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Parameters estimation of solar photovoltaic models via a self-adaptive ensemble-based differential evolution

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ABSTRACT

Photovoltaic (PV) system as a vital element in the utilize of solar energy, its optimization, control, and simulation are significant. The performance of the PV system is mainly influenced by its model parameters that are varying and unavailable, thus identifying these model parameters is always desired. However, accurate and robust parameters estimation of PV models brings great challenges to the existing methods, since the complicated characteristics when estimating the parameters. Hence, to efficiently provide accurate parameters for the PV model, this study develops a self-adaptive ensemble-based differential evolution algorithm. Three different mutation strategies with different properties are combined into two groups for updating each individual. Furthermore, in order to make the best of different mutation strategies, a self-adaptive scheme is suggested to equilibrate population diversity and convergence, by adjusting the proportion of the mutation strategies used in the population. To evaluate the performance of SEDE, it is used to obtain the parameters of three PV models and compared with other well-established algorithms. Systematic comparison results indicate that SEDE is capable of estimating the model parameters with higher efficiency.

1. Introduction

Electricity has entered millions of households and people's lives. In general, electricity is converted from coal, but with the burning of coal, a large number of greenhouse gases cause serious pollution to the environment (Chen et al., 2020; Pourmousa et al., 2019). In addition, coal is non-renewable and its conversion efficiency is not very high. Therefore, it is always necessary to find a clean, pollution-free, and efficient alternative energy source for generating electricity (Kannan and Vakeesan, 2016). To achieve this aim, numerous alternative energy sources have been found, such as wind, solar, water, and tidal energy (Long et al., 2020). Among them, wind, water, and tidal energy put strict requirements on the site, and the construction cost of hydropower plants and windmills is extremely high. On the contrary, solar energy exists everywhere. Through photovoltaic (PV) power generation systems, the electricity generated can be transmitted to millions of households (Chen et al., 2019; Zhang et al., 2020). In order to make the PV system have a higher conversion efficiency under various weather and temperature (Yang et al., 2019), performing simulation, optimization, and control on the corresponding PV model is vital and helpful.

For PV models, there exist several commonly used models, for example, the single diode (SD) and double diode (DD) models (Kler et al., 2019). It is expected to find the models' parameter values that approach the experimental data to maximize the performance of PV models under specific conditions. Accurate parameters are always desired for obtaining high performance of PV models. Hence, searching for parameters of the PV model can be regarded as an optimization problem solved by a powerful optimization method. Recently, as the population-based search engines, the heuristic method has made great achievements in extracting parameters of PV models. They are differential evolution (DE) (Li et al., 2019), artificial fish swarm algorithm (AFSA) (Han et al., 2014), JAYA algorithm (Yu et al., 2019), genetic algorithm (GA) (Zagrouba et al., 2010), imperialist competitive algorithm (ICA) (Fathy and Rezk, 2017), bacterial foraging algorithm (BFA) (Rajasekar et al., 2013), artificial immune system (AIS) (Jacob et al., 2015), cat swarm optimization (CSO) (Guo et al., 2016), particle swarm optimization (PSO) (Liang et al., 2020a), whale optimization algorithm (WOA) (Oliva et al., 2017), grasshopper optimization algorithm (GOA) (Elazab et al., 2020), cuckoo search algorithm (CSA) (Kang et al., 2018), grey wolf optimization (GWO) (Nayak et al., 2019), wind-driven optimization (WDO) (Mathew et al., 2018), backtracking search algorithm (BSA) (Yu et al., 2018), teaching–learning-based optimization (TLBO) (Yu et al., 2017a), and flower pollination algorithm (FPA) (Xu and Wang, 2017). The reasons why heuristic algorithms can be widely

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Nomenclature

CR	crossover rate
D	decision variable dimension
DD	double diode
F	scaling factor
FES	the current number of function evaluation
G	generation
IAE	individual absolute error
I_d,I_{d1},I_{d2}	diode currents (μA)
I_L	cell output current (A)
I_{ph}	photo-generated current (A)
I_{sd}	reverse saturation current of diode
I_{sd1}	diffusion current
I_{sd2}	saturation current
I_{sh}	shunt resistor current (A)
I-V	current–voltage
j_{rand}	a number generated randomly in the set {1, 2, …, *D*}
k	Boltzmann constant (J/K)
Max	maximum
MaxFES	maximal function evaluations
Mean	average
Min	minimum
n,n_1,n_2	diode ideality factors
N	the number of experimental data
NP	population size
N_p	the number of solar cells in parallel
N_S	the number of solar cells in series
p	population
PV	photovoltaic
P-V	power–voltage
q	electron charge (C)
r_1, r_2, r_3	mutually different integers randomly generated within [1, *NP*]
rand(0,1)	random numbers in the interval of (0, 1)
RMSE	root mean square error
R_S	series resistance (Ω)
R_{sh}	shunt resistance (Ω)
SD	sing diode
SEDE	self-adaptive ensemble-based differential evolution
Std	standard deviation
T	cell temperature (K)
TSTC	temperature level at standard testing conditions
u_i^G	the *i*th trial vector in *G*th generation
V_L	cell output voltage (V)
v_i^G	the *i*th mutation vector in *G*th generation
x_{best}^G	the best individual in *G*th generation
x_i^G	the *i*th individual in *G*th generation
α	temperature coefficient

employed in practical applications include: 1) they only need to define the parameter search range and an objective function of the problem and do not need to know the specific information of the problem (Liang et al., 2020b), thus they can be easily implemented; 2) they are not sensitive to the initial solution of the problem, which is their advantage over other mathematical methods (Jordehi, 2016); 3) they adopt a model in which multiple individuals evolve simultaneously in the search domain, in this case, the optimal solution is not easily fall into a local optimum. Meanwhile, this allows them to better deal with the problems with multimodal property and discrete search domain (Das et al., 2016).

Inspired by the observation that the abovementioned algorithms still cannot obtain very accurate parameter values within a limited computation burden, this paper develops a new self-adaptive ensemble-based differential evolution (SEDE) to acquire more accurate parameters. Specially, SEDE employs multiple mutation strategies to compensate for the limitations of a single strategy. Meanwhile, these strategies form two overlapping groups, the first group (***group***$_1$) is dedicated to making the population search more spaces to avoid losing excellent solutions while the second group (***group***$_2$) aims at making individuals conduct a local search for accelerating the convergence rate. Meanwhile, each strategy is matched with one parameter combination from the parameters pool to produce promising solutions. Moreover, considering that the requirements for the population diversity and convergence are different in different evolution stages, a reasonable strategy selection is established on the basis of the proposed self-adaptive scheme.

To sum up, the main contributions of this paper are:

- A new self-adaptive ensemble-based differential evolution (SEDE) is proposed to identify the accurate parameters of varied PV models. In SEDE, the ensemble of multiple different strategies and parameters is employed to compensate for the limitations of a single strategy and fixed-parameter settings in the basic DE.
- A self-adaptive scheme without increasing the computing complexity significantly is designed to meet the requirements of the population in different evolution stages by adjusting the relationship between diversity and convergence.
- The proposed SEDE is tested on different PV models, and experimental results show that SEDE has better or competitive performance in comparison with other fifteen state-of-the-art algorithms.

The remainder of this paper is arranged as follows. The PV models, as well as the problem formulation, are reviewed in Section 2. The basic DE algorithm is described in Section 3, which is followed by Section 4 to introduce the proposed algorithm SEDE. Section 5 presents the simulation results. Conclusion and future studies are given in Section 6.

2. Mathematical model and problem formulation

For the PV system, one accurate mathematical model is particularly important to describe its nonlinear characteristics. Generally, the widely used models include SD and DD, and their model descriptions are presented in this Section.

2.1. Single diode model

SD is a simple yet popular model, and its structure is given in Fig. 1. The current output I_L can be calculated by Eq. (1) (Abbassi et al., 2018):

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

where I_{ph} is the photo-generated current, I_{sd} represents reverse saturation current of diode, V_L is the value the output voltage, n is used to denote the diode ideality factor, $k = 1.3806503 \times 10^{-23}$ J/K indicates the Boltzmann constant, $q = 1.60217646 \times 10^{-19}$C shows the electron

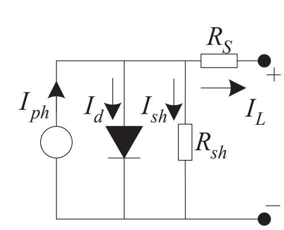

Fig. 1. The schematic diagram of the SD model.

charge, R_s is the value the series resistance, T is the cell temperature (°K), and R_{sh} is designed to represent the shunt resistance.

It can be seen that there are five unknown parameters (I_{ph}, I_{sd}, R_s, R_{sh}, n) need to be estimated in the SD model.

2.2. Double diode model

The DD model is also commonly used in practice and literature, and it has higher precision than the SD model. As presented in Fig. 2, its output current is computed based on Eq. (2) (Nunes et al., 2019):

$$\begin{aligned} I_L &= I_{ph} - I_{d1} - I_{d2} - I_{sh} \\ &= I_{ph} - I_{sd1}\cdot\left[\exp\left(\frac{q\cdot(V_L + R_S\cdot I_L)}{n_1\cdot k\cdot T}\right) - 1\right] - I_{sd2}\cdot\left[\exp\left(\frac{q\cdot(V_L + R_S\cdot I_L)}{n_2\cdot k\cdot T}\right) - 1\right] \\ &\quad - \frac{V_L + R_S\cdot I_L}{R_{sh}} \end{aligned} \tag{2}$$

where I_{sd1} and I_{sd2} are used to denote the diffusion and saturation currents, respectively. n_1 and n_2 are the ideal factors for the diffusion diode and the recombination diode, respectively.

Compared with the SD model, more parameters (I_{ph}, I_{sd1}, I_{sd2}, R_s, R_{sh}, n_1, n_2) should be identified accurately in the DD model.

2.3. Photovoltaic module model

Different from the above two models, the PV module typically includes several solar cells connected in parallel or in series. Based on the circuit presented in Fig. 3, the output current can be calculated by Eq. (3) (El-Naggar et al., 2012).

$$I_L/N_p = I_{ph} - I_{sd}\cdot\left[\exp\left(\frac{q\cdot(V_L/N_S + R_S\cdot I_L/N_p)}{n\cdot k\cdot T}\right) - 1\right] - \frac{V_L/N_S + R_S\cdot I_L/N_p}{R_{sh}} \tag{3}$$

where N_p and N_s indicate the size of solar cells used in parallel and series, respectively. It is clear that there exist five unknown parameters (I_{ph}, I_{sd}, R_s, R_{sh}, n) in the PV module.

2.4. Objective function

In the selection process of the heuristic algorithms, excellent individuals will be saved based on their values of objective function, thus designing an objective function is vital. For PV models parameter estimation, it is desired that the measured parameter values can approximate the experimental data as much as possible, that is, the error between them is as small as possible. Eqs. (4) and (5) (Gao et al., 2018) shows the calculation method on SD and DD models, respectively. Then, as shown in Eq. (6) (Muhsen et al., 2015), the overall error calculated by the root means square error (RMSE) (Muhsen et al., 2015) is regarded as the final objective.

$$\begin{cases} f_k(V_L, I_L, \mathbf{x}) = I_{ph} - I_{sd}\cdot\left[\exp\left(\frac{q\cdot(V_L + R_S\cdot I_L)}{n\cdot k\cdot T}\right) - 1\right] - \frac{V_L + R_S\cdot I_L}{R_{sh}} - I_L \\ \mathbf{x} = \{I_{ph}, I_{sd}, R_S, R_{Sh}, n\} \end{cases} \tag{4}$$

$$\begin{cases} f_k(V_L, I_L, \mathbf{x}) = I_{ph} - I_{sd1}\cdot\left[\exp\left(\frac{q\cdot(V_L + R_S\cdot I_L)}{n_1\cdot k\cdot T}\right) - 1\right] \\ \quad - I_{sd2}\cdot\left[\exp\left(\frac{q\cdot(V_L + R_S\cdot I_L)}{n_2\cdot k\cdot T}\right) - 1\right] - \frac{V_L + R_S\cdot I_L}{R_{sh}} - I_L \\ \mathbf{x} = \{I_{ph}, I_{sd1}, I_{sd2}, R_S, R_{Sh}, n_1, n_2\} \end{cases} \tag{5}$$

$$\mathrm{RMSE}(\mathbf{x}) = \sqrt{\frac{1}{N}\sum_{k=1}^{N} f_k(V_L, I_L, \mathbf{x})^2} \tag{6}$$

where N shows the number of experimental data.

3. Differential evolution

Duo to its easy operations and high efficacy, DE (Storn, 1996) has become a widely accepted optimizer. In DE, NP solutions of the Gth generation form a population p is represented by $(x_1^G, x_2^G, \cdots, x_{NP}^G)$, and each individual in the p is represented by $x_i^G = (x_{i,1}^G, x_{i,2}^G, \ldots, x_{i,D}^G)$, where D is the decision variable dimension. In the evolutionary process, each individual is updated through the following mutation, crossover, and selection operations.

3.1. Mutation

As the core element of DE, mutation operation is used to generate one mutation vector v_i^G for the individual x_i^G. Several commonly used mutation strategies are as follows (Wu et al., 2016):

$$\text{DE/best/1:}\quad v_i^G = x_{\text{best}}^G + F\cdot(x_{r1}^G - x_{r2}^G) \tag{7}$$

$$\text{DE/rand/1:}\ v_i^G = x_{r1}^G + F\cdot(x_{r2}^G - x_{r3}^G) \tag{8}$$

$$\text{DE/current} - \text{to} - \text{best/1:}\ v_i^G = x_i^G + F\cdot(x_{\text{best}}^G - x_i^G) + F\cdot(x_{r1}^G - x_{r2}^G) \tag{9}$$

$$\text{DE/current} - \text{to} - \text{rand/1:}\ u_i^G = x_i^G + F\cdot(x_{r1}^G - x_i^G) + F\cdot(x_{r2}^G - x_{r3}^G) \tag{10}$$

where r_1, r_2, r_3, and i are mutually different integers uniformly generated from the set {1, 2, …, NP}, F is the scaling factor, and x_{best}^G is the best individual at the Gth generation.

3.2. Crossover

The crossover is carried out between x_i^G and v_i^G to generate the trial vector u_i^G.

$$u_{i,j}^G = \begin{cases} v_{i,j}^G, & \text{if } rand(0,1) < CR \text{ or } j{=}j_{rand} \\ x_{i,j}^G, & \text{otherwise} \end{cases} \tag{11}$$

where $rand(0,1)$ returns a number between 0 and 1 randomly, CR is the crossover rate, and j_{rand} is a number generated randomly in the set {1, 2, …, D}, which ensures that u_i^G different form x_i^G.

3.3. Selection

After performing the mutation and crossover, each individual will obtain its trail vector. Only one between them can enter into the next generation through selection operation, as shown in Eq. (12):

$$x_i^{G+1} = \begin{cases} u_i^G, & \text{if } f(u_i^G) < f(x_i^G) \\ x_i^G, & \text{otherwise} \end{cases} \tag{12}$$

where $f(\mathbf{x})$ indicates the objective function value (fitness).

4. Self-adaptive ensemble-based differential evolution (SEDE)

4.1. Motivation

The parameter space of PV models has a large number of locally optimal solutions, which is a challenge for basic DE that has strong global exploration ability. In addition, in the different evolutionary

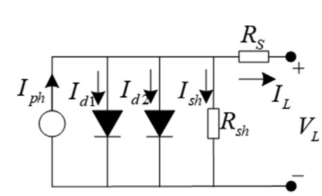

Fig. 2. The schematic diagram of the DD model.

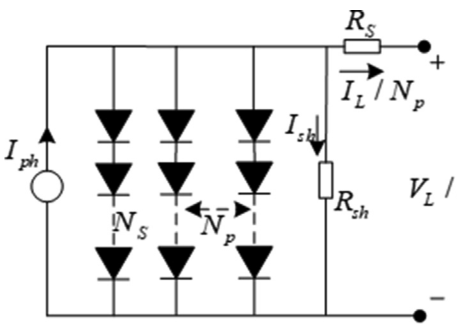

Fig. 3. The schematic diagram of the PV module model.

Table 1
Parameters ranges of different PV models.

Parameter	SD/ DD		PV module	
	Lower bound	Upper bound	Lower bound	Upper bound
$I_{ph}(A)$	0	1	0	2
I_{sd},I_{sd1},I_{sd2}(μA)	0	1	0	50
$R_S(\Omega)$	0	0.5	0	2
$R_{sh}(\Omega)$	0	100	0	2000
n,n_1,n_2	1	2	1	50

Table 2
The parameters of comparative algorithms.

Algorithm	Parameter
SEDE	$NP = 30$
SaDE	$NP = 50$
JADE	$NP = 100$, $p = 0.05$
CoDE	$NP = 30$
MLBSA	$NP = 50$
BLPSO	$NP = 40$, $w = 0.9 \sim 0.2$, $c = 1.496$, $I = E = 1$
IJAYA	$NP = 20$
CLPSO	$NP = 40$, $w = 0.9 \sim 0.2$, $c = 1.496$, $m = 5$
GWO	$NP = 30$, $a = 2 \sim 0$
PGJAYA	$NP = 20$
GOTLBO	$NP = 50$, Jr $= 0.3$
STLBO	$NP = 20$
WDO	$NP = 20$, $RT = 3$, $g = 0.2$, $\alpha = 0.4$, $c = 0.4$
SATLBO	$NP = 40$
MPEDE	$NP = 100$, $\lambda_1 = \lambda_2 = \lambda_3 = 0.2$, $\Delta = 20$
SGDE	$NP = 150$, $LP = 20$

stages, it requires the algorithm has different functions (Wu et al., 2019). For example, the exploration ability is needed to help the population to search for more spaces to prevent missing partial solutions. Meanwhile, the excellent exploitation ability is important to conduct the local search around the optimal solution for finding a more accurate solution. However, one kind of strategy of DE has only one capability, either the exploration or the exploitation, which results in that DE generally can only solve one specific problem. To solve this shortcoming, it is a promising approach that combines multiple strategies to make up for the limitations of a single strategy. This method can be called the ensemble method. Recently, many ensemble DE algorithms, such as self-adaptive DE (Qin et al., 2008), multi-role based DE (Gui et al., 2019), multi-population ensemble DE (Wu et al., 2016), and composite DE (Wang et al., 2011), have been used to exert the functions of multiple different mutation strategies for solving different types of problems. These algorithms address the problems that exist in the ensemble method, which is how to determine the strategies of the strategy pool and how to select the strategy from the strategy pool for different individuals or in the evolutionary stages. However, the design of the self-adaptive method in these ensemble DE algorithms increases the computation complexity. In addition, these algorithms are proposed to deal with complex high-dimension problems, and the parameters extracted by them are not quite accurate. To overcome these issues, a self-adaptive ensemble-based DE is proposed in this paper. Similar to above ensemble DE variants, multiple distinct strategies and parameter settings are used in SEDE. Differently, SEDE employs a simple self-adaptive scheme without increasing the computing complexity significantly to adjust the proportion of strategies used in the population rather than the method based on performance feedback.

4.2. The strategies group and parameters pool

In SEDE, three different strategies DE/rand/1, DE/current-to-rand/1, and DE/current-to-best/1 are employed. Among them, DE/rand/1 is helpful to increase the population diversity because each base vector in it is selected randomly; DE/current-to-rand/1 has a unique function in rotated problems (Wu et al., 2016); DE/current-to-best/1 can converge the population into the vicinity of the best individual for improving the accuracy of the solution. These three strategies have different characteristics, so the ensemble of them can solve complex optimization problems. In SEDE, these three strategies form two overlapping groups, that is, the exploration group (denoted as $\boldsymbol{group_1}$: DE/rand/1 and DE/current-to-rand/1) and the exploitation group (denoted as $\boldsymbol{group_2}$: DE/current-to-best/1 and DE/current-to-rand/1). It is clear that DE/current-to-rand/1 is employed in both two groups due to its unique effect on rotated problems. Moreover, based on the preference of each mutation strategy, $\boldsymbol{group_1}$ has good exploration ability while $\boldsymbol{group_2}$ features outstanding exploitation ability.

In addition, scaling factor F and crossover rate CR are also related to

Table 3
Comparison between SEDE and other algorithms regarding the optimal parameters on the SD model.

Algorithm	$I_{ph}(A)$	$I_{sd}(\mu A)$	$R_s(\Omega)$	$R_{sh}(\Omega)$	n	RMSE
SEDE	0.760776	0.323021	0.03637709	53.718524	1.4811836	**9.86021877891476E-04**
SaDE	0.76078	0.3230	0.036377	53.71852	1.481184	9.86021877891557E-04
JADE	0.76077553	0.3230	0.036377093	53.71852243	1.48118359	9.86021877891591E-04
CoDE	0.76077553	0.3230	0.036377092	53.71852508	1.4811836	9.86021877891547E-04
MLBSA	0.76077553	0.3230	0.036377093	53.71852455	1.48118359	9.86021877891623E-04
BLPSO	0.760805444	0.3484	0.03611479	53.41719109	1.48886167	1.03121787143969E-03
CLPSO	0.760698867	0.3173	0.036434309	54.04802381	1.47938431	9.92075087272021E-04
PGJAYA	0.76078	0.3230	0.036377	53.71850	1.481183	9.86021877893623E-04
GOTLBO	0.760817079	0.3228	0.036386639	53.2963674	1.48112404	9.86608457485554E-04
IJAYA	0.760775532	0.3230	0.036377097	53.7184795	1.48118347	9.86021877894489E-04
SATLBO	0.760776275	0.3233	0.036375251	53.7447871	1.48125974	9.86024899841195E-04
STLBO	0.760775532	0.3230	0.036377068	53.71861617	1.48118416	9.86021877957989E-04
GWO	0.760058925	0.3278	0.036776143	71.48825037	1.48240297	1.28030073330309E-03
WDO	0.760831099	0.4283	0.035070711	55.85740062	1.5102104	1.22100778490443E-03
MPEDE	0.76077553	3.23E-01	0.036377093	53.7185213	1.48118359	9.86021877891610E-04
SGDE	0.76078	0.32302	0.036377	53.71853	1.481184	9.86021877891530E-04

Table 4
IAE obtained by SEDE on the SD model.

Item	Measured data		Simulated current data		Simulated power data	
	V (V)	*I* (A)	*I*sim (A)	IAEI (A)	*P*sim (W)	IAEP(W)
1	−0.206	0.764	0.7641	0.0001	−0.1572	0.0000
2	−0.129	0.762	0.7627	0.0007	−0.0985	0.0001
3	−0.059	0.761	0.7614	0.0009	−0.0448	0.0001
4	0.006	0.761	0.7602	0.0003	0.0043	0.0000
5	0.065	0.760	0.7591	0.0009	0.0490	0.0001
6	0.119	0.759	0.7580	0.0010	0.0898	0.0001
7	0.168	0.757	0.7571	0.0001	0.1270	0.0000
8	0.213	0.757	0.7561	0.0009	0.1612	0.0002
9	0.255	0.756	0.7551	0.0004	0.1922	0.0001
10	0.292	0.754	0.7537	0.0003	0.2204	0.0001
11	0.327	0.751	0.7514	0.0009	0.2456	0.0003
12	0.359	0.747	0.7474	0.0009	0.2679	0.0003
13	0.387	0.739	0.7401	0.0016	0.2866	0.0006
14	0.414	0.728	0.7274	0.0006	0.3009	0.0003
15	0.437	0.707	0.7070	0.0005	0.3092	0.0002
16	0.459	0.676	0.6753	0.0002	0.3100	0.0001
17	0.478	0.632	0.6308	0.0012	0.3018	0.0006
18	0.496	0.573	0.5719	0.0011	0.2837	0.0005
19	0.512	0.499	0.4996	0.0006	0.2557	0.0003
20	0.527	0.413	0.4136	0.0006	0.2178	0.0003
21	0.540	0.317	0.3175	0.0010	0.1714	0.0005
22	0.552	0.212	0.2122	0.0002	0.1171	0.0001
23	0.563	0.104	0.1023	0.0012	0.0576	0.0007
24	0.574	0.010	−0.0087	0.0013	−0.0050	0.0007
25	0.583	0.123	−0.1255	**0.0025**	−0.0732	**0.0015**
26	0.590	0.210	−0.2085	0.0015	−0.1230	0.0009
Sum of IAE				0.0215		0.0087

Table 5
Comparison between SEDE and other algorithms regarding the optimal parameters on the DD model.

Algorithm	$I_{ph}(A)$	$I_{sd1}(\mu A)$	$R_s(\Omega)$	$R_{sh}(\Omega)$	n_1	$I_{sd2}(\mu A)$	n_2	RMSE
SEDE	0.7608	0.7493	0.0367	55.4854	2.0000	0.2260	1.4510	**9.824849E-04**
SaDE	0.7608	0.7391	0.0367	55.4882	2.0000	0.2273	1.4515	9.824871E-04
JADE	0.7606	0.2568	0.0365	55.2848	1.4635	0.2030	1.7873	9.94383E-04
CoDE	0.7608	0.7248	0.0367	55.4359	2.0000	0.2288	1.4521	9.824906E-04
MLBSA	0.7608	0.7427	0.0367	55.4394	2.0000	0.2266	1.4513	9.824860E-04
BLPSO	0.7602	0.1488	0.0360	63.4574	1.8067	0.3256	1.4852	1.082E-03
CLPSO	0.7607	0.4010	0.0364	55.0103	1.8763	0.2449	1.4594	9.94316E-04
PGJAYA	0.7608	0.2116	0.0368	55.7920	1.4455	0.8740	2.0000	9.82605E-04
GOTLBO	0.7608	0.2416	0.0366	55.6964	1.4580	0.4059	1.8796	9.851E-04
IJAYA	0.7608	0.2300	0.0367	55.4047	1.4525	0.7152	2.0000	9.824935E-04
SATLBO	0.7608	0.6952	0.0367	55.5707	1.9741	0.2238	1.4504	9.82824E-04
STLBO	0.7608	0.2381	0.0367	55.2369	1.4554	0.6473	2.0000	9.825605E-04
GWO	0.7609	0.5099	0.0370	56.8758	1.9140	0.2161	1.4472	1.027E-03
WDO	0.7608	0.2990	0.0354	44.6653	1.5443	0.1208	1.4551	1.681176E-03
MPEDE	0.760781355	0.753097242	0.036743204	55.47951222	1.9999954	0.225464756	1.450824442	9.82485E-04
SGDE	0.76079	0.2807	0.03648	54.3667	1.469655	0.24996	1.93228	9.84413E-04

the performance of DE (Yu et al., 2014). In the ensemble circumstances, it is difficult to design unified parameters suitable for three mutation strategies. Simplicity, three different combinations of F and CR values, i.e., [F = 1.0, CR = 0.1], [F = 1.0, CR = 0.9], and [F = 0.8, CR = 0.2], are used in SEDE (Gui et al., 2019). These combinations also have different properties. [F = 1.0, CR = 0.1] can be applied to solve separable problems, [F = 1.0, CR = 0.9] can lead the population to global exploration, and [F = 0.8, CR = 0.2] is believed to be able to enhance convergence rate. Note that, for simplicity, each individual randomly selects one parameter combination from the parameter pool and a strategy based on the self-adaptive scheme to generate a mutation vector.

4.3. The self-adaptive scheme

In the different stages, the population should focus on different tasks. A better exploration ability is desired in the early stage because any promising solution does not want to be ignored. As the population evolves, the exploitation ability should be strengthened for improving the quality of the best solution quickly. Keeping this in mind, we propose a self-adaptive scheme to meet the requirements of the population in different stages by adjusting the proportion of two strategy groups used in the population. To be specific, the strategy used by each individual is determined by Eq. (13).

$$\begin{cases} \text{Randomly select one strategy from } group_1, & \text{if } \operatorname{rand}(0,1) > \frac{FES}{MaxFES} \\ \text{Randomly select one strategy from } group_2, & \text{otherwise} \end{cases} \tag{13}$$

where FES indicates the number of function evaluations that have been consumed by population and $MaxFES$ is the biggest number of function evaluations when the evolution is terminated.

Table 6
IAE obtained by SEDE on the DD model.

Item	Measured data		Simulated current data		Simulated power data	
	V (V)	*I* (A)	*Isim* (A)	IAEI (A)	*Psim* (W)	IAEP(W)
1	−0.206	0.764	0.763999	0.000001	−0.157155	0.000000
2	−0.129	0.762	0.762614	0.000614	−0.098453	0.000079
3	−0.059	0.761	0.761342	0.000842	−0.044767	0.000049
4	0.006	0.761	0.760173	0.000327	0.004333	0.000002
5	0.065	0.760	0.759103	0.000897	0.049038	0.000058
6	0.119	0.759	0.758113	0.000887	0.089836	0.000105
7	0.168	0.757	0.757177	0.000177	0.127054	0.000030
8	0.213	0.757	0.756231	0.000769	0.161229	0.000164
9	0.255	0.756	0.755166	0.000334	0.192190	0.000085
10	0.292	0.754	0.753714	0.000286	0.220386	0.000084
11	0.327	0.751	0.751397	0.000897	0.245632	0.000293
12	0.359	0.747	0.747305	0.000805	0.267909	0.000289
13	0.387	0.739	0.740020	0.001520	0.286610	0.000589
14	0.414	0.728	0.727259	0.000741	0.300867	0.000306
15	0.437	0.707	0.706861	0.000361	0.309110	0.000158
16	0.459	0.676	0.675215	0.000285	0.309924	0.000131
17	0.478	0.632	0.630757	0.001243	0.301754	0.000594
18	0.496	0.573	0.571986	0.001014	0.283705	0.000503
19	0.512	0.499	0.499696	0.000696	0.255794	0.000356
20	0.527	0.413	0.413728	0.000728	0.217828	0.000383
21	0.540	0.317	0.317548	0.001048	0.171412	0.000566
22	0.552	0.212	0.212133	0.000133	0.117119	0.000074
23	0.563	0.104	0.102179	0.001321	0.057557	0.000744
24	0.574	−0.010	−0.008783	0.001217	−0.005038	0.000698
25	0.583	−0.123	−0.125548	**0.002548**	−0.073232	**0.001486**
26	0.590	−0.210	−0.208401	0.001599	−0.122956	0.000944
Sum of IAE				0.021289579		0.008769912

Table 7
Comparison between SEDE and other algorithms regarding the optimal parameters on the PV module.

Algorithm	$I_{ph}(A)$	$I_{sd}(\mu A)$	$R_s(\Omega)$	$R_{sh}(\Omega)$	n	RMSE
SEDE	1.03051	3.48226	1.201271	981.98223	48.642835	**2.42507486809495E-03**
SaDE	1.03051	3.48226	1.201271	981.98222	48.642835	2.42507486809502E-03
JADE	1.0305143	3.4823	1.201270999	981.982194	48.6428351	2.42507486809504E-03
CoDE	1.0305143	3.4823	1.201271014	981.9822058	48.6428347	2.42507486809500E-03
MLBSA	1.030514299	3.4823	1.201271006	981.9822353	48.642835	2.42507486809509E-03
BLPSO	1.03048375	3.4854	1.201341778	986.6686444	48.6460261	2.42512012617770E-03
CLPSO	1.030639556	3.4856	1.200637398	975.6466349	48.6470897	2.42784458407373E-03
PGJAYA	1.03051	3.4823	1.201270	981.98890	48.642855	2.42507486814234E-03
GOTLBO	1.030439441	3.4573	1.201258232	982.1210971	48.6153767	2.42712964990705E-03
IJAYA	1.030514331	3.4822	1.201271619	981.9763477	48.6428136	2.42507486814672E-03
SATLBO	1.030508371	3.4838	1.201230359	982.7888989	48.6445037	2.42507543392315E-03
STLBO	1.030514472	3.4822	1.201273957	981.9501081	48.6427256	2.42507486938538E-03
GWO	1.029825039	4.3863	1.175731013	1186.592624	49.5468686	2.52608800172134E-03
WDO	1.029485112	4.0585	1.173311293	973.1519899	49.2486966	2.79601941233004E-03
MPEDE	1.030514299	3.48226305	1.201271007	981.9823097	48.642835	2.42507486809505E-03
SGDE	1.0305	3.4823	1.20127	981.9822	48.6428	2.42507486809514E-03

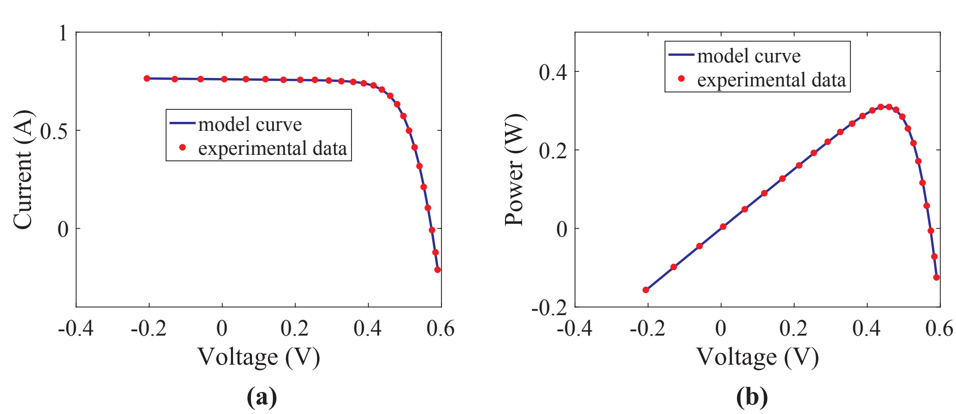

Fig. 4. The curves of (a) *I-V* characteristic, (b) *P-V* characteristic based on the parameters identified by SEDE on the SD model.

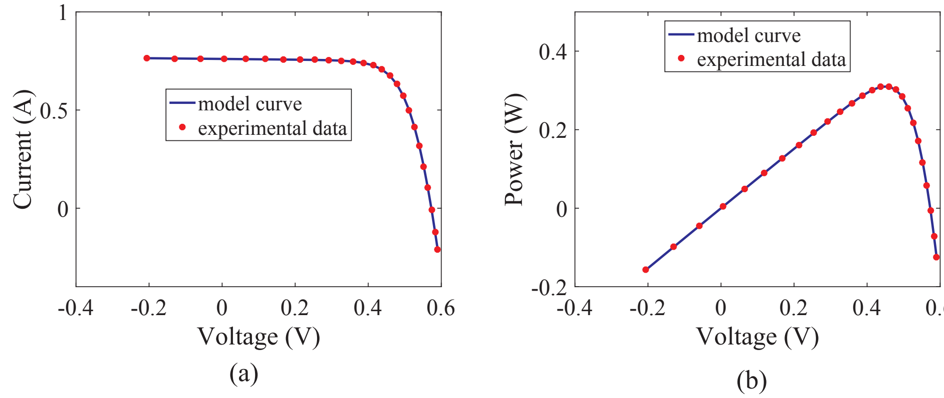

Fig. 5. The curves of (a) *I-V* characteristic, (b) *P-V* characteristic based on the parameters identified by SEDE on the DD model.

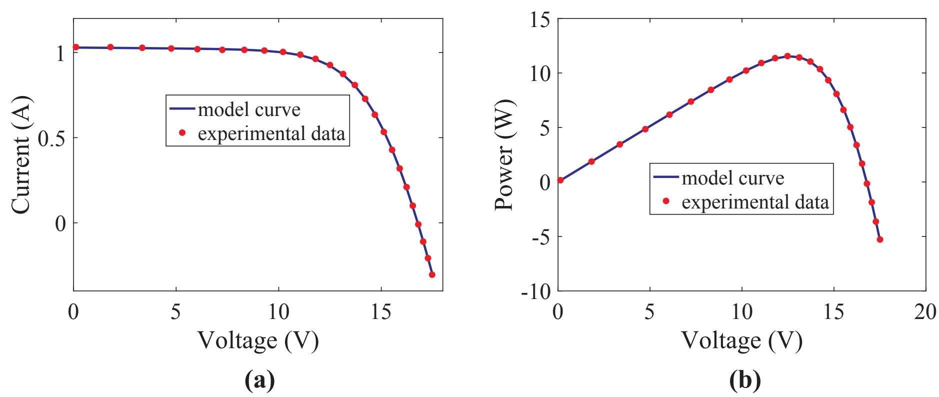

Fig. 6. The curves of (a) *I-V* characteristic, (b) *P-V* characteristic based on the parameters identified by SEDE on the PV module.

Table 8
IAE obtained by SEDE on the PV module.

Item	Measured data		Simulated current data		Simulated power data	
	V (V)	*I* (A)	*Isim* (A)	IAEI (A)	*Psim* (W)	IAEP(W)
1	0.125	1.032	1.02912	0.00238	0.12843	0.00030
2	1.809	1.030	1.02738	0.00262	1.85884	0.00474
3	3.351	1.026	1.02574	0.00026	3.43736	0.00087
4	4.762	1.022	1.02411	0.00211	4.87700	0.01003
5	6.054	1.018	1.02229	0.00429	6.18875	0.02598
6	7.236	1.016	1.01993	0.00443	7.38063	0.03206
7	8.319	1.014	1.01636	0.00236	8.45502	0.01966
8	9.310	1.010	1.01050	0.00050	9.40742	0.00462
9	10.216	1.004	1.00063	0.00287	10.22273	0.02933
10	11.045	0.988	0.98455	0.00345	10.87424	0.03812
11	11.802	0.963	0.95952	0.00348	11.32408	0.04105
12	12.493	0.926	0.92284	0.00266	11.52893	0.03325
13	13.123	0.873	0.87260	0.00010	11.45121	0.00131
14	13.698	0.808	0.80727	0.00023	11.05829	0.00309
15	14.222	0.727	0.72834	0.00184	10.35847	0.02612
16	14.700	0.635	0.63714	0.00264	9.36561	0.03878
17	15.135	0.535	0.53621	0.00171	8.11537	0.02593
18	15.531	0.428	0.42951	0.00201	6.67078	0.03124
19	15.893	0.319	0.31877	0.00027	5.06625	0.00436
20	16.223	0.209	0.20739	0.00111	3.36446	0.01802
21	16.524	0.101	0.09617	**0.00483**	1.58908	**0.07986**
22	16.799	−0.008	−0.00833	0.00033	−0.13986	0.00547
23	17.050	−0.111	−0.11094	0.00006	−1.89146	0.00108
24	17.279	−0.209	−0.20925	0.00025	−3.61565	0.00427
25	17.489	−0.303	−0.30086	0.00214	−5.26165	0.03736
Sum of IAE				0.04892		0.51689

Algorithm 1: Framework of SEDE.

Input: *NP*: population size;

Algorithm 1: Framework of SEDE.

MaxFES: maximal function evaluations;
***group*$_1$**;

Table 9
Statistical results obtained by all algorithms on three PV models.

Model	Algorithm	RMSE				rank-sum	p-value
		Max	Min	Mean	Std		
SD model	SEDE	9.8602188E-04	**9.8602188E-04**	**9.8602188E-04**	4.20E-17		
	SaDE	9.8602188E-04	9.8602188E-04	9.8602188E-04	2.67E-16	'+'	6.73E-04
	JADE	1.1222886E-03	9.8602188E-04	1.0051705E-03	3.22E-05	'+'	2.15E-10
	CoDE	**9.8602188E-04**	9.8602188E-04	9.8602188E-04	**2.31E-17**	'+'	2.60E-05
	MLBSA	9.8602227E-04	9.8602188E-04	9.8602189E-04	7.08E-11	'+'	4.08E-11
	BLPSO	1.7459204E-03	1.0312179E-03	1.3137725E-03	1.90E-04	'+'	3.02E-11
	CLPSO	1.2527413E-03	9.9207509E-04	1.0608115E-03	7.04E-05	'+'	3.02E-11
	PGJAYA	9.8603542E-04	9.8602188E-04	9.8602301E-04	2.80E-09	'+'	3.02E-11
	GOTLBO	1.3955859E-03	9.8660846E-04	1.0829972E-03	9.71E-05	'+'	3.02E-11
	IJAYA	9.8684109E-04	9.8602188E-04	9.8605089E-04	1.49E-07	'+'	3.02E-11
	SATLBO	1.0067430E-03	9.8602490E-04	9.8879877E-04	4.81E-06	'+'	3.02E-11
	STLBO	1.0203295E-03	9.8602188E-04	9.8720656E-04	6.26E-06	'+'	3.02E-11
	GWO	4.4307338E-02	1.2803007E-03	1.1344287E-02	1.48E-02	'+'	3.02E-11
	WDO	4.4257692E-03	1.2210078E-03	2.1802131E-03	7.64E-04	'+'	3.02E-11
	MPEDE	9.8602188E-04	9.8602188E-04	9.8602188E-04	9.80E-14	'+'	6.70E-11
	SGDE	9.8603540E-04	9.8602188E-04	9.8602241E-04	2.47E-09	'+'	1.20E-07
DD model	SEDE	9.8602188E-04	**9.8248485E-04**	**9.8289309E-04**	9.17E-07		
	SaDE	1.0588434E-03	9.8248710E-04	9.8795979E-04	1.37E-05	'+'	1.73E-07
	JADE	1.8475075E-03	9.9438350E-04	1.2088918E-03	2.20E-04	'+'	3.02E-11
	CoDE	1.5496690E-03	9.8249059E-04	1.0036120E-03	1.03E-04	'+'	6.05E-07
	MLBSA	9.8613803E-04	9.8248603E-04	9.8506340E-04	1.24E-06	'+'	6.01E-08
	BLPSO	1.9365422E-03	1.0821787E-03	1.5346179E-03	2.46E-04	'+'	3.02E-11
	CLPSO	1.3883539E-03	9.9431568E-04	1.1395950E-03	9.40E-05	'+'	3.02E-11
	PGJAYA	9.9599929E-04	9.8260471E-04	9.8603057E-04	2.37E-06	'+'	2.23E-09
	GOTLBO	1.5335944E-03	9.8509732E-04	1.1633515E-03	1.52E-04	'+'	3.69E-11
	IJAYA	9.9941024E-04	9.8249354E-04	9.8686005E-04	3.22E-06	'+'	3.20E-09
	SATLBO	1.2306210E-03	9.8282397E-04	1.0054396E-03	5.03E-05	'+'	4.62E-10
	STLBO	1.5243327E-03	9.8256053E-04	1.0343469E-03	1.42E-04	'+'	2.87E-10
	GWO	4.0797273E-02	1.0274192E-03	9.9084730E-03	1.29E-02	'+'	3.02E-11
	WDO	4.9345320E-03	1.6811764E-03	3.2917820E-03	8.41E-04	'+'	3.02E-11
	MPEDE	1.3929121E-03	9.8248541E-04	1.0601810E-03	1.36E-04	'+'	1.43E-08
	SGDE	**9.8602175E-04**	9.8441324E-04	9.8577384E-04	**4.02E-07**	'+'	8.48E-09
Photowatt-PWP201 module	SEDE	**2.4250749E-03**	2.4250749E-03	**2.4250749E-03**	3.14E-17		
	SaDE	2.4250749E-03	**2.4250749E-03**	2.4250749E-03	**1.36E-17**	'+'	3.75E-03
	JADE	2.4379007E-03	2.4250749E-03	2.4259790E-03	2.61E-06	'+'	2.10E-08
	CoDE	2.4250749E-03	2.4250749E-03	2.4250749E-03	2.17E-17	'+'	5.25E-05
	MLBSA	2.4336069E-03	2.4250749E-03	2.4253769E-03	1.56E-06	'+'	3.02E-11
	BLPSO	2.4804311E-03	2.4251201E-03	2.4363530E-03	1.29E-05	'+'	3.02E-11
	CLPSO	2.5077587E-03	2.4278446E-03	2.4636382E-03	2.46E-05	'+'	3.02E-11
	PGJAYA	2.4260516E-03	2.4250749E-03	2.4251251E-03	1.79E-07	'+'	3.02E-11
	GOTLBO	2.5749440E-03	2.4271296E-03	2.4698443E-03	3.12E-05	'+'	3.02E-11
	IJAYA	2.4253326E-03	2.4250749E-03	2.4250977E-03	5.08E-08	'+'	3.02E-11
	SATLBO	2.4315332E-03	2.4250754E-03	2.4254816E-03	1.16E-06	'+'	3.02E-11
	STLBO	2.7425078E-01	2.4250749E-03	2.9609792E-02	8.29E-02	'+'	3.01E-11
	GWO	2.7431406E-01	2.5260880E-03	2.2099352E-02	6.86E-02	'+'	3.02E-11
	WDO	3.3263610E-01	2.7960194E-03	3.3690385E-02	9.17E-02	'+'	3.02E-11
	MPEDE	2.4250749E-03	2.4250749E-03	2.4250749E-03	4.60E-17	'+'	2.38E-08
	SGDE	2.4250772E-03	2.4250749E-03	2.4250749E-03	4.17E-10	'+'	3.02E-11

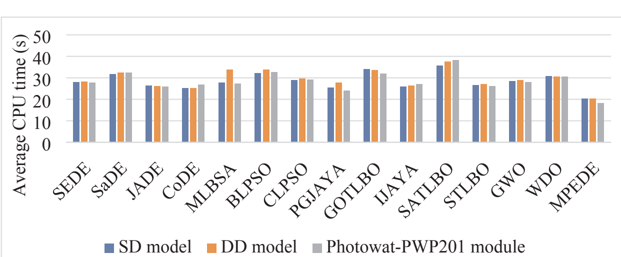

Fig. 7. The average CPU time consumed by different algorithms on three models.

Algorithm 1: Framework of SEDE.

***group*₂**;
parameter pool.
Output: The optimal solution in the population.
$G = 1$, $FES = 0$;
Generate an initial population p and evaluate each individual;
$FES = NP$;

Algorithm 1: Framework of SEDE.

While $FES < MaxFES$
For $i = 1 : NP$
Select one parameter combination from the parameter pool randomly;
Select one mutation strategy based on Eq. (13);
Generate mutation vector v_i^G based on mutation operation;
Perform crossover operation to generate the trial vector u_i^G and evaluate it;
$FES = FES + 1$;
Perform selection operation between u_i^G and x_i^G to get x_i^{G+1};
End for
$G = G + 1$;
End while

From Eq. (13), it can be found that the proportion of two strategy groups used in the population is dynamic, which means that the $\boldsymbol{group_1}$ will be used by more individuals in the early evolution stage. As the population evolves, more individuals will choose the strategy from $\boldsymbol{group_2}$ to accelerate the convergence rate in the late stage. In this case, the tradeoff between diversity and convergence can be properly handled by SEDE.

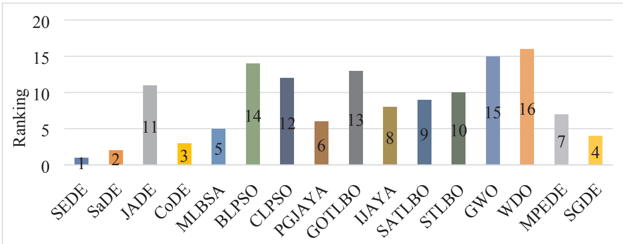

Fig. 8. Rankings of SEDE and other algorithms by the Friedman test.

4.4. The framework of SEDE

Algorithm 1 gives the pseudo-code of SEDE. First, in the search space, *NP* individuals are initialized and evaluated. Next, each individual randomly selects one parameter combination from the parameters pool and a strategy based on the self-adaptive scheme. Then, the DE algorithm is performed. If $FES < MaxFES$, the main loop continues; otherwise the optimal solution is output.

In summary, the advantages of SEDE are as follows: 1) The combinations of multiple parameters avoid the trouble of setting proper parameter for specific problems; 2) The ensemble of multiple mutation strategies and parameter combinations effectively improve the search efficiency of basic DE; 3) The proposed SEDE does not significantly increase the overall complexity of the basic DE. The additional complexity of SEDE is derived from parameter selection and strategy selection, as shown in Algorithm 1 (lines 6–7). The complexity of parameter selection and strategy selection both are $O(NP)$. Since the total complexity of basic DE is $O(MaxG \cdot NP \cdot D)$, where *MaxG* is the maximal number of generations, SEDE has a total complexity of $O(MaxG \cdot NP \cdot (D + 2)) = O(MaxG \cdot NP \cdot D)$, which is same as the basic DE and many other DE variants. Thus, SEDE inherits the advantages of basic DE including the easy to be implemented and simple structure.

5. Simulation

In this Section, a common test set includes SD, DD, and PV module is established to conduct the comparison experiment among SEDE and other advanced algorithms. For the SD and DD models, prior researchers (Easwarakhanthan et al., 1986) used a 57 mm diameter commercial R.T.C. France silicon solar cells at a temperature of 33°C to acquire true Current-Voltage values. For Photowatt-PWP201, 36 polycrystalline silicon cells in series form were operated at 45°C with the irradiance of 100 W/m^2. From (Askarzadeh and Rezazadeh, 2012), the lower and upper bounds of parameters for each model are presented in Table 1. The compared algorithms include three ensemble DE algorithms (SaDE (Qin et al., 2008), CoDE (Wang et al., 2011), and MPEDE (Wu et al., 2016)), one popular DE variant for global optimization (JADE (Zhang and Sanderson, 2009)), one recently proposed DE variant for parameter identification of PV models (SGDE (Liang et al., 2020b)), and several advanced algorithms designed for extracting the parameters of PV models (MLBSA (Yu et al., 2018), BLPSO (Chen et al., 2017), CLPSO (Liang et al., 2006), PGJAYA (Yu et al., 2019), GOTLBO (Chen et al., 2016), IJAYA (Yu et al., 2017b), SATLBO (Yu et al., 2017a), STLBO (Niu et al., 2014), GWO (Mirjalili et al., 2014), and WDO (Bayraktar et al., 2013)). For each model, *MaxFES* is set to 50000. The parameters configuration for each algorithm are listed in Table 2, and each algorithm needs to be executed 30 independent times to obtain the statistical results.

5.1. Detailed results on three PV models

The best RMSE value obtained by each method as well as the related parameters on three models are presented in Tables 3, 5, and 7, respectively, where the best results are marked **in bold**. Besides, to reflect the performance of SEDE, the error between experimental data and measured data is recorded, which are plotted in Figs. 4, 5, and 6, and tabulated in Tables 4, 6, and 8 where the maximal individual absolute

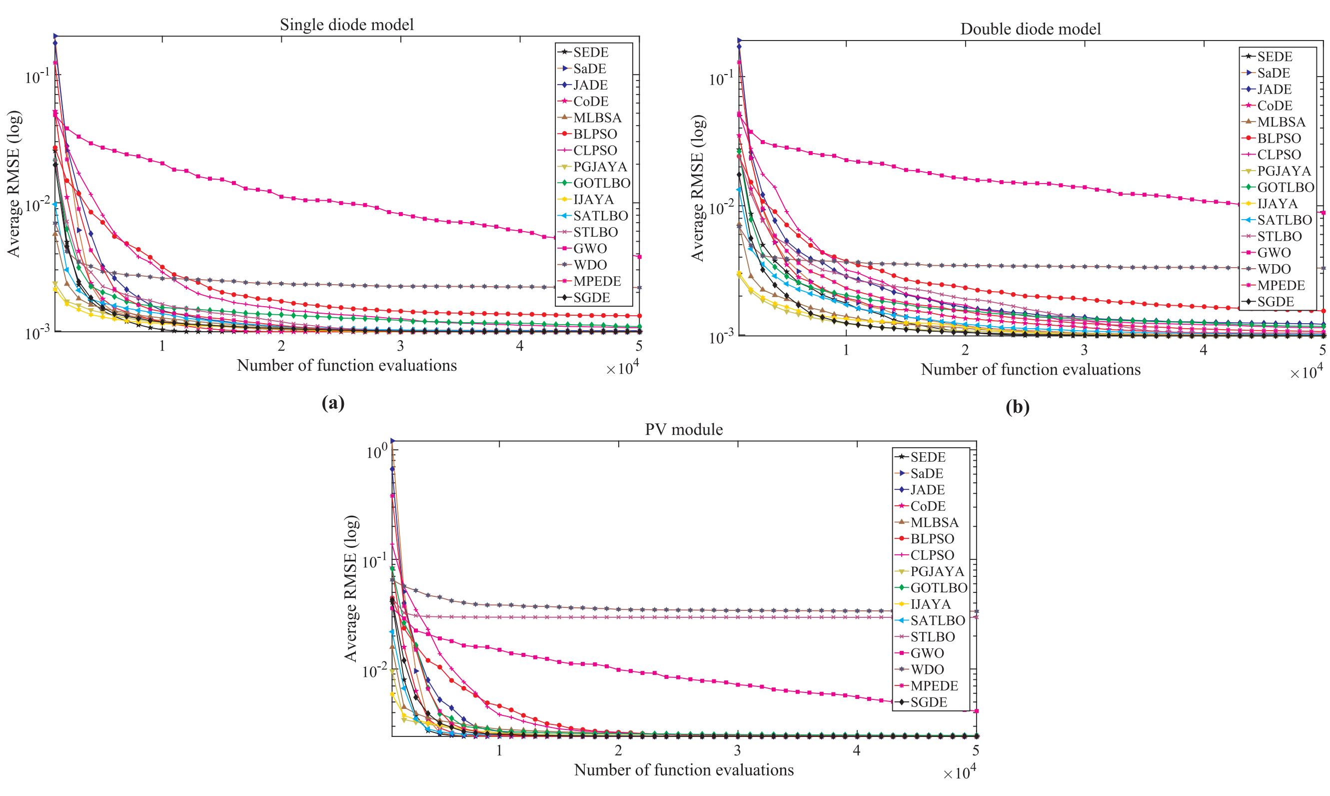

Fig. 9. Convergence performance of different algorithms on: (a) SD model, (b) DD model, (c) PV module.

error (IAE) values are highlighted **in bold**.

5.1.1. Result on single diode model

From Table 3, only SEDE obtains the best RMSE value, which indicates that SEDE performs the best among 16 algorithms. In addition, the optimal parameters obtained by the SaDE, JADE, CoDE, MLBSA, IJAYA, PGJAYA, STLBO, MPEDE, and SGDE are also competitive. In Fig. 4, the values of I and P obtained by SEDE are in high accordance with measured data under different V conditions for the SD model. In addition, Table 4 shows the maximum IAEI and IAEP are 2.5E-03 and 1.5E-03, respectively, which reflects SEDE is able to accurately extract the parameters for the SD model.

5.1.2. Result on double diode model

For the parameter estimation in the DD model, although its landscape is more complex than that in the SD model, the smallest RMSE value on the DD model is still obtained by SEDE, as seen in Table 5. Meanwhile, SaDE, CoDE, MLBSA, IJAYA, PGJAYA, STLBO, SATLBO, and MPEDE all obtain relatively small RMSE values. In addition, Table 6 shows the IAEI under 26 different V is no larger than 2.548E-03, and the IAEP is less than 1.486E-03. Moreover, it is evident from Fig. 5 that all errors between experimental data and measured data are very small. These results fully demonstrate SEDE is effective for the parameter estimation of the DD model.

5.1.3. Result on PV module

For the PV module, it can be seen from Table 7 that except for CLPSO, GWO, GOTLBO, and WDO, the remaining 12 algorithms get very small RMSE values, and only SEDE gets the most accurate parameters, which shows the outstanding performance of SEDE. In addition, from Table 8 and Fig. 6, it is clear the simulated results obtained by SEDE is almost equal to the measured data, which means SEDE can extract very accurate parameters.

5.2. Comparisons on statistical and convergence results

To make the comparison more clear, the statistical results are also saved. We record the best value (Min), the mean value (Mean), the worst value (Max), and the standard deviation (Std) of RMSE over 30 runs in Table 9, where the best values are marked **in bold**. Moreover, to study the significant difference between SEDE with each compared algorithm, the rank-sum test at the significance degree of 0.05 is adopted. The '+' indicates SEDE outperforms than the comparative algorithm, and the p-value represents the degree of difference, where a smaller value means a higher significant difference. Fig. 7 records the average CPU times of 30 independent runs consumed by different algorithms on three models. Please note that the CPU time used by SGDE on each model is not recorded since SGDE extracts three model parameters at the same time. Specially, the CPU time is obtained by using the MATLAB 2014a software on a server, which is configured by Intel Xeon 2.60 GHz CPU and 128 GB RAM. Additionally, the Friedman test (Alcalá-Fdez et al., 2009), as a method for performance ranking of all methods, is used in this paper. Furthermore, Fig. 9 provides the convergence curves obtained by all comparative algorithms on each model to insight the convergence performance.

Based on these results, some observations can be obtained:

- For the SD model, only SEDE, SaDE, CoDE, and MPEDE can obtain better results on four indexes. SEDE can obtain the optimal values regarding Min and Mean. For Max and Std, the difference between SEDE and the best algorithm is very small.
- For the DD model, the best results on Min and Mean are achieved by SEDE, and SGDE gets the best results regarding Max and Std. In addition, MLBSA, PGJAYA, and IJAYA also get good mean values.
- For the PV module, the best results regarding the Max and Mean are obtained by SEDE, which reflects the most accurate parameter is identified by SEDE. In addition, SaDE performs the best on the Min and Std, which demonstrates SaDE has the most stable performance.
- From the rank-sum test, SEDE outperforms all other algorithms for the three models, which proves the superiority of SEDE.
- Fig. 7 shows that there is not much difference in the average CPU time among these algorithms. MPEDE consumes the shortest time for three models, and SEDE requires lower computational time in comparison to most other algorithms, which implies that SEDE has good computational efficiency.
- From Fig. 8, we can conclude that SEDE gets the best average ranking. In addition, SaDE and CoDE get the second-best and third-best average rankings, respectively, which means the ensemble-based method is a more promising approach to extract very accurate parameters of varied solar cells. Besides, SGDE ranks fourth and MPEDE ranks seventh. These DE-based methods get better rankings, which proves the efficiency of DE.
- From Fig. 9, the convergence speed of SEDE for three models is competitive than that of other algorithms.
- In summary, from the above experimental results, SEDE has better performance or competitiveness regarding the accuracy, stability, as well as rapidity compared with other peer methods including several well-established DE variants and some parameter estimation methods.

6. Conclusions

A self-adaptive ensemble-based DE (SEDE) optimizer is proposed in this paper to estimate the parameters of different PV models. In SEDE, the ensemble of three distinct mutation strategies with complementarity assists the algorithm to solve complex problems. Meanwhile, for the control parameters which influence the evolutionary trend of the algorithm, different parameter combinations are established. By combing the different strategies and parameter settings, individuals can exhibit different search behaviors to strengthen different searching abilities. Moreover, a self-adaptive scheme is proposed to determine the strategy used by each individual, so as to keep the equilibrium between population diversity and convergence. The comprehensive experiments on different PV models are conducted, and the results prove that SEDE gets better results regarding accuracy and stability than other algorithms. In future studies, we will apply the reinforcement learning technique to design a strategy that can combine different mutation strategies more efficiently, and also the proposed algorithm will be tested on other complicated optimization problems. Moreover, the methods proposed in recent years for parameter identification of PV models will be investigated to form a comprehensive comparative study. The source code of SEDE can be downloaded from http://www5.zzu.edu.cn/ecilab/.

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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