAYA is carried out by identifying the parameters for SDM, DDM, and PV modules. The results prove that CJAYA performs better than other selected algorithms in terms of reliability and accuracy. CJAYA can, therefore, be a promising algorithm to solve PV parameter estimation problems. The potential applications of the proposed CJAYA in future work to solve the optimal load flow, solar MPPT techniques, urban traffic-signal scheduling problem, economic dispatch problems, and other complex engineering problems. In order to expand the use of optimization algorithms for complex problems, there might be few more adjustments; however, more computational resources are needed in the enhanced versions. In addition, while solving complex engineering optimization problems with higher dimensions, the algorithm traps into local optima, and these limitations direct and motivates the researchers to improve the solution accuracy by proposing the enhanced version of the presented algorithm.

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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Appendix. Benchmark test functions

See Tables A.1–A.3.

References

[1] Premkumar M, Kumar C, Sowmya R. Mathematical modelling of solar photovoltaic cell/panel/array based on the physical parameters from the manufacturer's datasheet. Int J Renew Energy Dev 2020;9:7–22. http://dx.doi.org/10.14710/ijred.9.1.7-22.
[2] Premkumar M, Umashankar S, Sudhakar Babu T, Elavarasan RM, Mihet-Popa Lucian. Evaluation of Mathematical Model to Characterize the Performance of Conventional and Hybrid PV Array Topologies under Static and Dynamic Shading Patterns. Energies 2020;13(12):3216. http://dx.doi.org/10.3390/en13123216.
[3] Premkumar M, Sumithira TR. Design and implementation of new topology for solar PV based transformerless forward microinverter. J Electr Eng Technol 2019;14:1–11. http://dx.doi.org/10.1007/s42835-018-00036-2.
[4] Guo L, Meng Z, Sun Y, Wang L. Parameter identification and sensitivity analysis of solar cell models with cat swarm optimization algorithm. Energy Convers Manag 2016;108:520–8. http://dx.doi.org/10.1016/j.enconman.2015.11.041.
[5] Muhammad FF, Karim Sangawi AW, Hashim S, Ghoshal SK, Abdullah IK, Hameed SS. Simple and efficient estimation of photovoltaic cells and modules parameters using approximation and correction technique. PLoS One 2019;14:1–19. http://dx.doi.org/10.1371/journal.pone.0216201.
[6] Azizi K, Ghaffari A. Parameter estimation of photovoltaic panels and a model-based maximum power point tracking algorithm. J Renew Sustain Energy 2016;8:043504. http://dx.doi.org/10.1063/1.4959975.
[7] Xiao WB, Liu WQ, Wu HM, Zhang HM. Review of parameter extraction methods for single-diode model of solar cell. Wuli Xuebao/Acta Phys Sin 2018;67. http://dx.doi.org/10.7498/aps.67.20181024.
[8] Humada AM, Hojabri M, Mekhilef S, Hamada HM. Solar cell parameters extraction based on single and double-diode models: A review. Renew Sustain Energy Rev 2016;56:494–509. http://dx.doi.org/10.1016/j.rser.2015.11.051.
[9] Yeh WC, Lin P, Huang CL. Simplified swarm optimisation for the solar cell models parameter estimation problem. IET Renew Power Gener 2017;11:1166–73. http://dx.doi.org/10.1049/iet-rpg.2016.0473.
[10] Abbassi A, Abbassi R, Heidari AA, Oliva D, Chen H, Habib A, et al. Parameters identification of photovoltaic cell models using enhanced exploratory salp chains-based approach. Energy 2020;198:117333. http://dx.doi.org/10.1016/j.energy.2020.117333.
[11] Gnetchejo PJ, Ndjakomo Essiane S, Ele P, Wamkeue R, Mbadjoun Wapet D, Perabi Ngoffe S. Important notes on parameter estimation of solar photovoltaic cell. Energy Convers Manag 2019;197:111870. http://dx.doi.org/10.1016/j.enconman.2019.111870.
[12] Rashedi E, Nezamabadi-pour H, Saryazdi S. GSA: A gravitational search algorithm. Inf Sci (Ny) 2009;179:2232–48. http://dx.doi.org/10.1016/j.ins.2009.03.004.
[13] Mirjalili S, Mirjalili SM, Hatamlou A. Multi-verse optimizer: a nature-inspired algorithm for global optimization. Neural Comput Appl 2016;27:495–513. http://dx.doi.org/10.1007/s00521-015-1870-7.
[14] Mirjalili S. SCA: A Sine Cosine Algorithm for solving optimization problems. Knowl-Based Syst 2016;96:120–33. http://dx.doi.org/10.1016/j.knosys.2015.12.022.
[15] Liao Z, Chen Z, Li S. Parameters extraction of photovoltaic models using triple-phase teaching-learning-based optimization. IEEE Access 2020;8:69937–52. http://dx.doi.org/10.1109/ACCESS.2020.2984728.
[16] Venkata Rao R. Jaya: A simple and new optimization algorithm for solving constrained and unconstrained optimization problems. Int J Ind Eng Comput 2016;7:19–34. http://dx.doi.org/10.5267/j.ijiec.2015.8.004.
[17] Premkumar M, Sudhakar T, Umashankar S, Sowmya R. A new metaphor-less algorithms for the photovoltaic cell parameter estimation. Opt - Int J Light Electron Opt 2020;208:164559. http://dx.doi.org/10.1016/j.ijleo.2020.164559.
[18] Kumar S, Tejani GG, Pholdee N, Bureerat S. Multi-objective modified heat transfer search for truss optimization. Eng Comput 2020;1–16, doi:10.1007/s00366-020-01010-1 In press.
[19] Jervase JA, Bourdoucen H, Al-Lawati A. A solar cell parameter extraction using genetic algorithms. Meas Sci Technol 2001;12:1922–5. http://dx.doi.org/10.1088/0957-0233/12/11/322.
[20] Xiong G, Zhang J, Yuan X, Shi D, He Y, Yao G. Parameter extraction of solar photovoltaic models by means of a hybrid differential evolution with whale optimization algorithm. Sol Energy 2018;176:742–61. http://dx.doi.org/10.1016/j.solener.2018.10.050.
[21] Rong J, Wang B, Liu B, Zha X. Parameter optimization of PV based on hybrid genetic algorithm. IFAC-PapersOnLine 2015;48:568–72. http://dx.doi.org/10.1016/j.ifacol.2015.12.189.
[22] Dhiman G, Kaur A. STOA: A bio-inspired based optimization algorithm for industrial engineering problems. Eng Appl Artif Intell 2019;82:148–74. http://dx.doi.org/10.1016/j.engappai.2019.03.021.
[23] Mirjalili S, Mirjalili SM, Lewis A. Grey wolf optimizer. Adv Eng Softw 2014;69:46–61. http://dx.doi.org/10.1016/j.advengsoft.2013.12.007.
[24] Dhiman G, Kumar V. Spotted hyena optimizer: A novel bio-inspired based metaheuristic technique for engineering applications. Adv Eng Softw 2017;114:48–70. http://dx.doi.org/10.1016/j.advengsoft.2017.05.014.
[25] Oliva D, Abd El Aziz M, Ella Hassanien A. Parameter estimation of photovoltaic cells using an improved chaotic whale optimization algorithm. Appl Energy 2017;200:141–54. http://dx.doi.org/10.1016/j.apenergy.2017.05.029.
[26] Faramarzi A, Heidarinejad M, Stephens B, Mirjalili S. Equilibrium optimizer: A novel optimization algorithm. Knowl-Based Syst 2020;191. http://dx.doi.org/10.1016/j.knosys.2019.105190.
[27] Dhiman G, Kumar V. Emperor penguin optimizer: A bio-inspired algorithm for engineering problems. Knowl-Based Syst 2018;159:20–50. http://dx.doi.org/10.1016/j.knosys.2018.06.001.
[28] Faramarzi A, Heidarinejad M, Mirjalili S, Gandomi AH. Marine predators algorithm: A nature-inspired metaheuristic. Expert Syst Appl 2020;152:113377. http://dx.doi.org/10.1016/j.eswa.2020.113377.
[29] Kumar S, Tejani GG, Mirjalili S. Modified symbiotic organisms search for structural optimization. Eng Comput 2019;35:1269–96. http://dx.doi.org/10.1007/s00366-018-0662-y.
[30] Mirjalili S, Gandomi AH, Mirjalili SZ, Saremi S, Faris H, Mirjalili SM. Salp swarm algorithm: A bio-inspired optimizer for engineering design problems. Adv Eng Softw 2017;114:163–91. http://dx.doi.org/10.1016/j.advengsoft.2017.07.002.
[31] Dhiman G, Kumar V. Seagull optimization algorithm: Theory and its applications for large-scale industrial engineering problems. Knowl-Based Syst 2019;165:169–96. http://dx.doi.org/10.1016/j.knosys.2018.11.024.
[32] Tejani GG, Pholdee N, Bureerat S, Prayogo D. Multiobjective adaptive symbiotic organisms search for truss optimization problems. Knowl-Based Syst 2018;161:398–414. http://dx.doi.org/10.1016/j.knosys.2018.08.005.
[33] Yang X-S, Deb S. Cuckoo search via levy flights. In: World congr. nat. biol. inspired comput. Coimbatore, India: IEEE; 2010, p. 210–4.
[34] Shah-Hosseini H. Intelligent water drops algorithm: A new optimization method for solving the multiple knapsack problem. Int J Intell Comput Cybern 2008;1:193–212. http://dx.doi.org/10.1108/17563780810874717.
[35] Romero B, del Pozo G, Arredondo B. Exact analytical solution of a two diode circuit model for organic solar cells showing S-shape using Lambert W-functions. Sol Energy 2012;86:3026–9. http://dx.doi.org/10.1016/j.solener.2012.07.010.
[36] Kumar S, Singh A, Dhar A. Parameter extraction using global particle swarm optimization approach and the influence of polymer processing temperature on the solar cell parameters. AIP Adv 2017;7:085117. http://dx.doi.org/10.1063/1.4993999.
[37] Nodes A. Resilient multiscale coordination control against adversarial nodes. Energies 2018;11:1844. http://dx.doi.org/10.3390/en11071844.
[38] Abido MA, Khalid MS. Seven-parameter PV model estimation using differential evolution. Electr Eng 2018;100:971–81. http://dx.doi.org/10.1007/s00202-017-0542-2.
[39] Zhang Y, Lin P, Chen Z, Cheng S. A population classification evolution algorithm for the parameter extraction of solar cell models. Int J Photoenergy 2016;2016:2174573. http://dx.doi.org/10.1155/2016/2174573.
[40] Wang R, Zhan Y, Zhou H. Application of artificial bee colony in model parameter identification of solar cells. Energies 2015;8:7563–81. http://dx.doi.org/10.3390/en8087563.
[41] Rajasekar N, Krishna Kumar N, Venugopalan R. Bacterial foraging algorithm based solar PV parameter estimation. Sol Energy 2013;97:255–65. http://dx.doi.org/10.1016/j.solener.2013.08.019.
[42] Niu Q, Zhang L, Li K. A biogeography-based optimization algorithm with mutation strategies for model parameter estimation of solar and fuel cells. Energy Convers Manag 2014;86:1173–85. http://dx.doi.org/10.1016/j.enconman.2014.06.026.
[43] Patel SJ, Panchal AK, Kheraj V. Extraction of solar cell parameters from a single current–voltage characteristic using teaching learning based optimization algorithm. Appl Energy 2014;119:384–93. http://dx.doi.org/10.1016/j.apenergy.2014.01.027.

[44] Wu Z, Yu D, Kang X. Parameter identification of photovoltaic cell model based on improved ant lion optimizer. Energy Convers Manag 2017;151:107–15. http://dx.doi.org/10.1016/j.enconman.2017.08.088.
[45] Sheng H, Li C, Wang H, Yan Z, Xiong Y, Cao Z, et al. Parameters extraction of photovoltaic models using an improved moth-flame optimization. Energies 2019;12:3527. http://dx.doi.org/10.3390/en12183527.
[46] Ketkar M, M. Chopde A. Efficient parameter extraction of solar cell using modified ABC. Int J Comput Appl 2014;102:1–6. http://dx.doi.org/10.5120/17776-8535.
[47] Askarzadeh A, Rezazadeh A. Extraction of maximum power point in solar cells using bird mating optimizer-based parameters identification approach. Sol Energy 2013;90:123–33. http://dx.doi.org/10.1016/j.solener.2013.01.010.
[48] Biswas PP, Suganthan PN, Wu G, Amaratunga GAJ. Parameter estimation of solar cells using datasheet information with the application of an adaptive differential evolution algorithm. Renew Energy 2019;132:425–38. http://dx.doi.org/10.1016/j.renene.2018.07.152.
[49] Nunes HGG, Pombo JAN, Bento PMR, Mariano SJPS, Calado MRA. Collaborative swarm intelligence to estimate PV parameters. Energy Convers Manag 2019;185:866–90. http://dx.doi.org/10.1016/j.enconman.2019.02.003.
[50] Askarzadeh A, Rezazadeh A. Parameter identification for solar cell models using harmony search-based algorithms. Sol Energy 2012;86:3241–9. http://dx.doi.org/10.1016/j.solener.2012.08.018.
[51] Chen X, Yu K, Du W, Zhao W, Liu G. Parameters identification of solar cell models using generalized oppositional teaching learning based optimization. Energy 2016;99:170–80. http://dx.doi.org/10.1016/j.energy.2016.01.052.
[52] Krishnakumar N, Venugopalan R, Rajasekar N. Bacterial foraging algorithm based parameter estimation of solar PV model. In: 2013 annu. int. conf. emerg. res. areas, AICERA 2013 2013 int. conf. microelectron. commun. renew. energy, ICMiCR 2013 - Proc. 2013, p. 1–6. http://dx.doi.org/10.1109/AICERA-ICMiCR.2013.6575948.
[53] Awadallah MA. Variations of the bacterial foraging algorithm for the extraction of PV module parameters from nameplate data. Energy Convers Manag 2016;113:312–20. http://dx.doi.org/10.1016/j.enconman.2016.01.071.
[54] Rezaee Jordehi A. Enhanced leader particle swarm optimisation (ELPSO): An efficient algorithm for parameter estimation of photovoltaic (PV) cells and modules. Sol Energy 2018;159:78–87. http://dx.doi.org/10.1016/j.solener.2017.10.063.
[55] Iqbal D, Ahmad T, Pervez I, Malick IH, Sarwar A, Tariq M. Performance of PSO based variants in tracking optimal power in a solar PV based generation system under partial shading condition. Smart Sci 2020;8:1–13. http://dx.doi.org/10.1080/23080477.2019.1700067.
[56] Xiong G, Zhang J, Shi D, Zhu L, Yuan X, Yao G. Modified search strategies assisted crossover whale optimization algorithm with selection operator for parameter extraction of solar photovoltaic models. Remote Sens 2019;11:2795.
[57] Kang T, Yao J, Jin M, Yang S, Duong T. A novel improved cuckoo search algorithm for parameter estimation of photovoltaic (PV) models. Energies 2018;11:1060. http://dx.doi.org/10.3390/en11051060.
[58] Wang L, Huang C. A novel elite opposition-based jaya algorithm for parameter estimation of photovoltaic cell models. Optik (Stuttg) 2018;155:351–6. http://dx.doi.org/10.1016/j.ijleo.2017.10.081.
[59] Mishra S, Ray PK. Power quality improvement using photovoltaic fed DSTATCOM based on JAYA optimization. IEEE Trans Sustain Energy 2016;7:1672–80. http://dx.doi.org/10.1109/TSTE.2016.2570256.
[60] Rao RV, More KC. Design optimization and analysis of selected thermal devices using self-adaptive Jaya algorithm. Energy Convers Manag 2017;140:24–35. http://dx.doi.org/10.1016/j.enconman.2017.02.068.
[61] Rao RV, Waghmare GG. A new optimization algorithm for solving complex constrained design optimization problems. Eng Optim 2017;49:60–83. http://dx.doi.org/10.1080/0305215X.2016.1164855.
[62] Venkata Rao R, Saroj A. A self-adaptive multi-population based jaya algorithm for engineering optimization. Swarm Evol Comput 2017;37:1–26. http://dx.doi.org/10.1016/j.swevo.2017.04.008.
[63] Singh SP, Prakash T, Singh VP, Babu MG. Analytic hierarchy process based automatic generation control of multi-area interconnected power system using jaya algorithm. Eng Appl Artif Intell 2017;60:35–44. http://dx.doi.org/10.1016/j.engappai.2017.01.008.
[64] Elattar EE, ElSayed SK. Modified JAYA algorithm for optimal power flow incorporating renewable energy sources considering the cost, emission, power loss and voltage profile improvement. Energy 2019;178:598–609. http://dx.doi.org/10.1016/j.energy.2019.04.159.
[65] Ravipudi JL, Neebha M. Synthesis of linear antenna arrays using jaya, self-adaptive Jaya and chaotic Jaya algorithms. AEUE - Int J Electron Commun 2018;92:54–63. http://dx.doi.org/10.1016/j.aeue.2018.05.022.
[66] Farah A, Belazi A. A novel chaotic Jaya algorithm for unconstrained numerical optimization. Nonlinear Dyn 2018;93:1451–80. http://dx.doi.org/10.1007/s11071-018-4271-5.
[67] Kaveh A, Hosseini SM, Zaerreza A. Improved Shuffled Jaya algorithm for sizing optimization of skeletal structures with discrete variables. Structures 2021;29:107–28. http://dx.doi.org/10.1016/j.istruc.2020.11.008.
[68] Premkumar M, Sowmya R. An effective maximum power point tracker for partially shaded solar photovoltaic systems. Energy Rep 2019;5:1445–62. http://dx.doi.org/10.1016/j.egyr.2019.10.006.
[69] Kumar C, Dharma Raj T, Premkumar M, Dhanesh Raj T. A new stochastic slime mould optimization algorithm for the estimation of solar photovoltaic cell parameters. Opt - Int J Light Electron Opt 2020;223:165277. http://dx.doi.org/10.1016/j.ijleo.2020.165277.
[70] Ridha HM, Gomes C, Hizam H. Estimation of photovoltaic module model's parameters using an improved electromagnetic-like algorithm. Neural Comput Appl 2020. http://dx.doi.org/10.1007/s00521-020-04714-z.
[71] Yu K, Liang JJ, Qu BY, Chen X, Wang H. Parameters identification of photovoltaic models using an improved JAYA optimization algorithm. Energy Convers Manag 2017;150:742–53. http://dx.doi.org/10.1016/j.enconman.2017.08.063.
[72] Oliva D, Ewees AA, El Aziz MA, Hassanien AE, Cisneros MP. A chaotic improved artificial bee colony for parameter estimation of photovoltaic cells. Energies 2017;10:865. http://dx.doi.org/10.3390/en10070865.
[73] Rao RV, Keesari HS, Oclon P, Taler J. An adaptive multi-team perturbation-guiding jaya algorithm for optimization and its applications. Eng Comput 2020;36:391–419. http://dx.doi.org/10.1007/s00366-019-00706-3.
[74] Kumar A, Wu G, Ali MZ, Mallipeddi R, Suganthan PN, Das S. A test-suite of non-convex constrained optimization problems from the real-world and some baseline results. Swarm Evol Comput 2020;56. http://dx.doi.org/10.1016/j.swevo.2020.100693.
[75] Arumugam MS, Rao MVC. On the performance of the particle swarm optimization algorithm with various inertia weight variants for computing optimal control of a class of hybrid systems. Discret Dyn Nat Soc 2006;2006:1–17. http://dx.doi.org/10.1155/DDNS/2006/79295.
[76] Ridha HM, Heidari AA, Wang M, Chen H. Boosted mutation-based harris hawks optimizer for parameters identification of single-diode solar cell models. Energy Convers Manag 2020;209:112660. http://dx.doi.org/10.1016/j.enconman.2020.112660.
[77] Shang Y. Subgraph robustness of complex networks under attacks. IEEE Trans Syst Man Cybern Syst 2019;49:821–32.
[78] Derrac J, García S, Molina D, Herrera F. A practical tutorial on the use of nonparametric statistical tests as a methodology for comparing evolutionary and swarm intelligence algorithms. Swarm Evol Comput 2011;1:3–18. http://dx.doi.org/10.1016/j.swevo.2011.02.002.