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# Perturbed stochastic fractal search for solar PV parameter estimation

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# ABSTRACT

Following the widespread use of solar energy all over the world, the design of high quality photovoltaic (PV) cells has attracted strong research interests. To properly evaluate, control and optimize solar PV systems, it is crucial to establish a reliable and accurate model, which is a challenging task due to the presence of non-linearity and multi-modality in the PV systems. In this work, a new meta-heuristic algorithm (MHA), called perturbed stochastic fractal search (pSFS), is proposed to estimate the PV parameters in an optimization framework. The novelty lies in two aspects: (i) employ its own searching operators, i.e., diffusion and updating, to achieve a balance between the global exploration and the local exploitation; and (ii) incorporate a chaotic elitist perturbation strategy to improve the searching performance. To examine the effectiveness of pSFS, this method is applied to solve three PV estimation problems for different PV models, including single diode, double diode and PV modules. Experimental results and statistical analysis show that the proposed pSFS has improved estimation accuracy and robustness compared with several other algorithms recently developed.

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# 1. Introduction

Solar energy is considered to be a promising renewable energy because of its affluent availability and cleanliness. Solar photovoltaic (PV) systems can convert solar energy into electricity and supply power. It has been widely used for several decades and the rapid growth is still continuing [1].

Mathematical models are important for control, optimization and assessment of solar PV systems [2]. Several PV models have been developed, among which the single diode model (SDM) and the double diode model (DDM) are most widely used [3]. The prediction quality of a PV model largely depends on the extracted model parameters. Therefore, accurate and robust estimation of model parameters is crucial for PV modeling.

# 1.1. Literature review

PV parameter estimation is often formulated as an optimization problem to minimize the residual errors statistically. Due to the non-linearity inherent in the dynamics and the noise involved in

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the experimental current-voltage (I-V) data, PV parameter estimation is usually a multimodal problem with multiple local optimums [4]. Deterministic techniques have been proposed for solving this problem, including the Lambert W-functions [5], the Newton-Raphson method [6], and the iterative curve fitting [7]. Most of the deterministic techniques are based on the gradient information. They show powerful local search abilities, but likely fall into local optimums. In addition, deterministic techniques require strict conditions such as the differentiability and convexity, which restricts their wide applications.

More recently, meta-heuristic algorithms (MHAs) have been developed and employed for PV parameters estimation problems. Inspired by natural phenomena, MHAs have advantages in solving complex global optimization problems [8,9], and have no requirements such as continuity, differentiability or convexity for the optimization problems [10,11]. There are three groups of MHAs used for parameter estimation, i.e., the classic MHAs, the latest MHAs and the hybrid MHAs.

The classic MHAs include algorithms such as differential evolution (DE), particle swarm optimization (PSO), harmony search (HS), artificial bee colony (ABC) and teaching-learning-based optimization (TLBO). DE has a simple structure and exhibits good accuracy, but its optimization results highly depend on two control parameters, namely the scaling factor and the crossover rate. In





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Nomencl	ature	IADE	Improved adaptive differential evolution
		IAPE	Individual absolute power error
$a, a_1, a_2$	Diode ideality constant	ĸ	Boltzmann constant (1.3806503 $\times$ 10 <sup>23</sup> J/K)
D	Problem dimension	NP	Population size
FES	Function evaluations	P <sub>best</sub>	Position of the best particle
<b>FES</b> <sub>max</sub>	Maximum number of function evaluations	$P_i$	Position of the <i>i</i> -th particle
G <sub>max</sub>	Maximum number of generations	q	Electron charge $(1.60217646 \times 10^{-19} \text{ C})$
$I_d, I_{d1}, I_{d2}$	Diode current (μA)	$R_S$	Series resistance $(\Omega)$
IL	Output current (A)	R <sub>sh</sub>	Shunt resistance (Ω)
I <sub>ph</sub>	Photo-generated current (A)	Т	Cell temperature (K)
Î <sub>sd</sub>	Reverse saturation current (A)	$V_L$	Cell output voltage (V)
I <sub>sd1</sub>	Diffusion current (A)	$V_t$	Junction thermal voltage (V)
I <sub>sd2</sub>	Saturation current (A)	$\mu_{BP}, \mu_P$	Gaussian parameters
I <sub>sh</sub>	shunt resistor current (A)	$\gamma_i$	Selection probability for the <i>i</i> -th particle
		MDN	Maximum diffusion number
Abbreviat	ions	MHA	Meta-heuristic algorithms
ABC	Artificial bee colony	pSFS	Perturbed stochastic fractal search
BHCS	Biogeography-based heterogeneous cuckoo search	P-DE	Penalty based differential evolution
BLPSO	Biogeography-based learning PSO	PSO	Particle swarm optimization
CLPSO	Comprehensive learning PSO	PV	Photovoltaic
DDM	Double diode mode	RMSE	Root mean square error
DE	Differential evolution	SD	Standard deviation
ELPSO	Enhanced leader PSO	SDM	Single diode model
FPA	Flower pollination algorithm	SFS	Stochastic fractal search
FWA	Fireworks algorithm	SSA	Salp swarm algorithm
GOTLBO	Generalized opposition TLBO	TLBO	Teaching-learning-based optimization
HFAPS	Hybrid firefly algorithm and pattern search	TLABC	Teaching-learning-based artificial bee colony
HS	Harmony search	TRR	Trust-region reflective
IACE	Individual absolute current error	WOA	Whale optimization algorithm
			-

Ref. [12], the fitness information was used to tune the control parameters, and an improved adaptive DE (IADE) was proposed for estimating parameters of PV models. PSO is also simple to implement and has fast convergence speed, but it often suffers from premature convergence. To overcome this drawback, several PSO variants including the enhanced leader PSO (ELPSO) [13], the adaptive mutation strategy (MPSO) [14] and the chaotic heterogeneous comprehensive learning PSO (CHCLPSO) [15], have been developed and applied to extract the PV model parameters. In Ref. [16], three HS algorithms were used to determine the unknown parameters of solar cell models. The simulation studies show that HS algorithms achieve improved results compared to the simulated annealing and the pattern search. In Ref. [17], artificial bee colony (ABC) was used to identify the parameters of two solar cells. It is observed that ABC has good search ability for multimodal objective

functions compared with HS, PSO, genetic algorithm and bacterial foraging algorithm. In Ref. [18], generalized oppositional TLBO (GOTLBO) algorithm was proposed to identify the parameters of solar cell models. By using the generalized opposition-based learning, GOTLBO accelerates the convergence speed compared to the basic TLBO.

There is not a single classic MHA that is competent for all optimization problems. The latest MHAs are used for PV parameter estimation. In Ref. [19], the whale optimization algorithm (WOA) was proposed for PV parameters estimation, in which the chaotic map was used to automatically adjust the internal parameters of WOA. This helps to avoid local optimum and also improves the convergence rate. In Ref. [20], two prey searching strategies were embedded into WOA, which overcomes the problem of premature convergence, and the improved WOA was applied to estimate the model parameters of two practical PV power stations. Alam et al. [3] proposed a flower pollination algorithm (FPA) based method for PV



Fig. 1. Equivalent electric circuit of single diode model.



Fig. 2. Equivalent electric circuit of double diode model.

parameters estimation method to improve the convergence performance. Improved JAYA algorithms were proposed to accurately and reliably identify the parameters of several PV models [4,21]. However, JAYA algorithms need relatively large number of iterations to converge. Several other latest MHAs including salp swarm algorithm (SSA) [22] and fireworks algorithm (FWA) [23] were also utilized to extract PV model parameters, and achieve competitive performance in the reported case studies.

Hybrid MHAs combine advantages from more than one MHA, thus provide more accurate parameters than the individual algorithms. Several hybrid MHAs were also developed for PV parameter estimation problems, including hybrid firefly algorithm and pattern search (HFAPS) [24], teaching-learning-based artificial bee colony (TLABC) [25], biogeography-based heterogeneous cuckoo search (BHCS) [26], and trust-region reflective artificial bee colony (ABC-TRR) [27].

#### 1.2. Contribution

The above short literature review shows that parameter estimation of PV models is still a challenging task that requires more effective and efficient tools. Recent development suggests that MHAs have good potential for parameter estimation of PV models. In this work, we will explore a particular MHA, the stochastic fractal search (SFS), for PV modeling.

SFS is an MHA which uses the diffusion and update processes based on random fractal properties [28]. This algorithm is developed to overcome the weaknesses of MHAs such as premature convergence and low robustness. SFS has been applied in solving several real-world problems, such as system reliability optimization [29], PID controller design [30], and electric power economic dispatch [31].

Inspired by the recent progress of SFS in applications, in this study, we investigate the further development of SFS for the challenging PV parameter estimation problems. Specifically, we propose a perturbed stochastic fractal search (pSFS) algorithm, which employs the diffusion and updating operators in searching. Moreover, a simple but efficient chaotic elitist perturbation is incorporated into the pSFS, which drives the local search around the best solution during the searching process. This designed perturbation can further improve the solution accuracy and robustness. The proposed pSFS is applied to solve three PV parameter estimation problems with different diode models, and the results are compared with several recently-developed MHAs to verify its performance.

The contributions of this paper are listed as follows:

- (1) A new perturbed SFS (pSFS) approach is proposed for solving PV parameter estimation problems.
- (2) A chaotic elitist perturbation strategy is implemented to improve the search efficiency.

- (3) pSFS is applied to three PV parameter estimation problems with different diode models, as well as three PV modules using survey data.
- (4) By comparing with the recently-developed algorithms, the superiority of pSFS in solution accuracy and robustness are demonstrated.

# 1.3. Paper organization

The remaining of this paper is organized as follows. In Section 2, three PV parameter estimation problems are defined for SDM, DDM and PV module, respectively. The basic SFS and the proposed pSFS algorithms are presented in Section 3. Comparisons are made in Section 4 between the pSFS and several recently-developed algorithms. In Section 5, the practical use of pSFS is examined by using surveyed experimental data from three different PV modules. Finally, conclusions are given in Section 6.

# 2. Problem statement

This section presents the mathematical formulation of PV parameter estimation problems with three different diode models, i.e., SDM, DDM, and PV module models.

# 2.1. Single diode model

The equivalent electric circuit of a SDM is shown in Fig. 1. In SDM, the output current  $I_{l}$  is calculated as follows [32,33]:

$$I_{L} = I_{ph} - I_{d} - I_{sh} = I_{ph} - I_{sd} \cdot \left[ \exp\left(\frac{V_{L} + R_{S} \cdot I_{L}}{a \cdot V_{t}}\right) - 1 \right] - \frac{V_{L} + R_{S} \cdot I_{L}}{R_{sh}}$$
(1)

where  $I_{ph}$ ,  $I_d$  and  $I_{sh}$  are the photo-generated current, diode current and shunt resistor current, respectively;  $V_L$  is the cell output voltage;  $I_{sd}$  is the reverse saturation current;  $R_S$  and  $R_{sh}$  are the series resistance and shunt resistance, respectively; a is the diode ideality constant; and  $V_t$  is the junction thermal voltage calculated as follows:

$$V_t = \frac{kT}{q} \tag{2}$$

where  $k = 1.3806503 \times 10^{23}$  J/K is the Boltzmann constant,  $q = 1.60217646 \times 10^{-19}$  C is the electron charge, and *T* is the cell temperature (*K*).

#### 2.2. Double diode model

The equivalent electric circuit of the DDM is shown in Fig. 2. In DDM, the cell output current  $I_L$  can be calculated as follows [32,33]:

$$I_{L} = I_{ph} - I_{d1} - I_{d2} - I_{sh}$$
  
=  $I_{ph} - I_{sd1} \cdot \left( \exp\left(\frac{V_{L} + I_{L}R_{s}}{a_{1}V_{t}}\right) - 1 \right) - I_{sd2} \cdot \left( \exp\left(\frac{V_{L} + I_{L}R_{s}}{a_{2}V_{t}}\right) - 1 \right) - \frac{V_{L} + I_{L}R_{s}}{R_{sh}}$ 

(3)

where  $I_{d1}$  and  $I_{d2}$  denote the first and the second diode currents, respectively;  $I_{sd1}$  and  $I_{sd2}$  denote the diffusion and saturation currents, respectively;  $a_1$  and  $a_2$  are the diffusion and recombination diode ideality factors, respectively.

# 2.3. PV module model

The PV module model consists of  $N_s \times N_p$  solar cells connected in series and/or in parallel as shown in Fig. 3. The cell output current  $I_L$  can be formulated as follows [32,33]:

$$I_{L} = N_{p} \cdot I_{ph} - N_{p} \cdot I_{sd} \cdot \left[ \exp\left(\frac{V_{L}/N_{S} + R_{S} \cdot I_{L}/N_{p}}{a \cdot V_{t}}\right) - 1 \right] - \frac{N_{p} \cdot V_{L}/N_{S} + R_{S} \cdot I_{L}}{R_{sh}}$$
(4)

where  $N_p$  and  $N_s$  are the numbers of solar cells in parallel and in series, respectively.

#### 2.4. Objective function of PV estimation problem

In order to extract the unknown parameters of PV models based on the experimental data, the PV parameter estimation is converted into an optimization problem. The objective function is defined as the overall root mean square error (RMSE) between experimental data and simulated data as follows [18,34]:

$$\text{RMSE}(\mathbf{x}) = \sqrt{\frac{1}{N} \sum_{k=1}^{N} f_k (V_L, I_L, \mathbf{x})^2}$$
(5)

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

For the SDM,

$$f_k(V_L, I_L, \mathbf{x}) = I_{ph} - I_{sd} \left( exp\left(\frac{V_L + I_L R_S}{aV_t}\right) - 1 \right) - \frac{V_L + I_L R_s}{R_{sh}} - I_L$$
(6)

$$\mathbf{x} = \left\{ I_{ph}, I_{sd}, R_S, R_{sh}, a \right\}$$
(7)

For the DDM,



Fig. 3. Equivalent electric circuit of PV module model.

$$\mathbf{x} = \left\{ I_{ph}, I_{sd}, R_S, R_{sh}, a \right\}$$
(11)

# **3.** Perturbed stochastic fractal search for PV model estimation

# 3.1. Stochastic fractal search

SFS is a recently developed MHA proposed by Salimi [28], taking inspiration from the natural growth phenomenon of random fractal. The SFS algorithm mainly uses two processes namely diffusion and updating to improve the searching. In the diffusion process, each particle (i.e., candidate solution) diffuses around its own location, and carries out the exploitation task. By contrast, in the updating process, each particle is updated according to the location of other particles, and this process leads to exploration properties. The two processes of SFS are shown in Fig. 4.

The diffusion process uses Gaussian random walks to generate points around each particle until a predetermined maximum diffusion number (MDN) is reached. There are two types of Gaussian walks in the diffusion process, which are described as follows:

$$GW_1 = Gaussian(\mu_{BP}, \delta) + (rand(0, 1) \times P_{best} - rand(0, 1) \times P_i)$$
(12)

$$f_{k}(V_{L}, I_{L}, \mathbf{x}) = I_{ph} - I_{sd1}\left(exp\left(\frac{V_{L} + I_{L}R_{S}}{a_{1}V_{t}}\right) - 1\right) - I_{sd2}\left(exp\left(\frac{V_{L} + I_{L}R_{S}}{a_{2}V_{t}}\right) - 1\right) - \frac{V_{L} + I_{L}R_{S}}{R_{sh}} - I_{L}$$
(8)

$$GW_2 = Gaussian(\mu_P, \delta) \tag{13}$$

$$\mathbf{x} = \left\{ I_{ph}, I_{sd1}, I_{sd2}, R_S, R_{sh}, a_1, a_2 \right\}$$
(9)

For the PV module model,

where  $P_i$  and  $P_{best}$  are the positions of the *i*-th and the best particles, respectively;  $i = 1, 2, \dots, NP$ , NP is the population size; rand(0, 1) is a random number generated within [0,1]. Gaussian parameters  $\mu_{BP}$ and  $\mu_P$  are equal to  $P_{best}$  and  $P_i$ , respectively. The standard deviation

$$f_k(V_L, I_L, \mathbf{x}) = N_p I_{ph} - N_p I_{sd} \left[ \exp\left(\frac{V_L/N_S + R_S I_L/N_p}{aV_t}\right) - 1 \right] - \frac{N_p V_L/N_S + R_S I_L}{R_{sh}} - I_L$$
(10)

 $\delta$  is dynamically adjusted based on the number of the generation *G*:

$$\delta = \left| \frac{\log(G)}{G} \times (P_i - P_{best}) \right| \tag{14}$$

The update process employs two statistical procedures to undertake the exploration in SFS. In the first updating process, each particle position is updated as follows:

$$P'_{i}(j) = \begin{cases} P_{r1}(j) - rand(0, 1) \times (P_{r2}(j) - P_{i}(j)) \text{if } \gamma_{i} < rand(0, 1) \\ P_{i}(j) \text{otherwise} \end{cases}$$

$$(15)$$

where  $j \in \{1, 2, \dots, D\}$  is the index for each optimization variable; *D* is the number of optimization variables;  $P'_i$  is the new position of  $P_i$ ;  $P_{r1}$  and  $P_{r2}$  are the positions of two randomly selected particles;  $\gamma_i$  is the selection probability for particle  $P_i$  that can be calculated as:

$$\gamma_i = 1 - \frac{\operatorname{rank}(P_i)}{NP} \tag{16}$$

where  $rank(P_i)$  is the fitness order from the best to the worst of the *i*-th particles in the population. Obviously, the worse particle has a smaller  $\gamma_i$  undergoing the first update process.

In the second updating process, the probability  $\gamma_i$  is recalculated and used to determine whether a particle  $P_i$  should be updated as follows:

$$P'_{i}(j) = \begin{cases} P_{i}(j) - rand(0, 1) \times (P'_{r1}(j) - P_{best}(j)) \text{ if } rand(0, 1) < 0.5\\ P_{i}(j) + rand(0, 1) \times (P'_{r1}(j) - P'_{r2}(j)) \text{ otherwise} \end{cases}$$
(17)

where  $P'_{r1}$  and  $P'_{r2}$  are the positions of two randomly selected particles.

# 3.2. Perturbed stochastic fractal search

#### 3.2.1. Chaotic elitist perturbation strategy

During the search process of SFS, the best solution found is recorded in each generation. Its quality affects both the search process and the final solution. Chaotic elitist perturbation strategy is introduced to perform adaptive local search around the best solution as follows:

$$P^{*}(j) = \begin{cases} P_{best}(j) + rand(0,1) \cdot (2z_{k} - 1) \text{ if } rand(0,1) < 1 - FES/FES_{\max} \\ P_{best}(j) \text{ otherwise} \end{cases}$$
(18)

where the logistic map  $z_k = 4z_{k-1}(1-z_{k-1})$  is used to generate the *k*-th chaotic iteration value, with its initial value  $z_0$  randomly generated within [0, 1]; *FES* and *FES*<sub>max</sub> are the current and

maximum number of function evaluations. The new solution  $P^*$  is compared with the worst solution  $P_{worst}$  in current population, and the better one is selected for the next generation.

According to Eq. (18), the chaotic elitist perturbation strategy can perform a self-adaptive perturbation during the optimization process. To be specific, the value of *FES* is relative small in the early search stage, thus more perturbations will be added to the best solution, which is useful for global exploration. By contrast, the value of *FES* is close to 1 in the latter search stage, therefore more information will be inherited from the best solution, which is beneficial for local exploitation.

# 3.2.2. Algorithmic framework

The flowchart of the proposed pSFS algorithm is presented in Fig. 5. A more detailed description of pSFS using the pseudocode is presented in Algorithm 1 in Appendix 1. It can be seen that, the proposed pSFS takes four searching stages, including the diffusion process, the first and second updating processes, and the chaotic elitist perturbation. These four stages have different roles in the searching process. The diffusion process focuses on local exploitation, the two updating processes focus on global exploration, and the chaotic elitist perturbation strategy performs adaptive local search to further improve the solution accuracy and robustness.

The computational complexity of pSFS mainly includes: (a) the time for the diffusion process  $T_{di}$ , (b) the time for the first updating process  $T_{up1}$ , (c) the time for the second updating process  $T_{up2}$ , and (d) the time for the chaotic elitist perturbation strategy  $T_{pe}$ . The total computational complexity of pSFS can be represented by a time metric as follows:

$$T_{pSFS} = (T_{di} + T_{up1} + T_{up2} + T_{pe}) \cdot G_{max}$$
  
=  $(O(NP \cdot MDN \cdot D) + O(NP \cdot \log(NP) + NP \cdot D)$   
 $+O(NP \cdot \log(NP) + NP \cdot D) + O(D))$  (19)  
=  $O(MDN \cdot D + 2\log(NP) + 2D) \cdot NP \cdot G_{max}$   
=  $O(MDN \cdot D + 2\log(NP) + 2D) \cdot FES_{max}$ 

where *D* is the problem dimension, *NP* is the population size, *MDN* is the maximum diffusion number,  $G_{max}$  is the maximum number of generations, and  $FES_{max}$  is the maximum number of function evaluations.

# 4. Results and analysis

The proposed pSFS algorithm is evaluated by solving three PV parameter estimation problems as described in Section 2. The experimental current-voltage data of the SDM and DDM are measured from a RTC France solar cell (under  $1000 \text{ W/m}^2$  at  $33 \degree \text{C}$ ) and are taken from Ref. [6]. The experimental current-voltage data of the PV module are from Photowatt-PWP201 module (under  $1000 \text{ W/m}^2$  at  $45 \degree \text{C}$ ) [6]. The searching ranges for the model parameters are listed in Table 1, which are the same as those in



Fig. 4. The main procedure of SFS algorithm.



Fig. 5. Flowchart of the pSFS algorithm.

 Table 1

 Parameter boundaries of three PV models.

Parameter	SDM/DDM		PV module	
	Lower	Upper	Lower	Upper
I <sub>ph</sub> (A)	0	1	0	2
$I_{sd}, I_{sd1}, I_{sd2}(\mu A)$	0	1	0	50
$R_S(\Omega)$	0	0.5	0	2
$R_{sh}(\Omega)$	0	100	0	2000
$a, a_1, a_2$	1	2	1	50

#### Table 2

Parameter settings for pSFS and the other algorithms.

Algorithm	Year	Parameter settings
CLPSO BLPSO ABC GOTLBO	2006 2017 2007 2016	$ \begin{array}{l} NP = 40, w = 0.9 \sim 0.2, c = 1.496, m = 5 \\ NP = 40, w = 0.9 \sim 0.2, c = 1.496, I = E = 1 \\ NP = 50, limit = 200 \\ NP = 50, Jr = 0.3 \end{array} $
TLABC	2018	NP = 50, limit = 200, F = rand(0, 1)
IJAYA	2017	NP = 20
SFS	2015	$NP = 30, MDN = 1$ , Gaussian walk $GW_1$
pSFS	proposed	$NP = 30, MDN = 1$ , Gaussian walk $GW_1$

Refs. [4,35,36]. This will ensure comparisons are made under the same system settings.

The pSFS is compared with seven recently-developed algorithms: basic SFS [28], CLPSO (comprehensive learning PSO) [37], BLPSO (biogeography-based learning PSO) [38], ABC (artificial bee colony) [39], GOTLBO (generalized oppositional TLBO) [18], TLABC (teaching-learning-based ABC) [25], and IJAYA (improved JAYA) [33]. These algorithms show good performance for PV parameter estimation, therefore chosen for comparison in this study.

The parameter settings for these algorithms under comparison are given in Table 2, mainly taken from their corresponding literature. The tuning parameters for the proposed pSFS are also given in Table 2. The maximum number of function evaluations is set to be  $FES_{max} = 50000$  for all three PV parameter estimation problems [4,25,36]. All the algorithms are coded in MATLAB and run 30 times independently to obtain the statistical results. The experiments are carried out on a DELL computer with a Core i5-4460 processor and 8G RAM.

## 4.1. Comparisons based on the best results

#### 4.1.1. Results on the single diode mode

We first compare the proposed pSFS with the other seven algorithms on the SDM. There are five unknown parameters to be estimated in the SDM model. Table 3 presents the comparison results for all these algorithms. The extracted model parameters are also presented. Note that, the results reported in Table 3 are the best RMSE values among 30 independent runs. The statistical results

 Table 3

 Results of pSFS and the compared algorithms on the single diode model.

will be compared in Section 4.2.

From the results in Table 3, the proposed pSFS, together with SFS and TLABC achieve the best RMSE value (i.e., 9.8602E-4). The RMSE reflects the estimation accuracy of the algorithms. Thus, the highest estimation accuracy has been achieved by pSFS, SFS and TLABC. IJAVA achieves the RMSE value of 9.8603E-04, followed by GOTLBO (9.8658E-04) and ABC (9.8815E-04). The performance of CLPSO and BLPSO stays on the lower end of the comparison, and their RMSE values are 9.9207E-04 and 1.1239E-03, respectively.

The extracted parameters of pSFS are used to plot the I-V and P-V curves. As shown in Fig. 6, both I-V and P-V characteristics curves demonstrate that the estimated model curves are highly consistent with the experimental data. Besides, Fig. 7 plots the individual absolute current error (IACE) and individual absolute power error (IAPE) over the whole voltage range. The maximal IACE value is smaller than 2.5E-3, and the maximal IAPE value is smaller than 1.5E-3. All these observations demonstrate the high estimation accuracy of the pSFS algorithm.

#### 4.1.2. Results on the double diode mode

The comparison results of pSFS with the other seven algorithms for the DDM are presented in Table 4. Since there are seven unknown parameters for a DDM model, the estimation of the DDM is more complicated than that of the SDM.

From Table 4, it can be found that the proposed pSFS and the basic SFS attain the best RMSE value (i.e., 9.8255E-04). This indicates the higher accuracy of SFS algorithms over those non-SFS algorithms for PV parameter estimation. TLABC achieves the third best RMSE value (i.e., 9.8414E-04), and IJAVA obtains the fourth best RMSE value (i.e., 9.8423E-04). CLPSO and BLPSO exihit relative poor performance for this case, and their RMSE values are the worst among the eight algorithms.

To further evaluate the pSFS's estimation accuracy over the whole voltage range, Fig. 8 plots the I-V and P-V characteristic curves. The estimated model curves of pSFS are in good agreement with the experimental data. Meanwhile, from Fig. 9, the maximal IACE value is less than 2.6E-3, and the maximal IAPE value is less than 1.5E-3. These results show that the proposed pSFS also achieves a very high estimation accuracy for the DDM.

## 4.1.3. Results on the PV module mode

A PV module model that has five estimation parameters is taken to further evaluate the estimation accuracy of the proposed pSFS. Table 5 presents the comparison results of pSFS and the other algorithms. From the results in Table 5, three algorithms (i.e., pSFS, SFS and TLABC) achieve the best RMSE value (i.e., 2.42507E-03), followed by IJAVA (2.42512E-03), GOTLBO(2.42513E-03), BLPSO (2.42520E-03), CLPSO (2.42661E-03) and ABC (2.44692E-03).

The optimal model parameters extracted by pSFS are used to construct the I-V and P-V curves. As shown in Fig. 10, high consistency can be observed between the estimated model curves and

Algorithm	$I_{ph}$ (A)	$I_{sd}(\mu A)$	$R_{sh}(\Omega)$	$R_S(\Omega)$	а	RMSE	Rank
CLPSO	0.76064	0.33454	56.03420	0.03623	1.48469	9.9207E-04	7
BLPSO	0.76063	0.42518	62.58528	0.03523	1.50940	1.1239E-03	8
ABC	0.76085	0.33016	53.59884	0.03629	1.48339	9.8815E-04	6
GOTLBO	0.76077	0.32256	53.33877	0.03637	1.48106	9.8658E-04	5
TLABC	0.76078	0.32302	53.71636	0.03638	1.48118	9.8602E-04	1
IJAYA	0.76078	0.32304	53.71441	0.03638	1.48119	9.8603E-04	4
SFS	0.76078	0.32302	53.71852	0.03638	1.48118	9.8602E-04	1
pSFS	0.76078	0.32302	53.71852	0.03638	1.48118	9.8602E-04	1

The best results are highlighted in bold font.



Fig. 6. Comparisons between experimental data and the data estimated from pSFS for the single diode model: (a) I-V characteristics, (b) P-V characteristics.



Voltage (V)

Fig. 7. Individual absolute errors for current and power using pSFS (single diode model).

the experimental data for both I-V and P-V characteristics. From Fig. 11, it can be observed that the maximal IACE value is less than 8.0E-2, and the maximal IAPE value is less than 5.0E-3. All these comparisons demonstrate the high estimation accuracy of the proposed pSFS for the PV module model.

# 4.2. Comparisons based on the statistical results

Since all the eight PV parameter estimation algorithms are stochastic approaches, it is helpful to compare their statistical results. Table 6 presents the best, the mean, the worst and the standard deviation (SD) of RMSE of the eight algorithms over 30 independent runs. Again three PV models are considered in the comparison. In addition, the Wilcoxon rank sum test is conducted to compare pSFS with the other algorithms, so as to establish a statistical view. The symbols "+" and " = " indicate that pSFS performs significantly better or similar to others, with a significance level of p = 0.05. The average computational times are also given in Table 6.

From Table 6, it can be found that:

- In terms of the best RMSE value, two SFS algorithms, i.e., pSFS and SFS, achieve the best results for all three PV models. TLABC achieves the best results for the SDM and PV module models. The other five algorithms, including CLPSO, BLPSO, ABC, GOTLBO and IJAVA, cannot obtain the best RMSE value on any PV models.
- Considering the mean and worst RMSE values, the proposed pSFS achieves the best results on two PV models, i.e., SDM and PV module. SFS gets the best result on the PV module model, but it performs worse than pSFS on SDM and DDM. This indicates that the chaotic elitist perturbation strategy improves the estimation accuracy of SFS. IJAVA is another competitive algorithm, as it attains the best result on DDM.
- The SD of RMSE can reflect the robustness of an algorithm in different runs. For this performance index, the proposed pSFS achieves the best results on the SDM and the PV module models. IJAVA gets the best SD result on DDM. It can also be observed that, pSFS achieves smaller SD values than SFS on all three PV models, which means the robustness of pSFS is enhanced by using the chaotic elitist perturbation strategy.
- According to the Wilcoxon rank sum test, the proposed pSFS performs significantly better than CLPSO, BLPSO, ABC, GOTLBO and TLABC on all three PV models. Compared with IJAVA and

Table	4
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Results of pSFS and the compared algorithms on the double diode model.

Algorithm	$I_{ph}(A)$	$I_{sd1}(\mu A)$	$I_{sd2}(\mu A)$	$R_{sh}(\Omega)$	$R_S(\Omega)$	<i>a</i> <sub>1</sub>	<i>a</i> <sub>2</sub>	RMSE	Rank
CLPSO	0.76112	0.00237	0.33875	52.40069	0.03619	1.68481	1.48612	1.0135E-03	7
BLPSO	0.76056	0.17895	0.31560	64.79937	0.03553	1.69574	1.48789	1.1042E-03	8
ABC	0.76071	0.14623	0.24605	55.36509	0.03654	1.68023	1.46226	9.8956E-04	6
GOTLBO	0.76081	0.27173	0.25952	53.61867	0.03655	1.46681	1.91606	9.8544E-04	5
TLABC	0.76081	0.42394	0.24011	54.66797	0.03667	1.90750	1.45671	9.8414E-04	3
IJAYA	0.76079	0.49461	0.22069	54.65515	0.03671	1.88559	1.45021	9.8423E-04	4
SFS	0.76078	0.65647	0.23721	55.30604	0.03669	1.99990	1.45509	9.8255E-04	1
pSFS	0.76078	0.84161	0.21545	55.72835	0.03679	2.00000	1.44705	9.8255E-04	1

The best results are highlighted in bold font.



Fig. 8. Comparisons between experimental data and the data estimated from pSFS for the double diode model: (a) I–V characteristics, (b) P–V characteristics.



Fig. 9. Individual absolute errors for current and power using pSFS (double diode model).

SFS, pSFS exhibits significantly better performance on the SDM and PV module.

• In terms of computational time, the eight algorithms use about 20 s for all three different PV models. Therefore, there are no clear differences among these algorithms.

Table 7 presents the Friedman rank values of the eight algorithms on the three problems PV parameter estimation problems. The proposed pSFS attains the best rank value (1.50), SFS the second (2.17), followed by IJAVA (2.67), TLABC(4.33), CLPSO(5.67), GOTLBO(6.33), ABC(6.33) and BLPSO(7.00).

Results of pSFS and the compared algorithms on the PV module model.

Based on the above statistical comparisons and analysis, it can be concluded that the proposed pSFS achieves the overall best parameter estimation accuracy and robustness among the eight algorithms. The chaotic elitist perturbation strategy enhances the performance of the pSFS algorithm. Therefore, pSFS can be used as an accurate and robust method for PV parameter estimation problems with different diode models.

#### 4.3. Comparisons of the convergence

We also compare the convergence of the eight algorithms for the three PV models. Fig. 12 plots the convergence curves in terms of average RMSE. From Fig. 12, it can be observed that:

- IJAVA has the fastest convergence speed, followed by pSFS, SFS, TLABC and GOTLBO.
- The proposed pSFS has reasonably fast convergence speed. Meanwhile, it achieves high final estimation accuracy for all three PV models.
- pSFS converges faster than SFS for all three PV models. This indicates the chaotic elitist perturbation strategy accelerates its convergence speed.
- GOTLBO and TLABC have the similar convergence speed as that of pSFS, but their final estimation accuracy is worse than pSFS.
- The other three algorithms, BLPSO, CLPSO and ABC, converge relative slow. Also, their estimation accuracy are lower in comparison with other algorithms.

Based on the above comparisions, it can be concluded that the proposed pSFS has a reasonably fast convergence speed, and its final convergence accuracy is the highest compared with all the other algorithms. In fact, an efficient seach process should balance

Algorithm	$I_{ph}$ (A)	$I_{sd}(\mu A)$	$R_{sh}(\Omega)$	$R_S(\Omega)$	а	RMSE	Rank
CLPSO	1.03036	3.45208	1001.18353	1.20269	48.60837	2.42661E-03	7
BLPSO	1.03052	3.50258	983.15030	1.20062	48.66526	2.42520E-03	6
ABC	1.03008	3.30190	968.65121	1.20631	48.44085	2.44692E-03	8
GOTLBO	1.03046	3.49907	989.68885	1.20080	48.66113	2.42513E-03	5
TLABC	1.03052	3.48226	981.84265	1.20127	48.64284	2.42507E-03	1
IJAYA	1.03054	3.47922	981.13257	1.20145	48.63942	2.42512E-03	4
SFS	1.03051	3.48226	981.98237	1.20127	48.64283	2.42507E-03	1
pSFS	1.03051	3.48226	981.98223	1.20127	48.64283	2.42507E-03	1

The best results are highlighted in bold font.

Table 5



Fig. 10. Comparisons between experimental data and the data estimated from pSFS for the PV module model: (a) I-V characteristics, (b) P-V characteristics.



Fig. 11. Individual absolute errors for current and power using pSFS (PV module model).

#### Table 6

Statistical results of pSFS and the compared algorithms for different PV models.

Table 7							
Friedman 1	rank values	of theses	algorithms	on all	three 1	problem	s.

	Friedman rank	Final rank
CLPSO	5.67	5
BLPSO	7.00	8
ABC	6.33	6
GOTLBO	6.33	7
TLABC	4.33	4
IJAYA	2.67	3
SFS	2.17	2
pSFS	1.50	1

the exploration and exploitation. In other words, too fast converge speed may make algorithms premature, while too solw converge speed may affect the final solution accuracy. For the multimodal PV parameter estimation problem, the proposed pSFS can keep an effective balance between global exploration and local exploitation. This is probably why pSFS can achieve high final estimation

	Algorithm	RMSE					
		Best	Mean	Worst	SD	Sig.	Time(s)
SDM	CLPSO	9.9207E-04	1.0587E-03	1.1872E-03	5.0109E-05	+	20.35
	BLPSO	1.1239E-03	1.4091E-03	1.7077E-03	1.6161E-04	+	22.40
	ABC	9.8815E-04	1.1213E-03	1.4174E-03	1.1982E-04	+	24.43
	GOTLBO	9.8658E-04	1.0774E-03	1.3536E-03	9.5825E-05	+	20.11
	TLABC	9.8602E-04	9.9852E-04	1.0397E-03	1.8602E-05	+	19.42
	IJAYA	9.8603E-04	9.8879E-04	9.9809E-04	2.8508E-06	+	24.52
	SFS	9.8602E-04	9.8610E-04	9.8819E-04	3.9677E-07	+	22.86
	pSFS	9.8602E-04	9.8602E-04	9.8608E-04	1.1063E-08		23.05
DDM	CLPSO	1.0135E-03	1.0911E-03	1.1991E-03	5.6863E-05	+	20.96
	BLPSO	1.1042E-03	1.5854E-03	2.1955E-03	2.6619E-04	+	23.29
	ABC	9.8956E-04	1.0576E-03	1.2848E-03	6.1867E-05	+	24.85
	GOTLBO	9.8544E-04	1.1663E-03	1.5962E-03	1.5617E-04	+	21.58
	TLABC	9.8414E-04	1.1555E-03	1.5048E-03	1.5503E-04	+	19.88
	IJAYA	9.8423E-04	1.0079E-03	1.1357E-03	4.0417E-05	=	25.03
	SFS	9.8255E-04	1.0566E-03	1.4994E-03	1.3042E-04	=	23.37
	pSFS	9.8255E-04	1.0122E-03	1.1930E-03	4.6733E-05		23.44
PV module	CLPSO	2.42661E-03	2.46260E-03	2.54232E-03	2.83008E-05	+	20.66
	BLPSO	2.42520E-03	2.43356E-03	2.47888E-03	1.10969E-05	+	22.85
	ABC	2.44692E-03	2.50414E-03	2.58639E-03	3.85744E-05	+	24.24
	GOTLBO	2.42513E-03	2.44733E-03	2.55767E-03	3.14372E-05	+	20.68
	TLABC	2.42507E-03	2.42647E-03	2.44584E-03	3.99568E-06	+	19.21
	IJAYA	2.42512E-03	2.43335E-03	2.58850E-03	2.97702E-05	+	24.47
	SFS	2.42507E-03	2.42507E-03	2.42507E-03	7.05992E-13	+	22.80
	pSFS	2.42507E-03	2.42507E-03	2.42507E-03	6.62209E-17		22.97



Fig. 12. Convergence graphs of different algorithms for three PV models (a) SDM (b) DDM (c) PV module.

#### Table 8

Comparison of the pSFS algorithm with different population size for three PV models.

		RMSE					
		Min	Mean	Max	SD		
SDM	pSFS-N10	9.8851E-04	1.6630E-03	3.6544E-03	6.1567E-04		
	pSFS-N20	9.8602E-04	1.0072E-03	1.0854E-03	3.2138E-05		
	pSFS-N30	9.8602E-04	9.8602E-04	9.8608E-04	1.1063E-08		
	pSFS-N40	9.8602E-04	9.8603E-04	9.8628E-04	4.7319E-08		
	pSFS-N50	9.8602E-04	9.8666E-04	9.9449E-04	1.6666E-06		
DDM	pSFS-N10	9.8774E-04	1.8195E-03	5.5085E-03	1.0045E-03		
	pSFS-N20	9.8248E-04	1.0946E-03	2.2346E-03	2.3917E-04		
	pSFS-N30	9.8255E-04	1.0122E-03	1.1930E-03	4.6733E-05		
	pSFS-N40	9.8268E-04	1.0118E-03	1.3399E-03	7.5648E-05		
	pSFS-N50	9.8291E-04	1.0411E-03	1.4825E-03	1.0548E-04		
PV module	pSFS-N10	2.42570E-03	1.22912E-02	2.74251E-01	4.94925E-02		
	pSFS-N20	2.42507E-03	2.46508E-03	3.17858E-03	1.51147E-04		
	pSFS-N30	2.42507E-03	2.42507E-03	2.42507E-03	6.62209E-17		
	pSFS-N40	2.42507E-03	2.42507E-03	2.42508E-03	2.53130E-10		
	pSFS-N50	2.42507E-03	2.42507E-03	2.42508E-03	3.13602E-10		

accuracy for all three PV models.

# 4.4. Parameter analysis

To implement an efficient algorithm, it is also very important to analyze the tuning parameters. We analyze the impacts of the population size and the two Gaussian random walks on the performance of the proposed pSFS algorithm.

## 4.4.1. Population size

Table 8 shows the results of the proposed pSFS algorithm with population size NP = 10, 20, 30, 40 and 50 for three PV estimation problems. From the results listed in Table 8, it can be observed that:

 For the SDM, pSFS-NP30 yields the best performance for all four statistical results. Although pSFS-NP20, pSFS-NP40, and pSFS-NP50 also provides the best results in terms of best RMSE,

#### Table 9

Comparison of the pSFS algorithm with two kinds of Gaussian walks.

		RMSE				
		Best	Mean	Worst	SD	
SDM	pSFS-GW1	9.8602E-04	9.8602E-04	9.8608E-04	1.1063E-08	
	pSFS-GW2	9.8602E-04	9.8608E-04	9.8782E-04	3.2842E-07	
DDM	pSFS-GW1	9.8255E-04	1.0122E-03	1.1930E-03	4.6733E-05	
	pSFS-GW2	9.8249E-04	1.0113E-03	1.4070E-03	8.3206E-05	
PV module	pSFS-GW1	2.42507E-03	2.42507E-03	2.42507E-03	6.62209E-17	
	pSFS-GW2	2.42507E-03	2.42507E-03	2.42507E-03	4.98125E-17	

#### Table 10

Model parameters estimated by the pSFS algorithm for three PV modules at different irradiance and temperature of 25 °C.

Parameters	Thin-film ST40	Mono-crystalline SM55	Multi-crystalline KC200GT	
$G = 1000 W/m^2$				
$I_{ph}$ (A)	2.67580	3.45010	8.21688	
$I_{sd}(\mu A)$	1.52880	0.17115	0.00225	
$R_{\rm S}(\Omega)$	1.11323	0.32915	0.34376	
$R_{sh}(\Omega)$	357.59844	483.90046	763.51258	
a	1.50028	1.39575	1.07653	
RMSE	7.34099E-04	1.14621E-03	1.53933E-03	
$G = 800 W/m^2$				
I <sub>ph</sub> (A)	2.13801	2.76038	6.57104	
$I_{sd}(\mu A)$	1.15810	0.14395	0.00098	
$R_{\rm S}(\Omega)$	1.12529	0.33759	0.35678	
$R_{sh}(\Omega)$	332.88893	459.87849	754.80161	
a	1.47315	1.38114	1.03680	
RMSE	7.73905E-04	6.68579E-04	1.64367E-03	
$G = 600 W/m^2$				
I <sub>ph</sub> (A)	1.60481	2.07090	4.93431	
$I_{sd}(\mu A)$	1.44187	0.15551	0.00386	
$R_{\rm S}(\Omega)$	1.11261	0.33050	0.33734	
$R_{sh}(\Omega)$	347.69469	450.06853	743.00159	
а	1.49582	1.38753	1.10402	
RMSE	6.74036E-04	8.23949E-04	1.29767E-03	
$G = 400 W/m^2$				
I <sub>ph</sub> (A)	1.06754	1.38284	3.28785	
$I_{sd}(\mu A)$	1.84875	0.10042	0.00149	
$R_{\rm S}(\Omega)$	1.08058	0.39665	0.35358	
$R_{sh}(\Omega)$	362.51450	427.05044	752.08941	
а	1.52445	1.35199	1.05504	
RMSE	6.30725E-04	7.07608E-04	1.42620E-03	
$G = 200 W/m^2$				
$I_{ph}$ (A)	0.53314	0.69151	1.64615	
$I_{sd}(\mu A)$	1.42968	0.14641	0.00052	
$R_S(\Omega)$	1.18572	0.28662	0.38111	
$R_{sh}(\Omega)$	344.98324	448.21071	690.14660	
а	1.49752	1.38066	1.00324	
RMSE	4.77201E-04	3.20688E-04	1.41847E-03	

## Table 11

Model parameters estimated by pSFS for three PV modules at different temperature and irradiance of 1000  $W/m^2$ .

	Temperature	$I_{ph}$ (A)	$I_{sd}(\mu A)$	$R_S(\Omega)$	$R_{sh}(\Omega)$	а	RMSE
Thin-film ST40	25 °C	2.67580	1.52880	1.11323	357.59844	1.50028	7.34099E-04
	40 °C	2.68091	5.66610	1.12930	364.10973	1.47648	1.32141E-03
	55 °C	2.69197	18.68073	1.14959	295.02177	1.44978	1.82326E-03
	70 °C	2.69233	87.52185	1.12589	367.75322	1.54824	7.77718E-04
Mono-crystalline SM55	25 °C	3.45010	0.17115	0.32915	483.90046	1.39575	1.14621E-03
	40 °C	3.46914	1.14511	0.31310	533.06920	1.41784	3.78881E-03
	60 °C	3.49461	6.90950	0.31871	484.88387	1.40514	3.78039E-03
Multi-crystalline KC200GT	25 °C	8.21688	0.00225	0.34376	763.51258	1.07653	1.53933E-03
	50 °C	8.29531	0.12595	0.33565	953.88989	1.11729	2.74651E-03
	75 °C	8.37766	1.63082	0.34250	790.55822	1.10148	4.47293E-03

their results are not as good as pSFS-NP30 when comparing other performance indices.

- For the DDM, pSFS-NP30 obtains the best results in terms of worst and SD of RMSE.
- For the PV module model, pSFS-NP30 yields the best performance in terms of best, mean, worst and SD of RMSE. Meanwhile, pSFS-NP30 is the only algorithm which gets the minimal SD value.



Fig. 13. Comparisons between the experimental data and estimated data obtained by pSFS for three PV models at different irradiance, using real data from: (a) Thin-film ST40; (b) Mon-crystalline SM55; (c) Multi-crystalline KC200GT.

These results indicate that pSFS with a moderate population size (i.e., pSFS-NP30) has the overall highest estimation accuracy and robustness. In fact, when the population size is too small, the population diversity is poor, which affects the global exploration and estimation accuracy. On the contrary, when the population size is too large, the algorithm needs more computational overheads (i.e., number of function evaluations) to converge. When the maximum number of function evaluations is fixed, too large population size may deteriorate the final performance. For the PV estimation problems, a moderate population size *NP* = 30 is recommended for pSFS.

# 4.4.2. Gaussian random walks

Table 9 shows the results of the pSFS with two different Gaussian walks (GW). From Table 9, it can be found that:

- For the SDM, both pSFS-GW1 and pSFS-GW2 achieve the best results for the best RMSE. However, pSFS-GW1 yields better performance than pSFS-GW2 when considering the mean, worst and SD of RMSE.
- For the DDM, pSFS-GW2 achieves the better results for the best RMSE. pSFS-GW1 yields better performance than pSFS-GW2 when considering the mean, worst and SD of RMSE.
- For the PV module model, both pSFS-GW1 and pSFS-GW2 get the best results in terms of best, mean and worst RMSE. pSFS-GW2 obtains a smaller SD value than pSFS-GW1.

Our results indicate that there is no significant difference between pSFS-GW1 and pSFS-GW2 for the PV estimation problems. According to reports [28], pSFS-GW1 has a faster convergence speed and is more suitable for solving simple problems. pSFS-GW2 is more suitable for complicated problems, which needs more iteration number to converge. From the case study results in this work, pSFS-GW1 is recommended for the PV estimation problems.

# 5. Validation of pSFS with survey experimental data

The above comparison studies demonstrate that pSFS has the highest estimation accuracy and robustness for parameter estimation for PV models. In this section, the practical use of pSFS is further examined by using experimental data from three different PV modules in the manufacturer data sheet: Thin-film ST40, Monocrystalline SM55 and Multi-crystalline KC200GT [14].

The experimental *I*–*V* data are extracted directly from the data sheet of five different irradiation levels at different temperature levels. The searching ranges for the five unknown parameters are:  $I_{ph} \in [0, 2I_{sc}]$  (A),  $I_{sd} \in [0, 100](\mu A)$ ,  $R_s \in [0, 2](\Omega)$ ,  $R_{sh} \in [0, 5000](\Omega)$  and  $a \in [1, 4]$ . The short circuit current  $I_{sc}$  at non-standard condition is calculated by Eq. (17):



Fig. 14. Comparisons between the experimental data and estimated data obtained by pSFS for three PV models at different temperatures, using real data from: (a) Thin-film ST40; (b) Mon-crystalline SM55; (c) Multi-crystalline KC200GT.

$$I_{sc}(G,T) = I_{sc\_STC} \frac{G}{G_{STC}} + \alpha(T - T_{STC})$$
<sup>(20)</sup>

where *G* and *T* are the irradiation and the temperature levels, respectively;  $G_{STC} = 1000 \text{W/m}^2$  and  $T_{STC} = 25 \text{ °C}$ ;  $I_{sc_{-}STC}$  is short circuit current at standard test condition.

Tables 10 and 11 present the optimal model parameters extracted by the proposed pSFS algorithm for three PV models under different irradiation and temperature levels, respectively. Furthermore, to verify the accuracy of the model parameters, the I-V characteristics of the three different PV modules under different irradiation and temperature levels are plotted in Figs. 13 and 14, respectively.

From the results in Tables 10 and 11 the optimal model parameters extracted by the proposed pSFS are in close with those by MPSO [14], and low RMSE values are achieved at different irradiation and temperature levels. From Figs. 13 and 14, the model curves calculated from the extracted model parameters match well with the experimental data under various environment conditions, i.e., at different irradiance and temperature levels. These observations indicate that the proposed pSFS approach can accurately extract the model parameters when the PV systems are under certain mismatch conditions such as partial shading.

# 6. Conclusion

In this work, we have proposed a perturbed stochastic fractal search (pSFS) algorithm to accurately and robustly extract the PV model parameters. The proposed pSFS algorithm employs diffusion and updating processes inspired from random fractal properties. Meanwhile, a chaotic elitist perturbation strategy is also employed to perform self-adaptive local search around the best solution in each generation. The proposed pSFS algorithm is evaluated on PV parameter estimation problems with different diode models. Also, the performance of pSFS is compared with the basic SFS and six non-SFS algorithms. The following conclusions can be drawn from the numerical results.

- pSFS achieves high parameter estimation accuracy for different PV models. The statistical results demonstrate that pSFS has the best results in terms of the optimal, the mean and the worst RMSE values. Moreover, for the SDM and DDM, the absolute current error of pSFS is smaller than 0.3%. For the PV module, the absolute current error of pSFS is smaller than 8%.
- pSFS also has superiority in robustness compared with the recently developed algorithms including SFS, IJAVA, TLABC and GOTLBO. For the SDM, pSFS achieves the smallest SD value, the value of which is smaller than 1e-7. For the PV module, pSFS achieves the smallest SD value less than 1e-16.

- pSFS performs better than the other compared algorithms under comparison according to the Wilcoxon rank sum test.
- pSFS has a reasonably fast convergence speed, and keeps a good balance between global exploration and local exploitation during the searching process by employing two search operators.
- pSFS is robust to various environment conditions. The tests on three real PV modules at different irradiance and temperature levels show that pSFS achieves accurate results under all

#### Algorithm 1

Perturbed stochastic fractal search algorithm.

1: Initialize the population $P_i(i = 1, 2, \dots, NP)$				
2: Evaluate the fitness of all the particles;				
3: while the terminal condition is not met do				
4: %% Diffusion process %%				
5: <b>for</b> Each particle <i>P<sub>i</sub></i> <b>do</b>				
6: <b>for</b> $k = 1$ to MDN <b>do</b>				
: Generate a new point $GP_k$ using the Gaussian walk;				
Evaluate the fitness of $GP_k$ ;				
9: end forv				
10: Select the best point $GP_{hest}$ from $\{GP_1, GP_2, \dots, GP_k\}$ ;				
11: <b>if</b> $GP_{hest}$ is better than $P_i$ <b>then</b>				
12: $P_i = GP_{hest}$				
13: end if				
14: end for				
15: %% First updating process %%				
16: Rank all particles from best to worst;				
17: <b>for</b> Each particle $P_i$ <b>do</b>				
18: Generate a new point $P'_i$ using Eq. (12);				
19: <b>if</b> $P'_i$ is better than $P_i$ <b>then</b>				
20: $P_i = P_i';$				
21: end if				
22: end for				
23: %% Second updating process %%				
24: <b>for</b> Each particle $P_i$ <b>do</b>				
25: <b>if</b> $\gamma_i \leq rand(0,1)$ <b>then</b>				
26: Generate a new point $P'_i$ using Eq. (14);				
27: <b>if</b> $P'_i$ is better than $P_i$ <b>then</b>				
28: $P_i = P_i';$				
29: end if				
30: end if				
31: end for				
32: %% Chaotic elitist perturbation %%				
33: Get the best particle <i>P</i> <sub>best</sub> ;				
34: Generate a new point <i>P</i> <sup>*</sup> using Eq. (15);				
35: <b>if</b> $P^*$ is better than the worst particle $P_{worst}$ <b>then</b>				
36: $P_{worst} = P^*;$				
37: end if				
38: end while				

#### circumstances.

The proposed pSFS gains the above benefits mainly from two aspects. The first is the diffusion and updating processes from the basic SFS, which helps to achieve balance between global and local search. The second is the chaotic elitist perturbation strategy, which further enhances the estimation accuracy and robustness. In the future, we are interested in applying the pSFS algorithm to modeling of more complicated PV systems such as integral and fractional order dynamic PV system models. This novel algorithm can be applied to wider energy optimization problems, such as economic dispatch and unit commitment.

### **Declaration of competing interest**

The authors have no conflict of interest, financial or otherwise.

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#### Appendix 1. Pseudocode of the pSFS algorithm

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