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Hybridizing cuckoo search algorithm with biogeography-based optimization for estimating photovoltaic model parameters

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ABSTRACT

Accurate estimation of model parameters plays a very important role in modeling solar photovoltaic (PV) systems. In the past decade, meta-heuristic algorithms (MHAs) have been used as promising methods for solving this problem. However, due to the non-linearity and multi-modality existed in the problem, many HMAs may present unsatisfactory performance due to their premature or slow convergence. Therefore, how to develop algorithms efficiently balancing the exploration and exploitation, and identify the PV model parameters accurately and reliably is still a big challenge. In this paper, to improve parameter estimation of solar photovoltaic models, we propose a hybrid meta-heuristic algorithm, called biogeography-based heterogeneous cuckoo search (BHCS) algorithm. Specifically, BHCS hybridizes cuckoo search (CS) and biogeography-based optimization (BBO) by employing two search strategies, namely heterogeneous cuckoo search and biogeography-based discovery. The cooperation of the two strategies helps BHCS achieve an efficient balance between exploration and exploitation. Furthermore, the proposed algorithm is applied to solve four parameters estimation problems of different photovoltaic models, including single diode model, double diode model and two PV panel modules. Experimental results demonstrate that BHCS has very competitive performance in terms of accuracy and reliability compared with CS, BBO and several other meta-heuristic algorithms.

1. Introduction

Today, due to several reasons such as energy crisis, environmental concerns, climate change, and political issues, the use of renewable energy sources is gradually increasing. Among renewable energy resources, solar energy is considered one of the most promising renewable energy in the near future, since it is free, abundant, and environmental friendly (Mojallizadeh and Badamchizadeh, 2016). In most part of the continents, large-scale photovoltaic (PV) plants have been commonly used for power generation (Mathew et al., 2018). Before its installation and practical implementation, the solar PV system should be optimized, and this can be assured by modeling, identification, and simulation of the PV systems.

Generally, the modeling of solar PV systems includes two steps: (1) mathematical model formulation, and (2) PV parameter estimation. Based on the *I-V* curves, mathematical models are established to describe the behavior of solar cells. Single diode model (SDM) and double diode model (DDM) are two most popular models (Gong and Cai, 2013; Chen et al., 2016). After selecting the PV model, it is necessary to identify the model parameters based on experimental current-voltage data. There are five and seven unknown parameters in the SDM and DDM respectively, which need to be extracted as accurately as possible.

The current parameter estimation techniques for solar PV models can be divided into analytical methods and numerical methods. Analytical methods mainly use the information given in the manufacturers data sheet such as open circuit voltage, short circuit current, maximum power voltage and maximum power current to model *I-V* characteristics (Ram et al., 2017). This method is easy to implement, but the accuracy greatly relies on the values of selected points, and inaccurate values may lead to a solution with significant error in some cases.

In order to overcome the disadvantages of the analytical methods, researchers have explored the numerical methods which takes all measured *I-V* data into consideration, so that a higher confidence level can be obtained. Numerical methods fall into two categories: deterministic and meta-heuristic. Deterministic approaches mainly include conventional methods such as Newton-Raphson method (Easwarakhanthan et al., 1986), Lambert W-functions (Ortiz-Conde et al., 2006), and the iterative curve fitting (Chan et al., 1986). The use of the deterministic approaches should satisfy several model restrictions

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Table 1
Meta-heuristic algorithms used for PV parameter estimation.

Authors	Algorithm	Remarks
Zagrouba et al. (2010)	Genetic algorithm (GA)	GA overcomes the problem of getting trapped in local minima in the case of non-convex optimization
El-Naggar et al. (2012)	Simulated annealing (SA)	SA oversimplifies assumptions such as continuity, convexity, and differentiability required by traditional estimation techniques
Jordehi (2016b)	Time varying acceleration coefficients PSO (TVACPSO)	TVACPSO dynamically adjusts its personal and social acceleration coefficients, and offers more accurate parameters than conventional PSO, TLBO, ICA, GWO, WCA, PS and Newton algorithm
Merchaoui et al. (2018)	Mutated PSO (MPSO)	MPSO employs adaptive mutation to alleviate the premature convergence problem. Experimental results prove that the MPSO algorithm achieves higher accuracy
Jordehi (2018)	Enhanced leader PSO (ELPSO)	ELPSO enhances the leader particle through a five-staged successive mutation strategy. It outperforms conventional PSO, GA, ABC, BSA, PS and Newton algorithm
Nunes et al. (2018)	Guaranteed convergence PSO (GCPSO)	GCPSO can find highly accurate solutions while demanding a reduced computational cost
Ishaque et al. (2012)	Penalty-based differential evolution (P-DE)	P-DE consistently converges to the global optimum values very rapidly, and outperforms SA, GA, and PSO
Gong and Cai (2013)	Repaired adaptive DE (RADE)	Experimental results indicate the superiority of RADE in terms of solution quality, success rate, and convergence speed
Jiang et al. (2013)	Improved adaptive DE (IADE)	IADE automatically adjusts its control parameters in the search process. IADE provides better performance than PSO, GA, conventional DE, SA, and an analytical method
Askarzadeh and Rezazadeh (2012)	Harmony search (HS)	HS has advantages such as simple concept, easy implementation and high performance. Results achieved by HS variants are quite promising
Niu et al. (2014a)	Simplified teaching-learning based optimization (STLBO)	STLBO has the advantages of being easy to understand and simple to implement. It performs more effectively than basic TLBO and other reported results
Chen et al. (2016)	Generalized oppositional TLBO (GOTLBO)	GOTLBO employs generalized opposition-based learning to accelerate its convergence speed. GOTLBO is very competitive compared with basic TLBO and other parameter identification techniques
Yu et al. (2017a)	Self-adaptive TLBO (SATLBO)	SATLBO self-adaptively selects different learning phases based on their knowledge level
Oliva et al. (2014)	Artificial bee colony (ABC)	ABC exhibits no sensitivity to noisy conditions and high performance in terms of robustness and accuracy
Askarzadeh and Rezazadeh (2013)	Artificial bee swarm optimization (ABSO)	ABSO yields better results than chaos PSO, GA, PS, SA, and HS
Niu et al. (2014b)	Biogeography-based optimization with mutation strategies (BBO-M)	BBO-M incorporates the mutation strategies, and gives comparable performance to basic BBO and other reported results
Hasanien (2015)	Shuffled frog leaping algorithm (SFLA)	SFLA is verified by the simulation results under different environmental conditions, and compared with GA and iteration approach
Ma et al. (2013)	Cuckoo search (CS)	CS is capable of obtaining the parameters with extremely high accuracy under different operating conditions
Alam et al. (2015)	Flower pollination algorithm (FPA)	FWA is simple, very efficient, and outperforms GA and PSO
Ram et al. (2017)	Bee pollinator FPA (BPFPA)	BPFPA combines FPA with honeybee search algorithm. It shows faster execution speed compared with GA, PS, HS, FPA and ABSO
Wu et al. (2017)	Improved ant lion optimizer (IALO)	IALO overcomes slow convergence and premature convergence of basic ALO. Comparisons show IALO is better than ALO, PSO, and bat algorithm
Guo et al. (2016)	Cat swarm optimization (CSO)	Results show CSO can be an effective tool for parameter identification problems of solar cell models
Allam et al. (2016)	Moth-flame optimization (MFO)	MFO can achieve optimal solution with the shortest execution compared with hybrid evolutionary algorithm (DEIM) and FPA
Yu et al. (2017b)	Improved JAYA (IJAYA)	IJAYA does not require algorithm-specific parameter. IJAYA exhibits superior performance in terms of accuracy and reliability
Kler et al. (2017)	Evaporation rate based Water cycle algorithm (ER-WCA)	ER-WCA is investigated under varying temperature and irradiation conditions. Experiments show ER-WCA is a promising optimization technique for PV cell/module identification
Beigi and Maroosi (2018)	Hybrid firefly algorithm and pattern search (HFAPS)	HFAPS combine pattern search as a local optimization method with firefly algorithm to improve the PV parameter identification
Yu et al. (2018)	Multiple learning backtracking search algorithm (MLBSA)	MLBSA employs multiple learning strategy and chaotic local search. Experimental and statistical analyses verify the superiority of MLBSA in terms of accuracy, reliability, and computational efficiency
Oliva et al. (2017)	Chaotic whale optimization algorithm (CWOA)	CWOA uses the chaotic maps to compute and automatically adapt the internal parameters. Experimental results support the improved performance of CWOA regarding accuracy and robustness
Xiong et al. (2018a)	Improved whale optimization algorithm (IWOA)	IWOA employs two prey searching strategies to effectively balance the local exploitation and global exploration. IWOA is significantly better than three advanced WOA variants and the reported results
Xiong et al. (2018b)	Hybrid DE with WOA (DE/WOA)	DE/WOA combines the exploration of DE with the exploitation of WOA. DE/WOA performs significantly better than the original DE, WOA, and five advanced variants of them

such as differentiability and convexity. Meanwhile, they are highly sensitive to the initial values, thus leading to be trapped in local optimal solutions.

Meta-heuristic algorithms (MHAs) have also been widely used for PV parameter estimation in the last decade (Ma et al., 2016). Most of MHAs are probabilistic, population-based optimization algorithms that commonly take inspiration from nature. They do not require convexity, continuity or differentiability of objective functions, and have proved to be very efficient in solving difficult engineering optimization problems (Jordehi, 2016a). Due to these advantages, different MHAs have been applied for solving PV parameter estimation problems, such as genetic algorithms (GA) (Zagrouba et al., 2010), particle swarm optimization (PSO) (Chen et al., 2018b), differential evolution (DE) (Xu et al., 2018a,b), simulated annealing (SA) (El-Naggar et al., 2012), harmony search (HS) (Askarzadeh and Rezazadeh, 2012), teaching-learning based optimization (TLBO) (Chen et al., 2018a), artificial bee colony (ABC) (Oliva et al., 2014), cuckoo search (CS) (Ma et al., 2013) and biogeography-based optimization (BBO) (Niu et al., 2014b). A summary of different MHAs for PV parameter estimation is presented in Table 1.

Although MHAs can achieve global solutions with higher probabilities in comparison with deterministic ones, they still have some critical limits. For example, PSO and BBO have fast convergence speed, but they are easily to get trapped into local optimal values due to their elitist mechanisms. DE has two performance sensitive parameters, i.e., scaling factor and crossover rate, which need to be carefully tuned. SA and HS use only one search agent, they are very sensitive to the initialization. ABC and CS are good at global exploration, but they suffer from slow convergence. On the other hand, since the parameter estimation of PV models is a multimodal problem containing many local optima, many of these MHAs may present unsatisfactory performance in the application over multi-modal objective functions. Therefore, how to develop a meta-heuristic algorithm efficiently balancing the global and local search abilities, and estimate the PV model parameters accurately and reliably is still a big challenging task.

Recently, developing hybrid meta-heuristic algorithms (HMAs) has been gaining increasing attentions for researchers in both scientific and engineering areas (Beigvand et al., 2017; Ghasemi et al., 2016; Mehdinejad et al., 2016; Zhang et al., 2017; Ting et al., 2015; Chen et al., 2018b). By combining two or more meta-heuristics, HMAs can improve the performance of individual algorithm, and they seem to be more effective and attractive in solving complex optimization problems.

Cuckoo search (CS) and biogeography-based optimization (BBO) are two meta-heuristic algorithms with different search mechanisms. CS employs Levy flights to generate step size and search the solution space, whereas BBO uses the migration operator to generate new solutions. The internal search mechanisms results in different characteristics of the two algorithms, i.e., CS is good at global exploration while BBO favors local exploitation. Based on these considerations, we are inspired to develop a novel HMA based on CS and BBO for identifying the solar PV parameters. The main innovations of this paper are listed as follow:

(1) Biogeography-based heterogeneous cuckoo search (BHCS) algorithm is developed for PV parameter estimation. To the best of our knowledge, it is the first attempt to design a hybrid algorithm based on CS and BBO.
(2) The proposed algorithm employs a heterogeneous cuckoo search strategy and a biogeography-based discovery operator to achieve a more efficient balance between exploration and exploitation.
(3) The proposed algorithm is applied to solve four different PV parameters estimation problems. The obtained results of BHCS are compared with well-established algorithms to confirm its effectiveness.

The rest of the paper is arranged as follows: Section 2 describes problem formulation of PV parameters estimation. Section 3 introduces the principles of CS, BBO, and develops our proposed BHCS algorithm. Section 4 presents the experimental results and comparisons. Section 5 concludes this paper.

2. Photovoltaic models and problem formulation

2.1. Solar cells

Due to its good simplicity and accuracy, single diode model (SDM) is widely used to describe the static characteristic of solar cell. The equivalent circuit of the SDM is described in Fig. 1. In this model, the output current of solar cell can be formulated as below (AlRashidi et al., 2011; Gong and Cai, 2013):

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

where I_L is the cell output current, I_{ph} is the photo generated current, I_d is the diode current, and I_{sh} is the shunt resistor current. According to Shockley equation, Eq. (1) can be rewritten as shown in Eq. (2):

$$I_L = I_{ph} - I_{sd}\cdot\left[\exp\left(\frac{V_L + R_S\cdot I_L}{a\cdot V_t}\right) - 1\right] - \frac{V_L + R_S\cdot I_L}{R_{sh}} \tag{2}$$

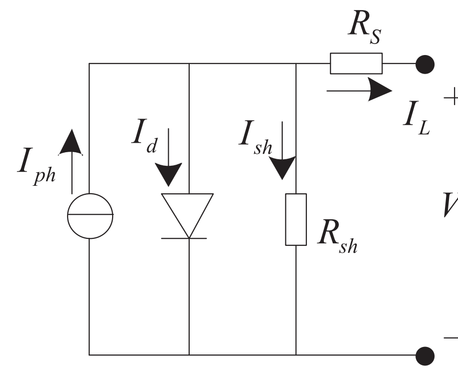

Fig. 1. The single diode model.

where V_L is the cell output voltage, I_{sd} is the reverse saturation current of the diode, R_S is the series resistance, R_{sh} denotes the shunt resistance, a is the diode ideality constant, and V_t is the junction thermal voltage calculated using Eq. (3):

$$V_t = \frac{kT}{q} \tag{3}$$

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

In the SDM, there are five parameters (i.e. I_{ph}, I_{sd}, R_S, R_{sh} and a) that need to be estimated from the *I-V* data of solar cell.

The SDM ignores the effect of recombination current loss in the depletion region, when considering this loss, a more precise model namely double diode model (DDM) can be obtained. The equivalent circuit of the DDM is shown in Fig. 2. In this model, the cell output current can be formulated as below (AlRashidi et al., 2011; Gong and Cai, 2013):

$$\begin{aligned} I_L &= I_{ph} - I_{d1} - I_{d2} - I_{sh} \\ &= I_{ph} - I_{sd1}(\exp(\tfrac{V_L + I_L R_S}{a_1 V_t}) - 1) - I_{sd2}(\exp(\tfrac{V_L + I_L R_S}{a_2 V_t}) - 1) - \tfrac{V_L + I_L R_S}{R_{sh}} \end{aligned} \tag{4}$$

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

In the DDM, there are seven parameters (i.e. I_{ph}, I_{sd1}, I_{sd2}, R_S, R_{sh}, a_1 and a_2) that need to be extracted from the IV data of the solar cell.

2.2. PV panels

A PV panel is composed of M cells connected in series. In the PV panel, it is common to use the SDM for each element, and *I-V* relation of PV panel can be formulated as below (Oliva et al., 2017):

$$I_L = I_{ph} - I_{sd}\cdot\left[\exp\left(\frac{V_L + M\cdot R_S\cdot I_L}{a\cdot M\cdot V_t}\right) - 1\right] - \frac{V_L + M\cdot R_S\cdot I_L}{M\cdot R_{sh}} \tag{5}$$

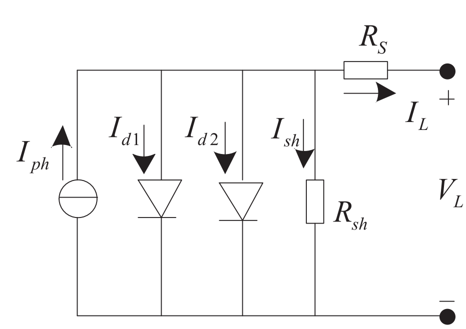

Fig. 2. The double diode model.

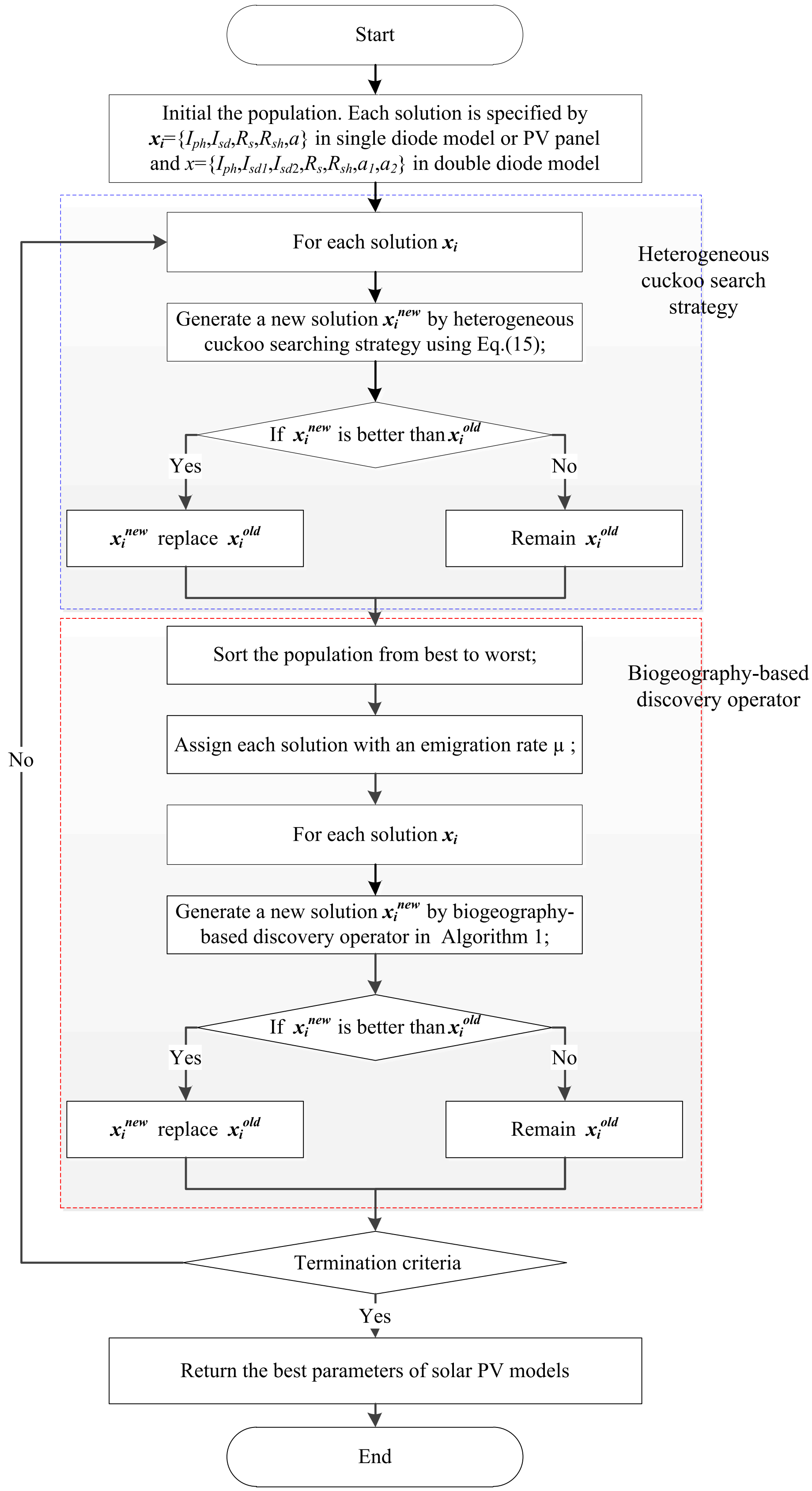

Fig. 3. Flowchart of the solar PV parameter estimation process by BHCS.

Table 2
Parameters range of the single and double diode models, and PV panel modules.

Parameter	RTC France single and double diode		STM6-40/36 module		STP6-120/36 module	
	Lower bound	Upper bound	Lower bound	Upper bound	Lower bound	Upper bound
I_{ph} (A)	0	1	0	2	0	8
I_{sd}, I_{sd1}, I_{sd2} (μA)	0	1	0	50	0	50
R_S (Ω)	0	0.5	0	0.36	0	0.36
R_{sh} (Ω)	0	100	0	1000	0	1500
a, a_1, a_2	1	2	1	60	1	50

In the above PV panel model, there are five parameters (i.e. I_{ph}, I_{sd}, R_S, R_{sh} and a) that need to be estimated from the *I-V* data of solar cell.

2.3. Problem formulation

The main objective of solar PV parameter estimation is to minimize the difference between the experimental data and simulated ones, so that the optimal values of these unknown model parameters can be extracted. The objective function is often defined as the overall root mean square error (RMSE) (Gong and Cai, 2013; Muhsen et al., 2015). Hence, the objective function is formulated as below:

$$\text{RMSE}(\boldsymbol{x}) = \sqrt{\frac{1}{N}\sum\nolimits_{k=1}^{N} f(V_L, I_L, \boldsymbol{x})^2} \tag{6}$$

where N is the number of experimental data, and $\boldsymbol{x}$ is solution vector.

In Eq. (6), for the SDM,

$$\begin{cases} f_{SDM}(V_L, I_L, \boldsymbol{x}) = I_{ph} - I_{sd}(exp(\frac{V_L + I_L R_S}{aV_t}) - 1) - \frac{V_L + I_L R_s}{R_{sh}} - I_L \\ \boldsymbol{x} = \{I_{ph}, I_{sd}, R_S, R_{sh}, a\} \end{cases} \tag{7}$$

For the DDM,

$$\begin{cases} f_{\text{DDM}}(V_L, I_L, \boldsymbol{x}) = I_{ph} - I_{sd1}(exp(\frac{V_L + I_L R_S}{a_1 V_t}) - 1) \\ \qquad - I_{sd2}(exp(\frac{V_L + I_L R_S}{a_2 V_t}) - 1) - \frac{V_L + I_L R_s}{R_{sh}} - I_L \\ \boldsymbol{x} = \{I_{ph}, I_{sd1}, I_{sd2}, R_S, R_{sh}, a_1, a_2\} \end{cases} \tag{8}$$

For the PV panel,

$$\begin{cases} f_{Panel}(V_L, I_L, \boldsymbol{x}) = I_{ph} - I_{sd}(exp(\frac{V_L + MI_L R_S}{aMV_t}) - 1) - \frac{V_L + MI_L R_s}{MR_{sh}} - I_L \\ \boldsymbol{x} = \{I_{ph}, I_{sd}, R_S, R_{sh}, a\} \end{cases} \tag{9}$$

The values of I_L and V_L are experimentally collected from *I-V* measurements of the solar cell models. Thus, the parameter estimation is a process that minimizes the objective function RMSE($\boldsymbol{x}$) by adjusting the solution vector $\boldsymbol{x}$.

3. Methodologies

This section presents the principles of cuckoo search (CS), biogeography-based optimization (BBO), and develops our biogeography-based heterogeneous cuckoo search (BHCS) algorithm.

3.1. Cuckoo search

Cuckoo search (CS) is a nature-inspired meta-heuristic algorithm, inspired by the breeding parasitism behavior of the cuckoo bird (Yang and Deb, 2009). The female cuckoo lays her eggs in nests of other host birds, and the host birds unwittingly raise her brood. If a cuckoo egg in a nest is discovered by the host bird, then the host bird will either throw it out or abandon the nest and start her own brood elsewhere (Ding et al., 2015).

Table 3
Parameter settings for the compared algorithms and BHCS.

Algorithm	Parameter settings
ABC	$NP = 50$, $limit = 200$
TLBO	$NP = 50$
TLABC	$NP = 50$, $limit = 200$, $F = rand(0, 1)$
CLPSO	$NP = 40$, $w = 0.9 \sim 0.2$, $c = 1.496$, $m = 5$
BLPSO	$NP = 40$, $w = 0.9 \sim 0.2$, $c = 1.496$, $I = E = 1$
RCBBOG	$NP = 50$, $I = E = 1$
BlendedBBO	$NP = 50$, $I = E = 1$
DE/BBO	$NP = 50$, $F = rand(0.1, 1)$, $CR = 0.9$, $I = E = 1$
CS	$NP = 20$, $pa = 0.25$, $\alpha = 0.01$, $\beta = 1.5$
ACS	$NP = 20$, $pa = 0.25$
NoCuSa	$NP = 20$, $pa = 0.3$, $\alpha = 1.1$, $\beta = 1.7$, $\delta = 1.6$
BHCS	$NP = 20$, $pa = 0.3$, $\alpha = 1.1$, $\beta = 1.7$, $\delta = 1.6$, $I = E = 1$

In CS, each egg of host birds represents a solution, and a cuckoo egg represents a new candidate solution. Also, three rules for CS are described as follows (Yang and Deb, 2010): (1) each cuckoo lays one egg (a candidate solution) at a time, and dumps it in a host nest; (2) the nests with high quality of egg (better solution) will be transferred to the next generation; and (3) when the number of available host nests is fixed, and the host bird can discover an alien egg with a probability.

Assume $\boldsymbol{x}_i = (x_{i1}, x_{i2}, \cdots, x_{iD})$ is the position of the i-th egg (solution), then the new solution $\boldsymbol{x}_i^{new}$ can be generate by Levy flights as below:

$$\begin{aligned} \boldsymbol{x}_i^{new} &= \boldsymbol{x}_i^{old} + \alpha(\boldsymbol{x}_i - \boldsymbol{x}_g) \oplus \text{Levy}(\beta) \\ &= \boldsymbol{x}_i^{old} + \tfrac{0.01u}{|v|^{1/\beta}}(\boldsymbol{x}_i - \boldsymbol{x}_g) \end{aligned} \tag{10}$$

where product ⊕ means entry-wise multiplications; β is Levy flight exponent; $\alpha > 0$ is a parameter determining the step size of a cuckoo; $\boldsymbol{x}_g$ is the best solution in the current population; u and v are random numbers subject to the normal distribution:

$$u \sim N(0, \sigma_u^2), \; v \sim N(0, \sigma_v^2) \tag{11}$$

$$\sigma_u = \left[\frac{\sin(\pi\beta/2)\cdot\Gamma(1+\beta)}{2^{(\beta-1)/2}\beta\cdot\Gamma(\frac{1+\beta}{2})}\right]^{1/\beta}, \; \sigma_v = 1 \tag{12}$$

where $\Gamma(\cdot)$ stands for a Gamma function, while β is used to control the value of σ_u.

CS also employs a discovery operator, which replaces the discovered nests with probability pa. The update equation in this operator is defined as below:

$$x_{ij}^{new} = \begin{cases} x_{ij}^{old} + rand\cdot(x_{r1,j}(k) - x_{r2,j}(k)) & if \;\; P > pa \\ x_{ij}^{old}(k) & else \end{cases} \tag{13}$$

where x_{ij}^{new} is the j-th element of the i-th solution $\boldsymbol{x}_i^{new}$;$x_{r1,j}$ and $x_{r2,j}$ are the j-th elements of two solutions $\boldsymbol{x}_{r1}$ and $\boldsymbol{x}_{r2}$, where $r1$ and $r2$ are two distinct integer in the interval [1, NP], NP is the population size; pa is the discovery probability; $rand$ and P are random real numbers in the interval [0, 1].

Based on the above descriptions, the pseudocode of CS is shown in Appendix A.

3.2. Biogeography-based optimization

Biogeography-based optimization (BBO) is a meta-heuristic algorithm inspired by island biogeography science (Simon, 2008). In BBO, each candidate solution is regarded as a habitat with a habitat suitability index (HSI), which is used to measure the quality of the individual. A solution can be represented by a set of suitability index variables (SIV). BBO employs two operators namely migration and mutation to evolve the population, and migration is the core operator. In the migration process, high HSI solutions share their features with

Table 4
Statistical results of the RMSE values achieved by different algorithms for the single diode model of R.T.C. France solar cell.

Algorithm	RMSE					
	Min	Median	Mean	Max	SD	Sig.
ABC	9.88148E−04	1.07990E−03	1.12125E−03	1.41740E−03	1.19818E−04	+
TLBO	9.87332E−04	1.02506E−03	1.04761E−03	1.23579E−03	6.58940E−05	+
TLABC	9.86022E−04	9.88004E−04	9.98523E−04	1.03970E−03	1.86022E−05	+
CLPSO	9.92075E−04	1.04638E−03	1.05871E−03	1.18724E−03	5.01090E−05	+
BLPSO	1.12390E−03	1.40625E−03	1.40911E−03	1.70774E−03	1.61610E−04	+
RCBBOG	1.08173E−03	1.82258E−03	1.82524E−03	3.27762E−03	5.90759E−04	+
BlendedBBO	9.88117E−04	1.58674E−03	1.63375E−03	2.44689E−03	4.02017E−04	+
DEBBO	9.86333E−04	1.26683E−03	1.30305E−03	1.83895E−03	2.48521E−04	+
CS	2.01185E−03	4.00093E−03	7.60819E−03	6.09130E−02	1.10512E−02	+
ACS	9.93886E−04	1.90799E−03	1.82633E−03	2.44805E−03	3.90975E−04	+
NoCuSa	**9.86022E−04**	**9.86022E−04**	**9.86022E−04**	**9.86022E−04**	2.99346E−17	=
BHCS	**9.86022E−04**	**9.86022E−04**	**9.86022E−04**	**9.86022E−04**	**2.61254E−17**	

The best results are highlighted in bold.

Table 5
Model parameters estimated by different algorithms for the single diode model of R.T.C. France solar cell.

Item	I_{ph} (A)	I_{sd} (μA)	R_S (Ω)	R_{sh} (Ω)	a	RMSE	Rank
ABC	0.76085	0.33016	0.03629	53.59884	1.48339	9.88148E−04	7
TLBO	0.76074	0.32938	0.0363	54.3015	1.48314	9.87332E−04	5
TLABC	0.76078	0.32302	0.03638	53.71636	1.48118	9.86022E−04	1
CLPSO	0.76064	0.33454	0.03623	56.0342	1.48469	9.92075E−04	8
BLPSO	0.76063	0.42518	0.03523	62.58528	1.5094	1.12390E−03	11
RCBBOG	0.76146	0.33781	0.03604	49.51049	1.48575	1.08173E−03	10
BlendedBBO	0.76076	0.33409	0.03625	54.67373	1.48458	9.88117E−04	6
DE/BBO	0.76078	0.31885	0.03643	53.36786	1.47988	9.86333E−04	4
CS	0.76048	0.36015	0.03492	43.84232	1.4929	2.01185E−03	12
ACS	0.76089	0.30381	0.03662	51.59775	1.47504	9.93886E−04	9
NoCuSa	0.76078	0.32302	0.03638	53.71853	1.48118	9.86022E−04	1
BHCS	0.76078	0.32302	0.03638	53.71852	1.48118	9.86022E−04	1

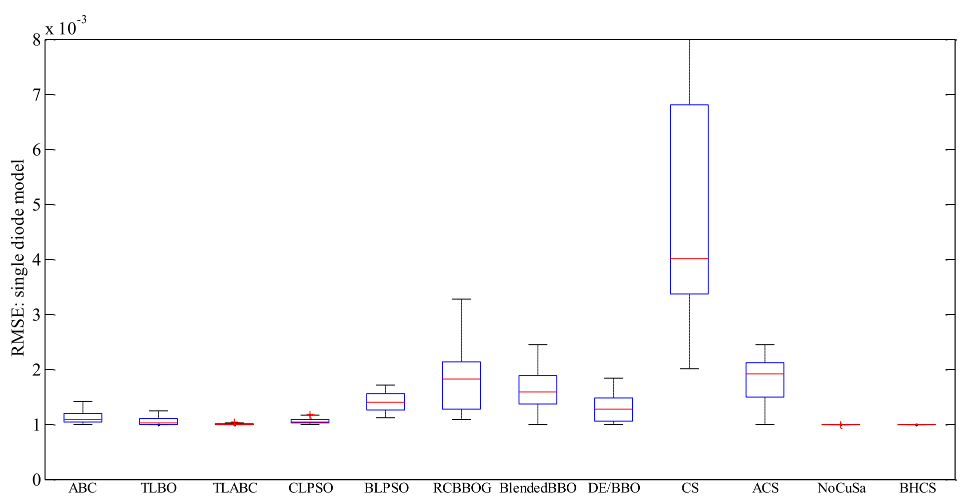

Fig. 4. Boxplot of RMSE values achieved by different algorithms for the single diode model of R.T.C. France solar cell.

low HSI ones, and low HIS solutions accept in a lot of new features from high HIS solutions.

In BBO, a population of NP habitats (solutions) is randomly initialized. In each generation, the population will be sorted from best to worst, and each solution $\boldsymbol{x}_i$ is assigned with an immigration rate λ and an emigration rate μ:

$$\begin{cases} \lambda_i = I(1 - \frac{S_i}{NP}) \\ \mu_i = E\frac{S_i}{NP} \end{cases} \tag{14}$$

where I and E are the maximum immigration and emigration rates, respectively, and $I = E = 1$; S_i is the number of species of the habitats and $S_i = NP - i$. Accordingly, the S_i value of the best solution is $NP - 1$, the S_i value of the second best solution is $NP - 2$, and the S_i value of the worst solution is 0.

The migration modifies solutions by mixing features within the population. After migration, BBO also use a mutation operator to modify solutions. The pseudo-code of the BBO is described in **Alppendix 2**.

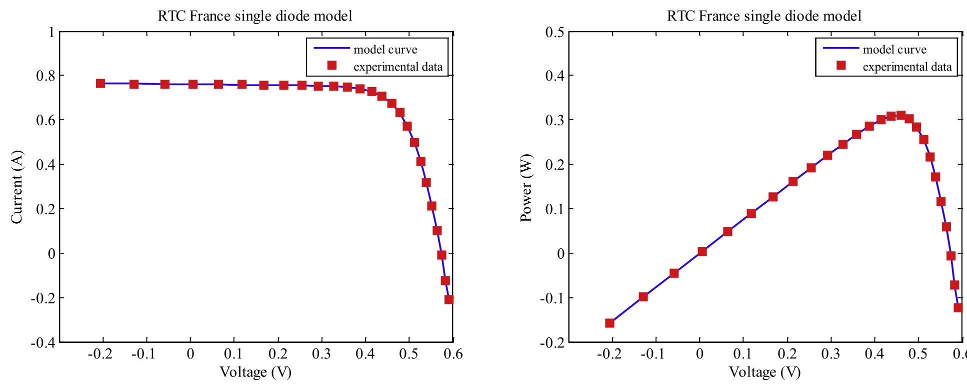

Fig. 5. Comparisons between the experimental data and simulated data obtained by BHCS for the single diode model of R.T.C. France solar cell: I-V and P-V characteristics.

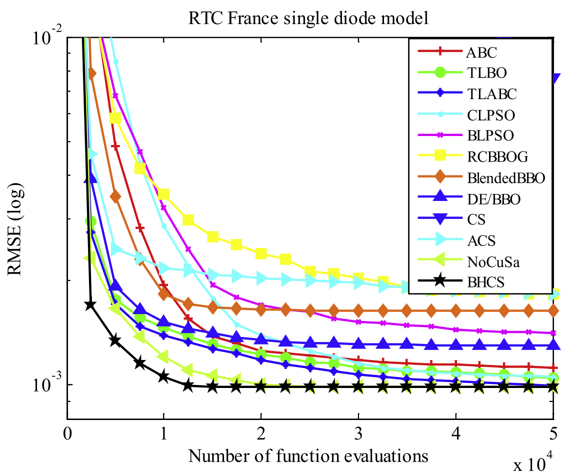

Fig. 6. Convergence graph of different algorithms for the single diode model of R.T.C. France solar cell.

3.3. Proposed biogeography-based heterogeneous cuckoo search algorithm

As stated above, CS mainly employs the Levy flights to generate new solutions, which is good at exploring the wide area. By contrast, BBO uses migration operator to produce new solutions, which is good at exploiting a local area. In this paper, we develop a hybrid meta-heuristic algorithm called biogeography-based heterogeneous cuckoo search (BHCS) algorithm, aiming at combining both the exploration of CS and exploitation of BBO. The proposed BHCS has two core optimization stages, namely heterogeneous cuckoo search and biogeography-based discovery. The details of these two stages are described as follows.

3.3.1. Heterogeneous cuckoo search strategy

In the first optimization stage, BHCS uses heterogeneous cuckoo search strategy based on the levy flight and quantum mechanism. This strategy is firstly presented in Ding et al. (2015), Cheung et al. (2017) and inspired from quantum mechanism. The new update rules of heterogeneous cuckoo search are described as below (Ding et al., 2015; Cheung et al., 2017):

$$\boldsymbol{x}_i^{new} = \begin{cases} \boldsymbol{x}_i^{old} + \alpha\cdot(\boldsymbol{x}_i - \boldsymbol{x}_g)\oplus \text{Levy}(\beta) & \frac{2}{3} < sr \leqslant 1 \text{ (a)} \\ \bar{\boldsymbol{x}} + L\cdot(\bar{\boldsymbol{x}} - \boldsymbol{x}_i^{old}) & \frac{1}{3} < sr \leqslant \frac{2}{3} \text{ (b)} \\ \boldsymbol{x}_i^{old} + \varepsilon\cdot(\boldsymbol{x}_g - \boldsymbol{x}_i^{old}) & else \text{ (c)} \end{cases} \tag{15}$$

where $L = \delta\ln(1/\eta)$, $\varepsilon = \delta\exp(\eta)$, $\boldsymbol{x}_g$ is the best solution in current iteration; $\bar{\boldsymbol{x}} = \frac{1}{NP}\sum_{i=1}^{NP}\boldsymbol{x}_i$ is the mean of all the solutions; sr and η are random numbers in the interval $[0, 1]$.

From Eq. (15), it can be observed that heterogeneous cuckoo search strategy uses three different update equations with equal probabilities for each solution. The first update equation is based on the Levy flight in the original CS, while the second and third update equations are based on the quantum mechanism. Employing heterogeneous update rules can create various solutions for diversifying the search and flying to a promising direction toward the real global region.

3.3.2. Biogeography-based discovery operator

In the second stage, BHCS employs a biogeography-based discovery operator to generate new solutions. The host bird can discover alien eggs with a probability pa, then abandoned old nests and generate new nests based on the biogeography-based migration operator.

Table 6
Statistical results of the RMSE values achieved by different algorithms for the double diode model of R.T.C. France solar cell.

Algorithm	RMSE					
	Min	Median	Mean	Max	SD	Sig.
ABC	9.89560E−04	1.04158E−03	1.05765E−03	1.28482E−03	6.18669E−05	+
TLBO	1.00692E−03	1.09483E−03	1.15977E−03	1.52057E−03	1.55921E−04	+
TLABC	9.84145E−04	1.10221E−03	1.15553E−03	1.50482E−03	1.55034E−04	+
CLPSO	1.01347E−03	1.08407E−03	1.09114E−03	1.19910E−03	5.68626E−05	+
BLPSO	1.10417E−03	1.59394E−03	1.58543E−03	2.19554E−03	2.66193E−04	+
RCBBOG	1.30768E−03	2.50873E−03	2.55013E−03	3.76805E−03	7.86040E−04	+
BlendedBBO	1.12764E−03	2.26869E−03	2.34301E−03	3.39825E−03	6.73322E−04	+
DEBBO	9.89182E−04	1.22103E−03	1.30090E−03	2.02743E−03	2.74715E−04	+
CS	2.44398E−03	6.42266E−03	7.90243E−03	4.37199E−02	8.06719E−03	+
ACS	9.86267E−04	1.11776E−03	1.23272E−03	1.89208E−03	2.53920E−04	+
NoCuSa	**9.82485E−04**	9.86021E−04	1.07747E−03	2.19854E−03	2.59704E−04	+
BHCS	**9.82485E−04**	**9.83062E−04**	**9.83800E−04**	**9.86865E−04**	**1.53897E−06**	

The best results are highlighted in bold.

Table 7
Model parameters estimated by different algorithms for the double diode model of R.T.C. France solar cell.

Item	I_{ph} (A)	I_{sd1} (μA)	R_S (Ω)	R_{sh} (Ω)	a_1	I_{sd2}	a_2	RMSE	Rank
ABC	0.76071	0.14623	0.03654	55.36509	1.68023	0.24605	1.46226	9.89560E−04	6
TLBO	0.76099	0.29465	0.03661	53.12099	1.47295	0.13727	1.99375	1.00692E−03	7
TLABC	0.76081	0.42394	0.03667	54.66797	1.90750	0.24011	1.45671	9.84145E−04	3
CLPSO	0.76112	0.00237	0.03619	52.40069	1.68481	0.33875	1.48612	1.01347E−03	8
BLPSO	0.76056	0.17895	0.03553	64.79937	1.69574	0.31560	1.48789	1.10417E−03	9
RCBBOG	0.76215	0.33429	0.03591	42.77882	1.48495	0.00390	1.85202	1.30768E−03	11
BlendedBBO	0.76063	0.14202	0.03544	64.20305	1.44782	0.38774	1.60576	1.12764E−03	10
DE/BBO	0.76072	0.33306	0.03627	55.49417	1.48429	0.00517	1.97515	9.89182E−04	5
CS	0.76223	0.02732	0.03530	97.73242	1.70274	0.50832	1.52893	2.44398E−03	12
ACS	0.76077	0.32412	0.03635	53.71697	1.48153	0.00040	1.97706	9.86267E−04	4
NoCuSa	0.76078	0.22705	0.03674	55.46103	1.45141	0.74019	2.00000	9.82485E−04	1
BHCS	0.76078	0.74935	0.03674	55.48544	2.00000	0.22597	1.45102	9.82485E−04	1

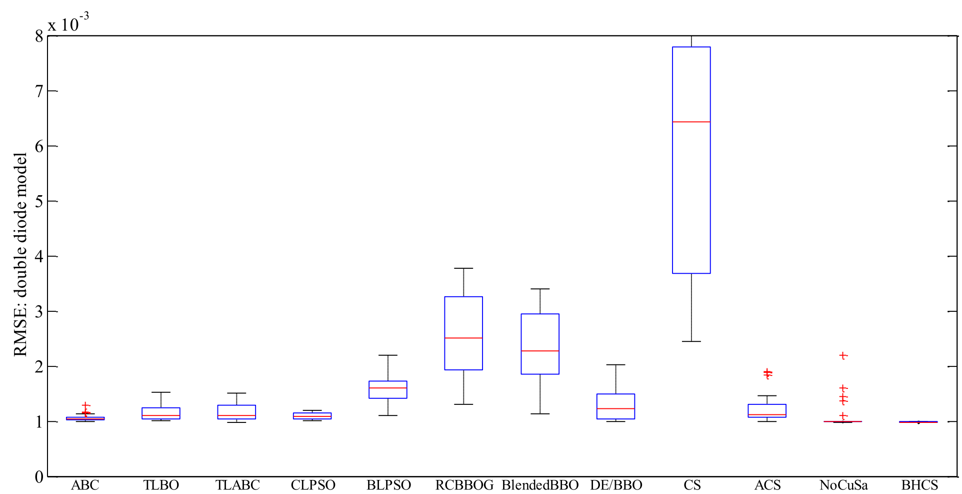

Fig. 7. Boxplot of RMSE values achieved by different algorithms for the double diode model of R.T.C. France solar cell.

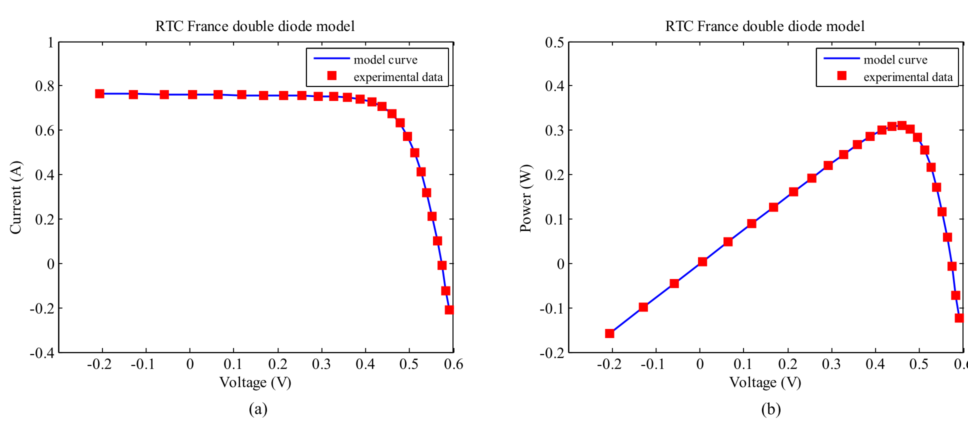

Fig. 8. Comparisons between the experimental data and simulated data obtained by BHCS for the double diode model of R.T.C. France solar cell: *I-V* and *P-V* characteristics.

First, the population is sorted from best to worst, and each solution is assigned with an emigration rates μ:

$$\mu_i = E\frac{S_i}{NP} \tag{16}$$

where $E = 1$ is the maximum emigration rate; $S_i = NP - i$ is the number of species in the solution.

Then, the biogeography-based discovery operator for generating i-th solution is described in Algorithm 1.

In the biogeography-based discovery operator, the solutions with high fitness can share more features to other solutions, and this is helpful for the enhancement of the exploitation.

Algorithm 1. Biogeography-based discovery operator

for $j = 1 \rightarrow D$ **do**
  if $rand > pa$ **then**
    Select a solution $\boldsymbol{x}_k$ with probability $\propto \mu_k$;
    Generate a random number α within $[0, 1]$;
    % Perform blended migration
    $x_{ij}^{new} = \alpha x_{ij}^{old} + (1 - \alpha) x_{kj}^{old}$;
  else
    $x_{ij}^{new} = x_{ij}^{old}$;
  end if
end for

3.3.3. Overall algorithm of BHCS

By using the heterogeneous cuckoo search and biogeography-based discovery, the detail implantation of the proposed BHCS algorithm is shown in Algorithm 2.

Fig. 3 depicts the flowchart of solar PV parameters estimation process by the proposed BHCS algorithm. The BHCS algorithm employs a cascading structure to implement its two search stages. Additionally, the cooperation of the heterogeneous cuckoo search strategy and biogeography-based discovery operator can achieve an efficient balance between exploration and exploitation.

Algorithm 2. Biogeography-based heterogeneous cuckoo search (BHCS) algorithm

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Initial the host nests $\boldsymbol{x}_i (i = 1, \cdots, NP)$;
Evaluate the fitness $f(\boldsymbol{x}_i)$ of each nest;
while the terminal condition is not reached **do**
    % First stage: heterogeneous cuckoo search strategy
    for $i = 1 \rightarrow NP$ **do**
        Generate a new cuckoo $\boldsymbol{x}_i^{new}$ by heterogeneous cuckoo search using Eq. (15);
        Evaluate the fitness $f(\boldsymbol{x}_i^{new})$;
        if $f(\boldsymbol{x}_i^{new})$ is better than $f(\boldsymbol{x}_i^{old})$ **then**
            Replace old nest $\boldsymbol{x}_i^{old}$ with $\boldsymbol{x}_i^{new}$;
        end if
    end for
    % Second stage: biogeography-based discovery operator
    Sort the population from best to worst;
    Assign each solution with an emigration rates μ;
    for $i = 1 \rightarrow NP$ **do**
        Using Algorithm 1 to generate a new solution $\boldsymbol{x}_i^{new}$;
        Evaluate the fitness $f(\boldsymbol{x}_i^{new})$;
        if $f(\boldsymbol{x}_i^{new})$ is better than $f(\boldsymbol{x}_i^{old})$ **then**
            Replace old nest $\boldsymbol{x}_i^{old}$ with $\boldsymbol{x}_i^{new}$;
        end if
    end for
    Record the global best solution $\boldsymbol{x}_g$;
end while

---

4. Experimental results and analysis

In this section, in order to verify the performance of the proposed BHCS algorithm, it is applied to solve four solar PV parameters estimation problems. The first two problems are two cases of solar cells corresponding to the single diode model and the double diode model taken from Gong and Cai (2013), Easwarakhanthan et al. (1986). The experimental *I-V* dataset are measured from a 57 mm diameter commercial R.T.C. France silicon solar cell at an irradiance of (1000 W/m^2) and a temperature of (33 °C), and there are totally 26 pairs of current and voltage values. The remaining two problems are two cases of solar PV panel models taken from Oliva et al. (2017), Tong and Pora (2016). One case is a commercial solar panel model STM6-40/36 manufactured by Schutten solar, and the panel contains 36 Monocrystalline cells (of size 38 mm × 128 mm) in series form. There are 20 points which is measured as at temperature 51 °C. The other case is a commercial solar panel model STP6-120/36 which consists of 36 polycrystalline cells (of size 156 mm × 156 mm) aligned in series. The dataset of this case contains 22 points which is measured as at temperature 55 °C. The lower and upper boundaries of the model parameters for the four problems are listed in Table 2, which are kept the same as those in the literature (Gong and Cai, 2013; Gao et al., 2018; Yu et al., 2018).

The proposed BHCS algorithm is compared with eleven well-established meta-heuristic algorithms, including three BBO, three CS, and five other meta-heuristic algorithms. They are ABC (Karaboga and Basturk, 2007), TLBO (Rao et al., 2012), TLABC (teaching-learning-based ABC) (Chen et al., 2018c), CLPSO (comprehensive learning particle PSO) (Liang et al., 2006), BLPSO (biogeography-based learning PSO) (Chen et al., 2017), RCBBOG (real-coded BBO with Gaussian mutation) (Gong et al., 2010b), blended BBO (Ma and Simon, 2011), DE/BBO (hybrid DE with BBO) (Gong et al., 2010a), CS (Yang and Deb, 2009), ACS (adaptive CS) (Naik and Panda, 2016), and NoCuSa (nonhomogeneous CS) (Cheung et al., 2017). The parameter settings for the compared algorithms and BHCS are presented in Table 3, which are set based on the suggestions in their corresponding literatures. For fair comparison, all algorithms use the same maximum number of function evaluations $MaxFES = 50,000$ for each problem, and all algorithms are run 30 times independently to obtain the statistical results.

4.1. Results on single diode model

Table 4 presents the statistical results including the minimum, median, mean, maximum, as well as the standard deviation (SD) of RMSE values, achieved by our BHCS and the other algorithms for the single diode model of R.T.C. France solar cell. The RMSE values quantify the solution accuracy, and the standard deviation of RMSE indicates the reliability of the algorithms. Besides, Wilcoxon rank sum test with a significance level of $\alpha = 0.05$ is employed to compare the significance between BHCS and its competitor. Symbols "+", "−" and "=" mean BHCS is significantly better than, worse than, or similar to its competitor, respectively.

From Table 4, it can be observed that, in terms of minimum, median, mean, and maximum of RMSE, the proposed BHCS can achieve the best results, which indicates that BHCS achieve the best solution accuracy for this case. Considering the standard deviation of RMSE, BHCS performs better than all the other algorithms, which means BHCS is the most reliable and stable method. NoCuSa and TLABC can also achieve the best minimum RMSE. However, their performances are worse than BHCS when considering the standard deviation of RMSE. In addition, according to the Wilcoxon rank sum test, the performance of BHCS is similar to that of NoCuSa and significantly better than all the other algorithms.

Table 5 shows the optimal model parameters and RMSE values estimated by different algorithms for the single diode model. BHCS, NoCuSa and TLABC achieve the best RMSE, followed by DE/BBO, TLBO, BlendedBBO, ABC, CLPSO, ACS, RCBBOG, BLPSO, and CS.

Fig. 4 presents the boxplot of different algorithms for the single diode model, which shows the distribution of results achieved by different algorithms in 30 runs. It can be observed that the proposed BHCS exhibits the best performance compared with other compared algorithms in terms of robustness.

Fig. 5 plots the *I-V* and *P-V* characteristics of the optimal model parameters estimated by BHCS. It is clear that the simulated data

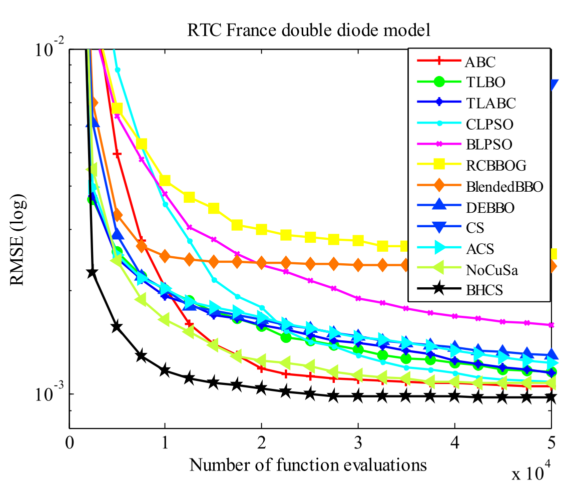

Fig. 9. Convergence graph of different algorithms for the double diode model of R.T.C. France solar cell.

Table 8
Statistical results of the RMSE values achieved by different algorithms for the STM6-40/36 module.

Algorithm	RMSE					
	Min	Median	Mean	Max	SD	Sig.
ABC	5.35097E−03	2.23293E−02	2.16333E−02	3.14836E−02	6.78987E−03	+
TLBO	2.08881E−03	2.63566E−03	2.70684E−03	3.36495E−03	3.56135E−04	+
TLABC	1.80612E−03	1.96880E−03	1.97321E−03	**2.21357E−03**	**8.76739E−05**	+
CLPSO	2.81059E−03	4.60132E−03	4.77029E−03	8.32222E−03	1.51852E−03	+
BLPSO	3.65883E−03	4.31558E−03	4.79399E−03	8.58023E−03	1.26862E−03	+
RCBBOG	7.50527E−03	3.24053E−02	3.01618E−02	4.98064E−02	7.80538E−03	+
BlendedBBO	2.57976E−02	3.25034E−02	3.17255E−02	3.29968E−02	1.89644E−03	+
DEBBO	3.01668E−03	8.96284E−03	1.01889E−02	2.85066E−02	6.61930E−03	+
CS	2.51591E−03	2.95886E−03	2.98811E−03	3.57418E−03	2.52342E−04	+
ACS	1.95543E−03	2.50738E−03	2.50712E−03	3.10610E−03	2.56530E−04	+
NoCuSa	**1.72981E−03**	5.36217E−03	4.12985E−02	3.10757E−01	9.22231E−02	+
BHCS	**1.72981E−03**	**1.72981E−03**	**1.83648E−03**	3.32985E−03	4.05942E−04	

The best results are highlighted in bold.

obtained by BHCS are in good agreement with the experimental data.

Fig. 6 plots the convergence graphs of all the algorithms. The proposed BHCS has faster convergence speed than all the other algorithms for this case.

4.2. Results on double diode model

Table 6 presents the statistical results achieved by our BHCS and the other algorithms for the double diode model of R.T.C. France solar cell. From Table 6, BHCS achieve the best results in terms of the minimum, median, mean, maximum and standard deviation of RMSE. According to the Wilcoxon rank sum test, BHCS is significantly better than all the other algorithms. NoCuSa can also achieve the best result in terms of the minimum RMSE, but its performance is worse than that of BHCS when considering the minimum, median, mean, maximum and standard deviation of RMSE. Therefore, BHCS is the best algorithm when considering both accuracy and reliably for double diode model.

Table 7 presents the optimal model parameters and RMSE values achieved by different algorithms for the double diode model. BHCS and NoCuSa obtain the best RMSE, followed by TLABC, ACS, DE/BBO, ABC, TLBO, CLPSO, BLPSO, BlendedBBO, RCBBOG, and CS.

Fig. 7 shows the boxplot of different algorithms. It is clear that the proposed BHCS exhibits the superior performance compared with other compared algorithms in terms of solution distribution.

Fig. 8 plots the *I-V* and *P-V* characteristics obtained by BHCS and the experimental data. The simulated data obtained by BHCS are highly in

Table 9
Model parameters estimated by different algorithms for the STM6-40/36 module.

Item	I_{ph} (A)	I_{sd} (μA)	R_S (Ω)	R_{sh} (Ω)	a	RMSE	Rank
ABC	1.65205	3.74780	0.00247	80.12646	1.60830	5.35097E−03	10
TLBO	1.66248	2.63871	0.00312	19.67204	1.56749	2.08881E−03	5
TLABC	1.66317	2.14043	0.00363	17.25952	1.54354	1.80612E−03	3
CLPSO	1.65953	3.71285	0.00197	26.48992	1.60812	2.81059E−03	7
BLPSO	1.66014	6.40784	0.00000	31.83647	1.67848	3.65883E−03	9
RCBBOG	1.66131	10.16407	0.00000	111.34376	1.74239	7.50527E−03	11
BlendedBBO	1.67643	33.40060	0.00000	953.90291	1.93580	2.57976E−02	12
DE/BBO	1.66135	4.89427	0.00071	24.12811	1.64323	3.01668E−03	8
CS	1.66172	3.72815	0.00173	21.74472	1.60905	2.51591E−03	6
ACS	1.66256	2.03860	0.00373	18.05646	1.53785	1.95543E−03	4
NoCuSa	1.66390	1.73866	0.00427	15.92829	1.52030	1.72981E−03	1
BHCS	1.66390	1.73866	0.00427	15.92829	1.52030	1.72981E−03	1

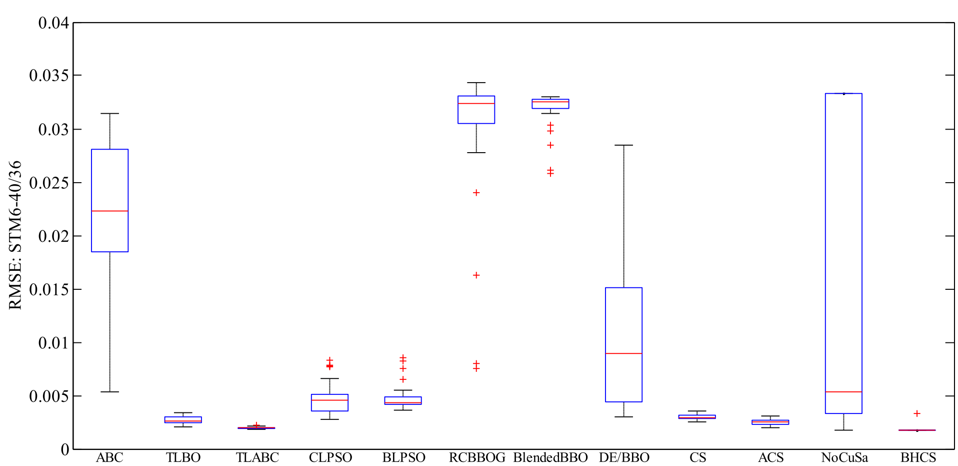

Fig. 10. Boxplot of RMSE values achieved by different algorithms for the STM6-40/36 module.

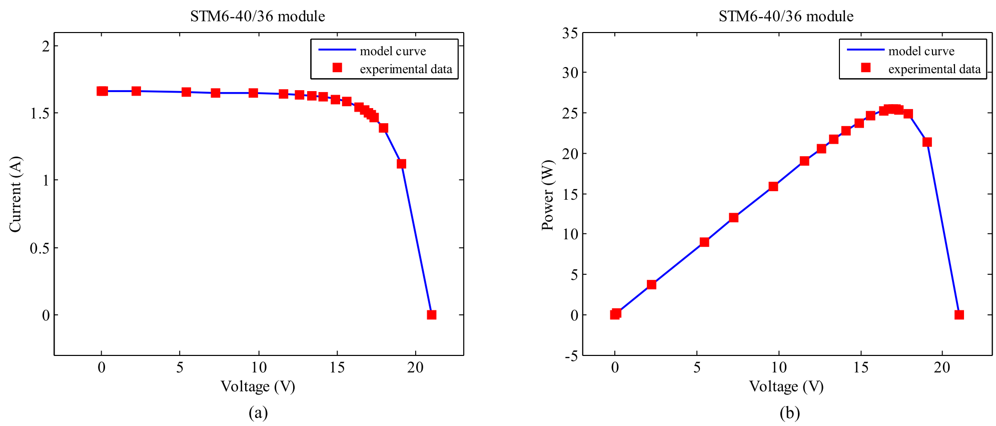

Fig. 11. Comparisons between the experimental data and simulated data obtained by BHCS for the STM6-40/36 module: *I-V* and *P-V* characteristics.

coincidence with the experimental data.

Fig. 9 plots the convergence graphs of all the algorithms. BHCS also has the fastest convergence speed among all the algorithms for this case.

4.3. Results on PV panel modules

In order to investigate the proposed BHCS in the real applications, the practical measured *I-V* data of two PV panels are considered, including a mono-crystalline STM6-40/36 module at 51 °C and a poly-crystalline STP6-120/36 module at 55 °C (Oliva et al., 2017; Tong and Pora, 2016).

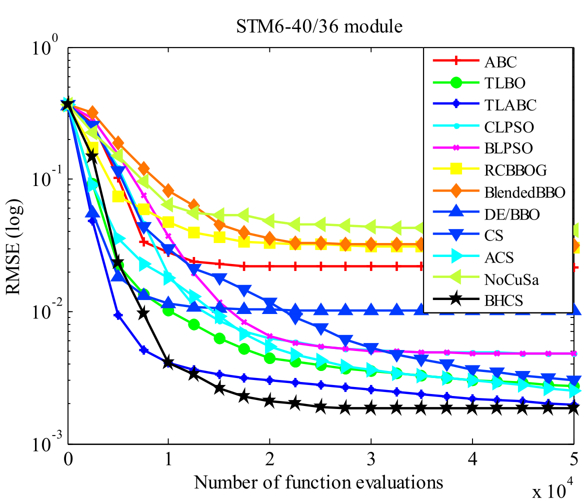

Fig. 12. Convergence graph of different algorithms for the STM6-40/36 module.

4.3.1. Parameter estimation of STM6-40/36 module

Table 8 presents the statistical results of RMSE values achieved by our BHCS and the other algorithms for the STM6-40/36 module. According to the results listed in Table 8, the performance of BHCS is also very competitive for this case. In detail, in terms of the minimum RMSE, BHCS together with NoCuSa outperform than the other algorithms. Considering the median and mean RMSE, BHCS is the only algorithm which achieves the best results among all the algorithms. Based on the Wilcoxon rank sum test, BHCS is significantly better than all the other algorithms. TLABC is state-of-the-art hybrid algorithm proposed in Chen et al. (2018c), and it obtains the best results in terms of maximum and standard deviation of RMSE.

Table 9 presents the optimal model parameters and RMSE values achieved by different algorithms for the STM6-40/36 module. BHCS and NoCuSa obtain the best RMSE, followed by TLABC, ACS, TLBO, CS, CLPSO, DE/BBO, BLPSO, ABC, RCBBOG, and BlendedBBO.

Fig. 10 shows the boxplot of all the algorithms for the STM6-40/36 module. Fig. 11 plots the *I-V* and *P-V* characteristics obtained by HCS and the experimental data. Fig. 12 plots the convergence graphs of all the algorithms for this case. It can be observed from Fig. 10–12 that the proposed BHCS also exhibits a superior performance in terms of robustness, solution precision and convergence speed in comparison with other algorithms.

Table 10
Statistical results of the RMSE values achieved by different algorithms for the STP6-120/36 module.

Algorithm	RMSE					
	Min	Median	Mean	Max	SD	Sig.
ABC	3.53240E−02	5.19659E−02	4.90401E−02	5.51203E−02	6.23031E−03	+
TLBO	1.70782E−02	2.03151E−02	2.17494E−02	4.08272E−02	5.12998E−03	−
TLABC	1.67694E−02	1.70559E−02	**1.71442E−02**	**1.81648E−02**	**3.44767E−04**	−
CLPSO	1.71932E−02	2.65921E−02	2.71432E−02	4.45544E−02	7.63878E−03	+
BLPSO	2.97469E−02	4.05000E−02	4.03323E−02	4.98700E−02	4.09791E−03	+
RCBBOG	2.24714E−02	6.18670E−02	8.55821E−02	2.26534E−01	4.78668E−02	+
BlendedBBO	4.94391E−02	5.53458E−02	5.55511E−02	6.03755E−02	1.86924E−03	+
DEBBO	2.20596E−02	4.17174E−02	4.31066E−02	8.07347E−02	1.03936E−02	+
CS	2.03166E−02	3.00398E−02	2.96234E−02	3.54597E−02	3.70849E−03	+
ACS	1.98653E−02	2.51348E−02	2.52902E−02	3.08127E−02	2.86145E−03	+
NoCuSa	**1.66006E−02**	5.29637E−02	2.15975E−01	1.41312E+00	4.15090E−01	+
BHCS	**1.66006E−02**	**1.66006E−02**	2.43602E−02	1.34824E−01	2.60620E−02	

The best results are highlighted in bold.

Table 11
Model parameters estimated by different algorithms for the STP6-120/36 module.

Item	I_{ph} (A)	I_{sd} (μA)	R_S (Ω)	R_{sh} (Ω)	a	RMSE	Rank
ABC	7.43276	2.19776	0.00463	160.97574	1.25650	3.53240E−02	11
TLBO	7.46374	2.96987	0.00450	633.97537	1.28053	1.70782E−02	4
TLABC	7.46346	2.64543	0.00454	114.70929	1.27051	1.67694E−02	3
CLPSO	7.45596	2.67067	0.00454	1070.90119	1.27147	1.71932E−02	5
BLPSO	7.49643	10.81803	0.00377	990.91204	1.40302	2.97469E−02	10
RCBBOG	7.46160	1.72407	0.00464	18.29851	1.23464	2.24714E−02	9
BlendedBBO	7.52906	35.95517	0.00294	1413.21459	1.53969	4.94391E−02	12
DE/BBO	7.48035	6.06747	0.00410	1499.78544	1.34540	2.20596E−02	8
CS	7.47840	5.02907	0.00422	476.90830	1.32784	2.03166E−02	7
ACS	7.47596	4.89414	0.00422	1285.52936	1.32516	1.98653E−02	6
NoCuSa	7.47253	2.33499	0.00459	22.21991	1.26010	1.66006E−02	1
BHCS	7.47253	2.33499	0.00459	22.21990	1.26010	1.66006E−02	1

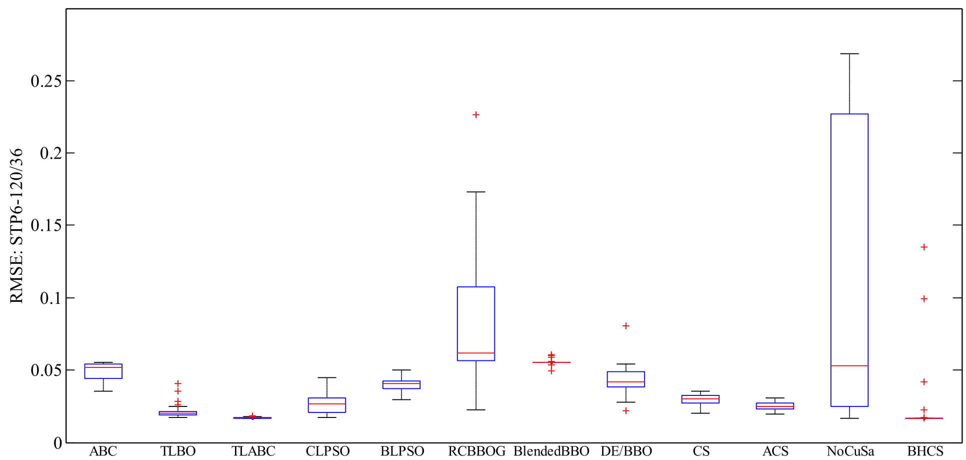

Fig. 13. Boxplot of RMSE values achieved by different algorithms for the STP6-120/36 module.

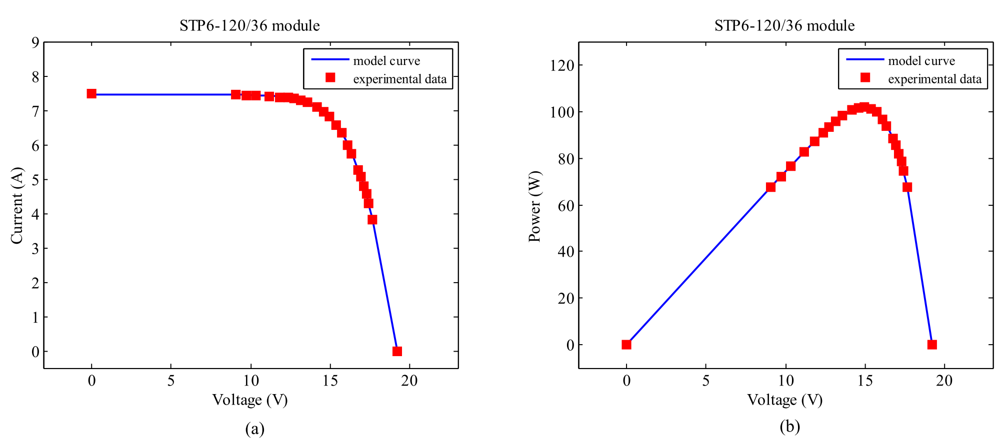

Fig. 14. Comparisons between the experimental data and simulated data obtained by BHCS for the STP6-120/36 module: *I-V* and *P-V* characteristics.

4.3.2. Parameter estimation of STP6-120/36 module

Table 10 presents the statistical results of RMSE values achieved by our BHCS and the other algorithms for the STP6-120/36 module. From Table 10, BHCS achieves the best results among all the algorithms in terms of the minimum and median RMSE. Additionally, BHCS performs significantly better than all the compared algorithms except TLBO and TLABC. TLABC achieves the best results in terms of mean, maximum and standard deviation of RMSE.

Table 11 presents the optimal model parameters and RMSE values achieved by different algorithms for the STP6-120/36 module. BHCS and NoCuSa obtain the best RMSE, followed by TLABC, TLBO, CLPSO, ACS, CS, DE/BBO, RCBBOG, BLPSO, ABC, and BlendedBBO.

Fig. 13 shows the boxplot of different algorithms for the STP6-120/36 module. Fig. 14 plots the *I-V* and *P-V* characteristics obtained by BHCS and the experimental data. The simulated data are highly in coincidence with the experimental data. Fig. 15 plots the convergence graphs of all the algorithms. After TLABC and TLBO, BHCS has the third fastest convergence speed.

4.4. Effectiveness of the two search strategies in BHCS

We also carry out experiments to demonstrate the effectiveness of two search strategies adopted in BHCS, i.e., heterogeneous cuckoo search and biogeography-based discovery. We compare four algorithms, namely RCBBOG, CS, HCS (heterogeneous cuckoo search) and BHCS, for all the four cases above. RCBBOG and CS are two basic

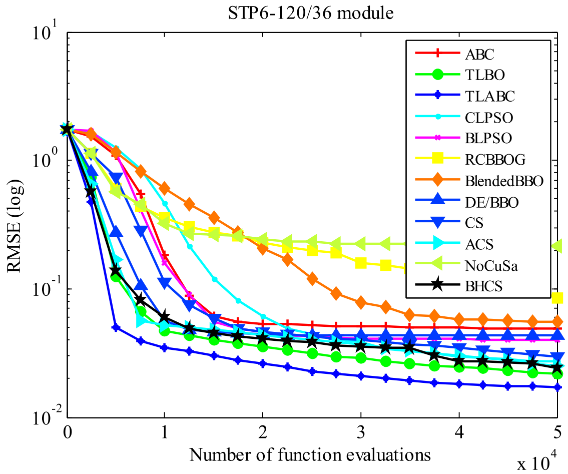

Fig. 15. Convergence graph of different algorithms for the STP6-120/36 module.

individual algorithms. HCS is an improved CS with heterogeneous cuckoo search. BHCS is the hybrid algorithm using both heterogeneous cuckoo search and biogeography-based discovery.

Table 12 presents the experimental results of RCBBOG, CS, HCS and BHCS. From Table 12, the following observations can be made:

(1) In term of minimum RMSE, HCS performs better than CS for all the four cases. In terms of median, mean, maximum and standard deviation of RMSE, HCS performs better than CS for case 1 and case 2. This observation demonstrates the effectiveness of heterogeneous cuckoo search strategy in HCS in comparison with the original CS without this strategy.
(2) In terms of minimum, median, mean, maximum and standard deviation of RMSE, BHCS exhibits better performance than HCS for case 2–4. This observation demonstrates the effectiveness of biogeography-based discovery operator employed in BHCS in comparison with HCS without this operator.
(3) In terms of minimum, median, and mean RMSE, BHCS performs better than two basic individual algorithms, i.e., RCBBOG and CS for all the four cases. It demonstrates the effectiveness of the proposed hybrid BHCS algorithm in comparisons with its individual algorithms.

5. Conclusion

In this paper, we have proposed a biogeography-based heterogeneous cuckoo search (BHCS) algorithm for estimating the parameters of different PV models. The proposed algorithm is developed by hybridizing two meta-heuristic algorithms, namely cuckoo search (CS) and biogeography-based optimization (BBO). Specifically, BHCS employs heterogeneous cuckoo search strategy based on the levy flight and quantum mechanism to explore the search space; meanwhile, a biogeography-based discovery operator is used to exploit the local solutions. The cooperation of the two search strategies helps BHCS achieve an efficient balance between exploration and exploitation.

We have applied BHCS to solve four different parameters estimation problems, including single diode model, double diode model, and PV panel modules. Based on the experimental results, the following conclusions can be drawn:

(i) According to the statistical results and Wilcoxon rank sum test, BHCS exhibits better or comparable performance compared with well-established algorithms such as ABC, TLBO, TLABC, CLPSO, BLPSO, RCBBOG, blended BBO, DE/BBO, CS, ACS, and NoCuSa.
(ii) The boxplots indicate BHCS has a superior performance in terms of robustness for different PV parameter estimation problems.
(iii) The convergence graphs show that BHCS also has a very fast convergence speed.
(iv) Based on the comparisons with CS and BBO, BHCS performs significantly better than its individual algorithms.
(v) The excellent performance of BHCS should be attributed to its two strategies, i.e., heterogeneous cuckoo search strategy and biogeography-based discovery operator.

These results confirm that the proposed BHCS algorithm is a valuable tool for PV parameters estimation. For future works, it will be interesting to apply BHCS for solving other optimization problems in energy field, such as optimal power flow and distributed generation planning.

Table 12
Statistical results of the RMSE values achieved by RCBBOG, CS, HCS and BHCS for the four cases.

	Algorithm	RMSE					
		Min	Median	Mean	Max	SD	Sig.
Case 1	RCBBOG	1.08173E−03	1.82258E−03	1.82524E−03	3.27762E−03	5.90759E−04	+
	CS	2.01185E−03	4.00093E−03	7.60819E−03	6.09130E−02	1.10512E−02	+
	HCS	**9.86022E−04**	**9.86022E−04**	**9.86022E−04**	**9.86022E−04**	2.99346E−17	=
	BHCS	**9.86022E−04**	**9.86022E−04**	**9.86022E−04**	**9.86022E−04**	**2.61254E−17**	
Case 2	RCBBOG	1.30768E−03	2.50873E−03	2.55013E−03	3.76805E−03	7.86040E−04	+
	CS	2.44398E−03	6.42266E−03	7.90243E−03	4.37199E−02	8.06719E−03	+
	HCS	**9.82485E−04**	9.86021E−04	1.07747E−03	2.19854E−03	2.59704E−04	+
	BHCS	**9.82485E−04**	**9.83062E−04**	**9.83800E−04**	**9.86865E−04**	**1.53897E−06**	
Case 3	RCBBOG	7.50527E−03	3.24053E−02	3.01618E−02	4.98064E−02	7.80538E−03	+
	CS	2.51591E−03	2.95886E−03	2.98811E−03	3.57418E−03	**2.52342E−04**	+
	HCS	**1.72981E−03**	5.36217E−03	4.12985E−02	3.10757E−01	9.22231E−02	+
	BHCS	**1.72981E−03**	**1.72981E−03**	**1.83648E−03**	**3.32985E−03**	4.05942E−04	
Case 4	RCBBOG	2.24714E−02	6.18670E−02	8.55821E−02	2.26534E−01	4.78668E−02	+
	CS	2.03166E−02	3.00398E−02	2.96234E−02	**3.54597E−02**	**3.70849E−03**	+
	HCS	**1.66006E−02**	5.29637E−02	2.15975E−01	1.41312E+00	4.15090E−01	+
	BHCS	**1.66006E−02**	**1.66006E−02**	**2.43602E−02**	1.34824E−01	2.60620E−02	

The best results are highlighted in bold.

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Appendix A. Cuckoo search algorithm

The pseudocode of cuckoo search is presented in Algorithm 3.

Algorithm 3. Cuckoo search (CS)

Initial the host nests $\boldsymbol{x}_i (i = 1, \ldots, NP)$;
Evaluate the fitness $f(\boldsymbol{x}_i)$ of each nest;
while the terminal condition is not reached **do**
  %Generate new solutions by Levy flights
  for $i = 1 \rightarrow NP$ **do**
    Generate a new cuckoo $\boldsymbol{x}_i^{new}$ by Levy flights using Eq. (10);
    Evaluate the fitness $f(\boldsymbol{x}_i^{new})$;
    if $f(\boldsymbol{x}_i^{new})$ is better than $f(\boldsymbol{x}_i^{old})$ **then**
      Replace old nest $\boldsymbol{x}_i^{old}$ with $\boldsymbol{x}_i^{new}$;
    end if
  end for
  % Discover and generate new nests
  for $i = 1 \rightarrow NP$ **do**
    for $j = 1 \rightarrow D$ **do**
      Abandon and generate x_{ij}^{new} according to *pa* using Eq. (13);
    end for
    Evaluate the fitness $f(\boldsymbol{x}_i^{new})$;
    if $f(\boldsymbol{x}_i^{new})$ is better than $f(\boldsymbol{x}_i^{old})$ **then**
      Replace old nest $\boldsymbol{x}_i^{old}$ with $\boldsymbol{x}_i^{new}$;
    end if
  end for
  Record the global best nest $\boldsymbol{x}_g$;
end while

Appendix B. Biogeography-based optimization

The pseudocode of biogeography-based optimization is presented in Algorithm 4.

Algorithm 4. Biogeography-based optimization (BBO)

Randomly Initialize the solutions $\boldsymbol{x}_i (i = 1, 2, \ldots, NP)$;
Evaluate the solutions $f(\boldsymbol{x}_i)$
while the terminal condition is not reached **do**
  Sort the population from best to worst;
  Assign the immigration rate λ_i and an emigration rate μ_i;
  % Perform migration operator
  for $i = 1 \rightarrow NP$ **do**
    for $j = 1 \rightarrow D$ **do**
      if $rand < \lambda_i$ **then**
        Select a habitat $\boldsymbol{x}_k$ with probability $\propto \mu_k$;
        $x_{ij}^{new} = x_{kj}^{old}$;
      else
        $x_{ij}^{new} = x_{ij}^{old}$;
      end if
    end for
  end for
  % Perform mutation operator
  for $i = 1 \rightarrow NP$ **do**
    if $rand < p_i$ **then**
      Modify $\boldsymbol{x}_i^{new}$ by mutation;
    end if
  end for
  Evaluate the new solutions $f(\boldsymbol{x}_i^{new})$;
  Perform elitism stage;
  Clear duplication stage;
end while

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