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Parameter identification and sensitivity analysis of solar cell models with cat swarm optimization algorithm

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ABSTRACT

Solar cell model is used in various studies of photovoltaic system. Different methods have been developed to determine model parameters. In this paper, an optimization technique based on cat swarm optimization (CSO) algorithm is proposed to estimate the unknown parameters of single and double diode models. To investigate the effectiveness of proposed approach, comparative studies with other techniques are presented. The evaluation for the quality of identified parameters is also given. Results demonstrate the high performance of developed approach, high accuracy of estimated parameters, and calculated *I–V* curve is in good agreement with experimental *I–V* data. In addition, the sensitivity of performance to control parameter of CSO is also investigated. Results show the proposed CSO algorithm can be an effective tool to solve the optimization problem of parameter identification of solar cell models.

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1. Introduction

Solar photovoltaic (PV) system has received significant attention due to its many advantages such as cleanness, abundance, sustainability and exploitation-free cost, although it also has the disadvantages including high initial investment cost and low conversion efficiency of PV modules [1]. In recent years, different works related to PV technology have been presented. Among many works, the photovoltaic thermal (PVT) system which produces not only electrical energy but also thermal energy has been addressed in the literature. In [2], a mathematical analysis has been implemented to obtain optimum PVT absorber configuration so as to reduce the cost. Based on a developed steady-state model, the optimal configuration is further validated. The authors in [3] presented a performance evaluation of a designed hybrid micro-channel PVT module under four weather conditions. Based on energy analysis and exergy analysis, the optimization of PVT water system has been performed in [4] and the optimal exergy efficiency is reported as 11.36%. In [5], a study was conducted to investigate the performance improvement of PVT system with optimized parameter, considering the climatic condition in New Delhi. The performance of glazed PVT system with optimal design parameters obtained by evolutionary algorithm has been evaluated by the authors in [6]. Study results showed that there was an increase of 69.52% in annual overall exergy gain and an increase of 88.05% in annual overall thermal gain.

Besides the efforts spent on PVT system, the work that aims to accurately model the behavior of solar cell also plays an important role in various studies of PV system due to the fact that solar cell is the basic component converting solar energy into electrical energy. Several equivalent circuit models have been developed over many years. Among circuit based models, the most popular ones are the single diode model and double diode model [7–9]. However, to describe the nonlinear current–voltage (*I–V*) characteristics of solar cell, these two models involve several unknown parameters. Thus, there is a need to provide a technique to effectively determine solar cell unknown parameters.

Many techniques have been proposed to solve such a problem, and can be grouped into two main types: analytical approaches [10–12] and numerical approaches [13–24]. In [10], solar cell model parameters were extracted from *I–V* characteristics. For the presented method, the model parameters were analytically calculated by using several key parameters including short circuit current (I_{SC}), open circuit voltage (V_{OC}), current and voltage (I_M and V_M) at maximum power point (MPP) and the slopes of *I–V* curve at short circuit point and open circuit point, and considering several approximations. Khan et al. [11] proposed an analytical method to calculate the diode parameters of solar cell subjected to high illumination. This method also uses the data obtained from *I–V* characteristics to determine the solar cell model parameters. However, only four parameters but not all five model parameters

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Nomenclature

AE	absolute error	N	number of points
$c1$	constant	NP	number of population
CDC	counts of dimensions to be changed	PV	photovoltaic
D	number of dimensions of search space	PVT	photovoltaic thermal
I	output current of solar cell (A)	q	electron charge ($1.60217646 \cdot 10^{-19}$ C)
$I_{calculated}$	calculated current (A)	R_S	series resistance (Ω)
I_D	diode current (A)	R_P	parallel resistance (Ω)
I_L	photocurrent (A)	RE	relative error
I_M	current at maximum power point	$RMSE$	root mean square error
$I_{measured}$	measured current (A)	SMP	seeking memory pool
I_O,I_{O1},I_{O2}	saturation current (A)	SRD	seeking range of the selected dimension
I_P	parallel resistor current (A)	STD	standard deviation
I_{SC}	short circuit current	T	cell temperature in Kelvin (K)
$iter$	index of iteration	v	velocity vector
$iter_{max}$	maximum number of iterations	V	output voltage of solar cell (V)
I–V	current–voltage	V_{OC}	open circuit voltage
K	Boltzmann constant ($1.3806503 \cdot 10^{-23}$ J/K)	V_M	voltage at maximum power point
MPP	maximum power point	w	inertia weight
MAE	mean absolute error	w_{max},w_{min}	maximum and minimum inertia weight
MR	mixture ratio	x	position vector
MRE	mean relative error	x_{best}	best position vector
n,n_1,n_2	diode ideality factor	$x_{bestcopy}$	best position vector for copies

are determined for single diode model. An analytical method to extract single diode model parameters was proposed in [12]. In order to solve the equations established by using information on there points (short circuit point, open circuit voltage point and MPP) on I–V curve, a piecewise curve-fitting method, together with a simplified solar cell model consisting of only four parameters, was developed to calculate the derivative of the V with respect to I at short circuit point and open voltage point. In general, for analytical approaches [10–12], model parameters are explicitly computed by the help of some particular point values on I–V curve of solar cell. Despite simplicity and relatively little time cost, the accuracy of analytical solution greatly relies on the values of selected points. Inaccurate values may lead to a solution with significant error in some cases. In addition, analytical approaches often need to make some assumptions and/or approximations. This may also cause a loss in solution accuracy.

To avoid the potential disadvantages of analytical approaches, many numerical approaches have been suggested, including Newton method [13], various heuristic algorithms such as Genetic Algorithm (GA) [14,15], Particle Swarm Optimization (PSO) [16,17], Simulated Annealing (SA) [18], Harmony Search (HS) [19], two variants of HS, Grouping-based Global Harmony Search (GGHS) [19] and Innovative Global Harmony Search (IGHS) [19] Pattern Search (PS) [20], bee swarm based algorithms including Artificial Bee Colony (ABC) [21] and Artificial bee swarm optimization (ABSO) [22], Differential Evolution (DE) [23], Levenberg–Marquardt algorithm based on simulated annealing (LMSA) [24]. As for Newton method based technique, a major deficiency is its sensitivity to initial parameter value [18]. It may fail to find global optima when solving a multimodal problem, if initial value is inappropriate. Besides, its application requires some necessary conditions such as convexity, continuity and differentiability [19]. On the other hand, heuristic algorithms, based on stochastic search technique which has no requirements for gradient information and accurate estimation of initial value, are more suitable to solve nonlinear optimization problem, and present better results than Newton method. However, most of the heuristic algorithms mentioned above have limitations. Although GA has been widely utilized as an optimization tool, it often suffers from the problem of local optimum [25], especially when low quality chromosomes are initialized or inappropriate control parameters are adopt. SA is a search technique imitating a physical process in which a metal is firstly heated to a given temperature and is then forced to cool down slowly. For this technique, an optimal cooling schedule is difficult to design, and it requires heavy computation burden during iterative search process [26]. LMSA also encounters the same problem as SA. Compared to SA, HS based algorithms produced better results [19]. However, HS based algorithms show a low ability to conduct local search, when used for numerical computation [27]. PSO and DE are the most popular heuristic algorithms, and have many advantages such as simplicity, easy programming and high convergence performance. However, due to fast convergence speed, the probability of premature convergence is also increasing [25,28]. For bee swarm based algorithms and PS, they also have to face the problem of getting trapped in local optimum [29,30].

Therefore, it is necessary to find a new algorithm with a more powerful ability to avoid local optima, which is a problem in the use of most of above mentioned algorithms. Cat swarm optimization (CSO) [31] is a recently devised heuristic algorithm, which mimics the behavior of a swarm of cats. By combining two different search strategies, CSO has the advantages of flexibility, fast convergence and producing highly consistent results. But it is slightly more complex than PSO. As a numerical optimization tool, CSO has been applied to different application domains [32,33]. To our knowledge, there are no reports on the application of CSO algorithm to the problem of parameter identification of solar cell model. In this work, we propose a CSO based optimization method to estimate the unknown parameters of sole cell models.

The main aim of this paper is to investigate the performance of proposed method. For this purpose, results are compared with other reported results. The quality of identified parameters is further evaluated. In addition, the effect of control parameter on the performance is also investigated.

2. Problem formulation

2.1. Solar cell models

2.1.1. Single diode model

The equivalent circuit of single diode model is depicted in Fig. 1. For this model, the output current, I, can be formulated as:

$$I = I_L - I_D - I_P \tag{1}$$

where I_L denotes the photocurrent generated by the solar cell, I_D is diode current, and I_P is parallel resistor current. Further, I_D is expressed as Eq. (2) by Shockley equation while I_P is computed as Eq. (3).

$$I_D = I_O\left[\exp\left(\frac{q(V+IR_S)}{nKT}\right) - 1\right] \tag{2}$$

$$I_P = \frac{V+IR_S}{R_P} \tag{3}$$

where V is the output voltage, I_O is the reverse saturation current of diode, n is the diode ideality factor, R_S and R_P are the series and parallel resistance, respectively. T is the temperature of solar cell in Kelvin, K is Boltzmann constant ($1.3806503 \times 10^{-23}$ J/K), and q is the electron charge ($1.60217646 \times 10^{-19}$ C).

Substituting Eqs. (2) and (3) into Eq. (1), the output current of single diode model is obtained as:

$$I = I_L - I_O\left[\exp\left(\frac{q(V+IR_S)}{nKT}\right) - 1\right] - \frac{V+IR_S}{R_P} \tag{4}$$

Eq. (4) contains five unknown parameters, I_L, I_O, n, R_S and R_P. To represent the I–V characteristics of single diode model, the values of these parameters are required to obtain. Here, it should be noted that the I–V characteristics of solar cell could be influenced by temperature. An increase in temperature will cause a decrease in efficiency and output power of solar cell. More details can be seen in [34,35].

2.1.2. Double diode model

Fig. 2 shows the equivalent circuit of double diode model. Compared with single diode model, this model includes an additional diode (D2). Similar to single diode model, the terminal current of double diode model can be described as Eq. (5), and unknown parameters include I_L, I_{O1}, I_{O2}, n_1, n_2, R_S and R_P.

$$\begin{aligned} I = I_L &- I_{O1}\left[\exp\left(\frac{q(V+IR_S)}{n_1KT}\right) - 1\right] \\ &- I_{O2}\left[\exp\left(\frac{q(V+IR_S)}{n_2KT}\right) - 1\right] - \frac{V+IR_S}{R_P} \end{aligned} \tag{5}$$

2.2. Objective function

As above description, single and double diode models have five and seven unknown parameters, respectively. However, the unknown parameters cannot be easily determined by analytical approach since Eqs. (4) and (5) are nonlinear transcendental equations. Thus, this problem can be transformed into an optimization problem, in which optimal solution can be sought by minimizing the error between experimental I–V form solar cell and calculated I–V from model at a set of points. In this work, CSO is proposed as an optimization tool to solve this problem.

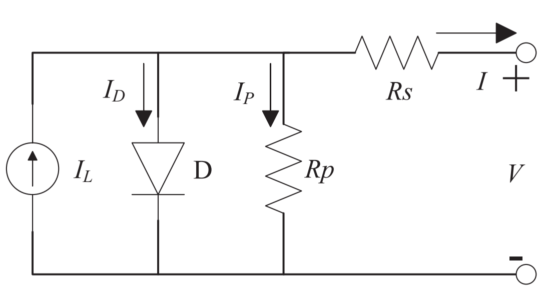

Fig. 1. Equivalent circuit for single diode model.

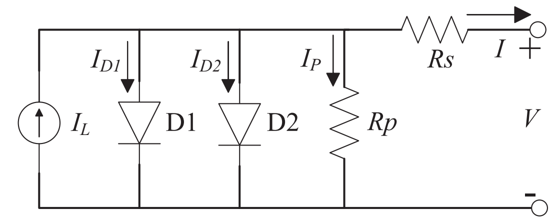

Fig. 2. Equivalent circuit for double diode model.

The objective function for this problem is defined as root mean square error ($RMSE$) and is given by:

$$RMSE = \left[\frac{1}{N}\sum_{i=1}^{N}(E_i(V,I,x))^2\right]^{1/2} \tag{6}$$

where V and I are experimental voltage and current from solar cell, respectively. And N is the number of I–V data points, x is the unknown parameter of solar cell model, $E(V, I, x)$ denotes the error between experimental current from solar cell and calculated current using solar cell model at given voltage. Rewriting Eqs. (4) and (5), $E(V, I, x)$ can be derived as Eqs. (7) and (8) for single diode model and double diode model, respectively.

$$E(V,I,x) = I - I_L + I_O\left[\exp\left(\frac{q(V+IR_S)}{nKT}\right) - 1\right] + \frac{V+IR_S}{R_P} \tag{7}$$

where $x = [I_L, I_O, n, R_S, R_P]$.

$$\begin{aligned} E(V,I,x) = I - I_L &+ I_{O1}\left[\exp\left(\frac{q(V+IR_S)}{n_1KT}\right) - 1\right] \\ &+ I_{O2}\left[\exp\left(\frac{q(V+IR_S)}{n_2KT}\right) - 1\right] + \frac{V+IR_S}{R_P} \end{aligned} \tag{8}$$

where $x = [I_L, I_{O1}, I_{O2}, n_1, n_2, R_S, R_P]$.

3. Proposed cat swarm optimization algorithm

CSO is a heuristic and population-based technique, and is initialized with a swarm (NP) of cats in a D-dimensional search space. Each cat (ith cat, $i = 1,2,\ldots,NP$) has a position ($x_i = [x_{i,1}, x_{i,2}, \ldots, x_{i,D}]$) and a velocity ($v_i = [v_{i,1}, v_{i,2}, \ldots, v_{i,D}]$). The position of each cat represents a solution to an optimization problem, and the quality of solution is evaluated by predefined fitness function or objective function. The position of the cat with best fitness value among all cats is found as best solution, x_{best}. For seeking a better position, each cat dynamically adjusts its position by two types of behaviors, seeking mode and tracking mode. For these two modes, the details and the combined use of them are described in following subsections, respectively.

3.1. Seeking mode

In this mode, a cat slowly moves and is always alert though it spends most of time in resting. It carefully observes its surroundings so as to find a better position from not only one but several candidate positions near current position. Before describing the details of this mode, several parameters are defined as follows.

(1) *SMP* (Seeking memory pool): It indicates the number of duplicates of a cat (i.e., the number of candidate positions).
(2) *CDC* (Counts of dimensions to be changed): It denotes the number of dimensions to be mutated (i.e., it determines how many dimensions are required to mutated.) and its value ranges from 0 to 1.
(3) *SRD* (Seeking range of the selected dimension): It specifies the change of value for the selected dimension.

For *i*th cat, the steps included in the seeking mode are described as follows:

Step 1: Create *SMP* copies of the *i*th cat.
Step 2: Change the position of each copy (*j*th cat, $j = 1,2,\ldots,$ *SMP*) as follows:

$$x_{j,d} = \begin{cases} [1 + (2 \times rand - 1) \times SRD] \times x_{i,d}, & \text{if } d \in \mathrm{M} \\ x_{i,d} & \text{, otherwise} \end{cases} \tag{9}$$

where *rand* is a random value ($rand \in [0,1]$), d is dimension index, and *M* denotes the mutated dimensions that are randomly selected according to *CDC*.
Step 3: Compute the fitness values of all copies and find the position ($x_{bestcopy}$) of the cat with best fitness value among all copies.
Step 4: Replace x_i with $x_{bestcopy}$ if x_i is worse than $x_{bestcopy}$ in terms of fitness value.

3.2. Tracking mode

This mode models a cat tracking a target. The cat rapidly moves toward a new position during chasing process. For *i*th cat, the contained steps for this mode are given as follows:

Step 1: Update the velocity by:

$$v_{i,d} = w \times v_{i,d} + r_1 \times c_1 \times (x_{best,d} - x_{i,d}) \tag{10}$$

where r_1 is a random value ($r_1 \in [0,1]$), c_1 is a constant, and w is inertia weight, which is defined as follows:

$$w = w_{max} - (w_{max} - w_{min}) \times iter/iter_{max} \tag{11}$$

where *iter* indicates iteration index, $iter_{max}$ is the maximum number of iterations, and w_{max} and w_{min} are the maximum and minimum value of inertia weight, respectively.
Step 2: Adjust the position as:

$$x_{i,d} = x_{i,d} + v_{i,d} \tag{12}$$

3.3. Algorithm description

To search an optimal solution, *NP* cats are randomly categorized into two kinds at each iteration. One kind works on seeking mode whereas the other kind carries out tracking mode. Based on another parameter termed as mixture ratio (*MR*), which defines the proportion of the cats performing seeking mode and ranges form 0 to 1, both kinds are combined to find a global optimal solution in searching space. According to fitness values of all cats, x_{best} is updated by CSO until maximum number of generations is reached. Fig. 3 illustrates the flowchart of CSO algorithm. The steps involved in CSO algorithm are described as follows:

Step 1: Create *NP* cats, and randomly initialize position and velocity within respective boundaries for each cat.

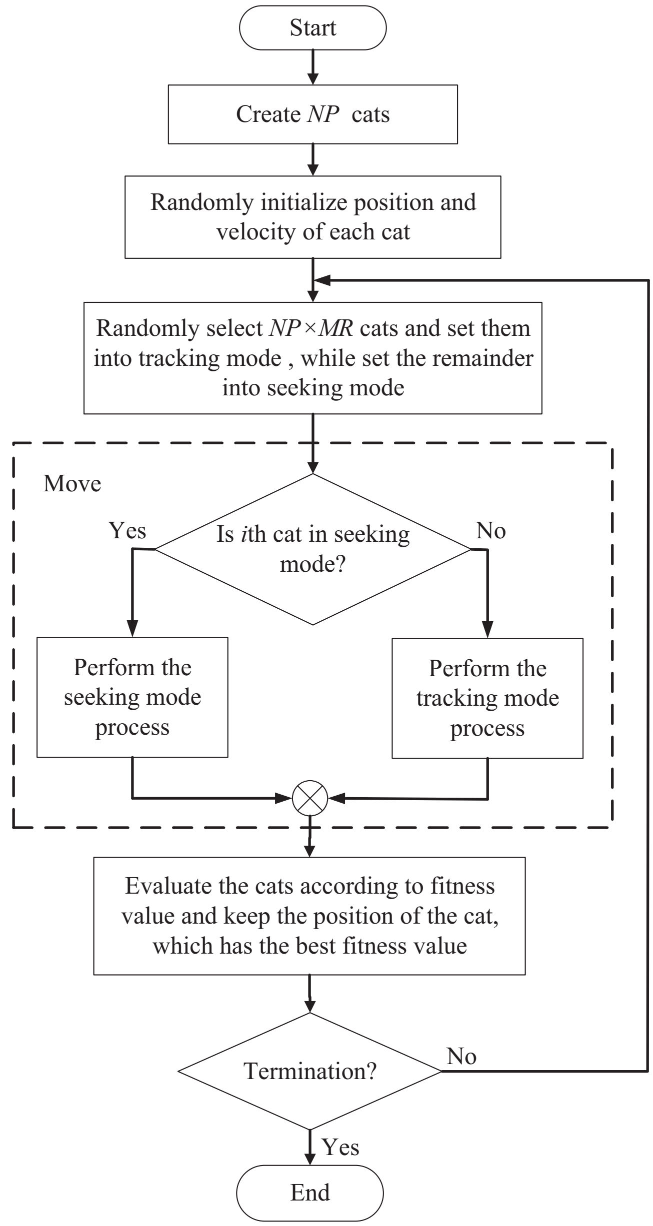

Fig. 3. Flowchart of proposed CSO algorithm.

Step 2: $NP \times MR$ cats are randomly selected and perform the process of seeking mode while the remainder cats perform the process of tracking mode.
Step 3: Evaluate the fitness values for all cats and update x_{best}.
Step 4: Go to step2 repeatedly until maximum number of generations is reached.

4. Parameter identification of solar cell models using cat swarm optimization algorithm

Using CSO algorithm to estimate the unknown parameters of solar cell models, the position of each cat represents a candidate solution. The fitness function is *RMSE* defined as Eq. (6) and the aim of optimization is to minimize the value of *RMSE*. After completing search process as described in Section 3, the optimal solution is obtained by CSO and is equal to x_{best}.

5. Results and discussions

To investigate the performance of proposed method for parameter identification of solar cell models, a set of experimental *I–V* data from [13] is adopt. The experimental data has been measured using a commercial silicon solar cell under test condition as irradiance and temperature are 1000 W/m^2 and 33 °C, respectively. Besides, the search ranges of unknown parameters for solar cell models are chosen the same as [19] and are given in Table 1. The parameters of CSO algorithm are set as $iter_{max} = 500$, $NP = 30$, $MR = 50\%$, $SMP = 4$, $CDC = 20\%$, $SRD = 0.1$, $c_1 = 2.0$, $w_{max} = 0.9$ and $w_{min} = 0.4$. The tuning of these parameters will be explained in Section 6.

Considering unknown parameters can influence the accuracy of solar cell models, the investigation mainly focuses on optimization results and accuracy of the optimal solution, without consideration of time cost. To conduct this study, the optimization result by proposed method is firstly presented and the evaluation for the quality of solution is secondly given. Moreover, results obtained by other methods are also presented for comparisons. The numerical computations were conducted on a personal laptop with a 2.0 GHz Intel dual-core processor and 4 GB RAM, under Windows 7 system.

5.1. Optimization results

The optimal solution and *RMSE* obtained by different approaches are shown in Tables 2 and 3 for single and double diode model, respectively. The comparative approaches including PSO [16], GA [14], SA [18], PS [20], Newton [13], HS [19], GGHS [19], IGHS [19], ABSO [22], DE [23], LMSA [24]. As before mentioned, the aim of optimization for discussing problem is to minimize the *RMSE* value. It means that the lesser *RMSE* value is, the more accurate solution is obtained. Thus, it can be observed from Table 2 that the result of CSO is better than those of other methods since CSO has found the minimum *RMSE* value, 9.8602e−4. This value is close to the values of HS-based algorithms, LMSA, ABSO, and is clearly better than the values of PSO, GA, SA, PS, Newton, DE. From Table 3, we can also see that CSO yields the best solution among all methods according to the obtained *RMSE* values. The value of CSO is close to the values of IGHS and ABSO, but is obviously less than other approaches. Moreover, when Table 2 is compared with Table 3, we can observe that performance difference between CSO and comparative methods for double diode model is more remarkable than for single diode model. It implies that when the number of unknown parameters is increased, CSO maintains high performance. Thus, comparative results indicate that proposed method has ability to find optimal result for the parameter identification problem of solar cell models.

For further checking optimization result, the mean and standard deviation (STD) of *RMSE* value are shown in Table 4 for both solar cell models. Here, for simplicity and the consideration of that PSO and GA are the most widely used algorithms in different optimization problem, we only consider these two algorithms for comparisons. To obtain the results, the CSO based method was independently run 50 times. The results of PSO and GA are taken from [21]. From this Table, it can be observed that considering the values of mean and STD, CSO significantly outperforms PSO and GA. In other words, using optimization strategy to solve the problem of parameter identification, the results of CSO show high accuracy and consistency. Moreover, Figs. 4 and 5 show the convergence performance of CSO during iteration process for single and double diode models, respectively. In both cases, it can be observed that the fitness value become relatively stable and is

Table 1
Upper and lower bounds for solar cell parameters.

Parameter	Lower	Upper
I_L (A)	0	1
I_O, I_{O1}, I_{O2} (μA)	0	1
n, n_1, n_2	1	2
R_S (Ω)	0	0.5
R_P (Ω)	0	100

Table 2
Optimization results of different methods for parameter estimation of single diode model.

Item	CSO	PSO	GA	SA	PS	Newton
I_L (A)	0.76078	0.7607	0.7619	0.7620	0.7617	0.7608
I_O (μA)	0.3230	0.4000	0.8087	0.4798	0.9980	0.3223
n	1.48118	1.5033	1.5751	1.5172	1.6000	1.4837
R_S (Ω)	0.03638	0.0354	0.0299	0.0345	0.0313	0.0364
R_P (Ω)	53.7185	59.012	42.3729	43.1034	64.1026	53.7634
RMSE	9.8602e−4	0.00139	0.01908	0.01900	0.01494	9.6964e−3
	HS	GGHS	IGHS	DE	LMSA	ABSO
I_L (A)	0.76070	0.76092	0.76077	0.7608	0.76078	0.7608
I_O (μA)	0.30495	0.32620	0.34351	0.3230	0.31849	0.30623
n	1.47538	1.48217	1.48740	1.4806	1.47976	1.47583
R_S (Ω)	0.03663	0.03631	0.03613	0.0364	0.03643	0.03659
R_P (Ω)	53.5946	53.0647	53.2845	53.7185	53.32644	52.2903
RMSE	9.9510e−4	9.9097e−4	9.9306e−4	2.3423e−3	9.8640e−4	9.9124e−4

Table 3
Optimization results of different methods for parameter estimation of double diode model.

Item	CSO	PSO	GA	SA	PS	HS	GGHS	IGHS	ABSO
I_L (A)	0.76078	0.7623	0.7608	0.7623	0.7602	0.76176	0.76056	0.76079	0.76078
I_{O1} (μA)	0.22732	0.4767	0.0001	0.4767	0.9889	0.12545	0.37014	0.97310	0.26713
I_{O2} (μA)	0.72785	0.0100	0.0001	0.0100	0.0001	0.25470	0.13504	0.16791	0.38191
n_1	1.45151	1.5172	1.3355	1.5172	1.6000	1.49439	1.49638	1.92126	1.46512
n_2	1.99769	2.0000	1.4810	2.0000	1.1920	1.49989	1.92998	1.42814	1.98152
R_S (Ω)	0.036737	0.0325	0.0364	0.0345	0.0320	0.03545	0.03562	0.03690	0.03657
R_P (Ω)	55.3813	43.1034	53.7185	43.1034	81.3008	46.82696	62.7899	56.8368	54.6219
RMSE	9.8252e−4	0.0166	0.3604	0.01664	0.01518	0.00126	0.00107	9.8635e−4	9.8344e−4

Table 4
Mean and standard deviation of *RMSE* obtained by different methods.

		CSO	PSO	GA
Single diode model	Mean	9.8602E−4	0.2544	0.0551
	STD	5.4941E−9	0.0289	0.0735
Double diode model	Mean	9.9619E−4	0.0715	0.0229
	STD	3.4671E−5	0.3109	0.0199

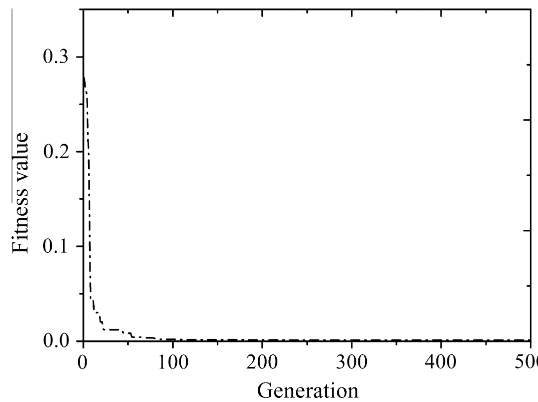

Fig. 4. Convergence curve of CSO during parameter identification for single diode model.

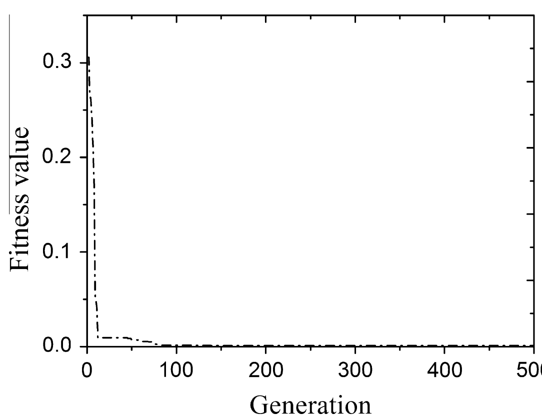

Fig. 5. Convergence curve of CSO during parameter identification for double diode model.

close to optimum value after about 100 generations, which shows that CSO presents high convergence speed. Additionally, the computation time required for running CSO are about 2.07 s and 2.50 s for single and double diode models, respectively.

5.2. Quality of solution

In order to further explore the performance of proposed method, the quality of obtained solution is evaluated. For this purpose, based on optimal solution, the value of calculated current using solar cell models is obtained by using Newton method. Then, experimental *I–V* from solar cell is compared with calculated *I–V* from solar cell models. Subsequently, the statistical analysis of the error between experimental current and calculated current is performed. In this paper, mean absolute error (*MAE*) and mean relative error (*MRE*) are chosen as criterion. They are given by:

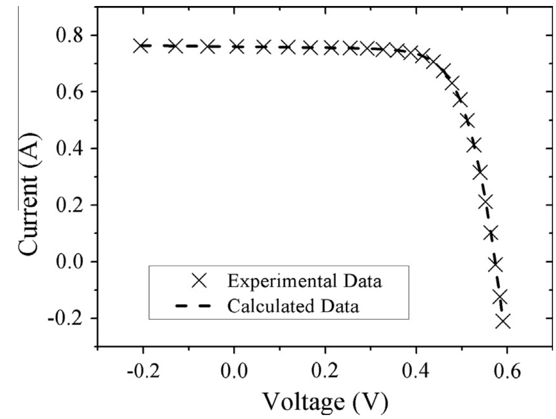

Fig. 6. Comparison between experimental and calculated *I–V* for single diode model.

$$\begin{cases} MAE = \frac{1}{N}\sum_{i=1}^{N} AE_i \\ AE = |I_{measured} - I_{calculated}| \\ MRE = \frac{1}{N}\sum_{i=1}^{N} RE_i \\ RE = |(I_{measured} - I_{calculated})/I_{measured}| \end{cases} \tag{13}$$

where $I_{measured}$ denotes experiment current and $I_{calculated}$ indicates calculated current.

Figs. 6 and 7 show the comparisons between the experimental *I–V* curve and calculated *I–V* curve for single and double diode model, respectively. Both figures show that the calculated *I–V* curve has a good agreement with experimental *I–V* cure. It demonstrates that when the solutions yielded by CSO are adopted, both solar cell models can accurately represent the characteristics of solar cell. It also indicates that CSO obtained solution has a good quality.

Meanwhile, the results of *MAE* and *MRE* are listed in Table 5. For single and double diode models, the values of *MAE* shown in Table 5 for CSO are significantly less than that for GA, and are also less than that for PSO. While considering *MRE*, the results for CSO are also obviously better than that for GA and PSO. The comparison presented in Table 5 further demonstrates that the solutions obtained by proposed method are accurate.

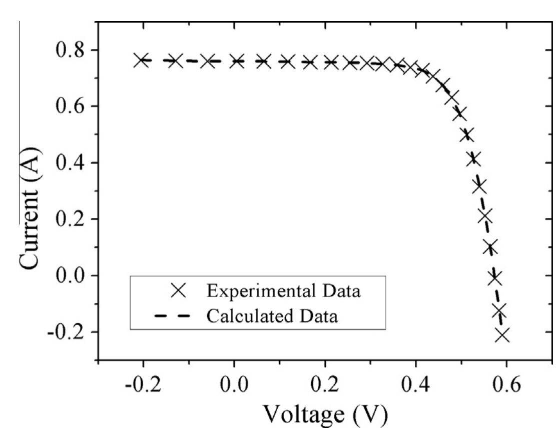

Fig. 7. Comparison between experimental and calculated *I–V* for double diode model.

Table 5
Statistical results of error for different methods.

		CSO	PSO	GA
Single diode model	*MAE*	6.7968E−4	8.5990E−4	7.4856E−3
	MRE	4.5555E−3	1.0110E−2	1.1682E−1
Double diode model	*MAE*	6.6682E−4	5.8944E−3	2.0210E−1
	MRE	4.4445E−3	1.0307E−1	3.8252

In CSO, seeking mode and tracking mode represent exploration and exploitation search process, respectively. The former conducts a search in an unseen region, whereas the latter implements a search in the neighborhood of a current solution. The high performance of CSO can be attributed to several factors related to exploration and exploitation abilities, including population diversity, mutation flexibility, and a good balance between exploration and exploitation. For population based heuristic algorithm, population diversity is one of the crucial aspects of influencing exploration ability. The high population diversity provides more different solutions in search space, then, resulting in a broad search. This further increases the probability to find global optima but not converge to local optima. In other words, this enhances the exploration ability, and vice versa. In seeking mode, each candidate solution (i.e., position) is updated from not only one but several mutated solutions. This means that more candidate solutions are involved to search global optima, and therefore increases the population diversity. This thus enhances the exploration ability of CSO. Besides population diversity, mutation strategy also influences the performance of heuristic algorithm. In general, the mutation strategy used in other algorithms such as PSO and GA is always that each dimension in search space has to be mutated simultaneously to search a new solution. Such a strategy can also be achieved by CSO. However, the seeking mode in CSO provides a more flexible mutation mechanism in which not all dimensions but only several dimensions, depending on control parameter *CDC*, have to be mutated. It can be very effective in the case that in multi-dimensions search space, the values for some dimensions are equal or close to optimal values while the values in other dimensions are far different from optimal values. Such a case can occur in search process for various optimization problems. Considering this, mutation flexibility also improves the exploration of CSO. However, it should be noted that population diversity and mutation flexibility also increase the complexity and computation time for CSO. In addition, dealing with optimization problem expects a fast convergence speed. As we known, in PSO, each particle's position (i.e., solution) is adjusted by personal best position found by each particle in historical search and global best position found by all particles. Based on such a search mechanism, PSO shows fast convergence. Due to the fact that the search mechanism of tracking mode is similar to that of PSO without considering personal best position, CSO thus inherits the advantage of PSO, fast convergence during iteration process. Finally, a good balance between exploration and exploitation plays an important role in the performance of any optimization algorithm [17]. In CSO, seeking and tracking modes can be adjusted by control parameters, mixture ratio and inertia weight, leading to a good balance between exploration and exploitation. All above factors considered in search mechanism ensure that CSO can find global optima but not local optima, and present highly consistent results and fast convergence.

6. Sensitivity analysis

Using proposed approach to solve the parameter identification problem, the included control parameters of CSO may influence its performance. In this section, this is investigated by measuring the sensitivity of performance to parameter change. Considering that the searching mechanism of the tracking mode is the same as that of simplified PSO, the parameters included in the tracking mode are not taken into account. Several experiments are carried out for this investigation. For each experiment, when one specified parameter is varied while the other parameters are kept constant, we measure the mean and STD of *RMSE* obtained by CSO. The experimental results are listed in Tables 6 and 9 where the best results are shown in bold.

6.1. Effect of seeking rang of dimension (SRD)

For this experiment, the different values of *SRD* are set as 0.1, 0.2, 0.3 and 0.5. The experimental results are presented in Table 6. As we can see that the best result of CSO is obtained when the value of *SRD* is equal to 0.1. This implies that smaller mutation step leads to the increasing probability of finding global optimal solution for the problem in this study.

6.2. Effect of changed dimensions of count (CDC)

The results for the varying values of *CDC*, 0.2, 0.4, 0.6 and 0.8, are tabulated in Table 7. It can be observed that the increasing

Table 6
Results for the effect of *SRD* on the performance of CSO.

Model		*SRD*			
		0.1	0.2	0.3	0.5
Single diode model	Mean	**1.1232E−03**	1.2571E−03	1.2512E−03	1.4624E−03
	STD	**3.06E−04**	3.88E−04	3.47E−04	5.39E−04
Double diode model	Mean	**1.2259E−03**	1.3039E−03	1.4085E−03	1.5225E−03
	STD	**3.48E−04**	3.52E−04	4.40E−04	5.34E−04

Table 7
Results for the effect of *CDC* on the performance of CSO.

Model		*CDC*			
		0.2	0.4	0.6	0.8
Single diode model	Mean	**9.8638E−04**	9.9433E−04	1.0788E−03	1.0745E−03
	STD	**1.37E−06**	2.10E−05	2.03E−04	1.20E−04
Double diode model	Mean	**9.9688E−04**	1.0319E−03	1.2063E−03	1.3130E−03
	STD	**3.99E−05**	1.37E−04	3.23E−04	3.86E−04

Table 8
Results for the effect of *SMP* on the performance of CSO.

Model		*SMP*			
		4	8	12	16
Single diode model	Mean	9.8641E−04	9.8605E−04	9.8602E−04	**9.8602E−04**
	STD	1.12E−06	1.71E−07	1.38E−10	**1.19E−10**
Double diode model	Mean	9.9650E−04	9.8625E−04	9.8558E−04	**9.8438E−04**
	STD	3.11E−05	3.83E−06	3.60E−06	**1.59E−06**

Table 9
Results for the effect of *MR* on the performance of CSO.

Model		*MR*			
		0.3	0.5	0.7	0.9
Single diode model	Mean	9.8617E−04	**9.8602E−04**	9.8602E−04	1.0104E−03
	STD	8.20E−07	**1.26E−12**	1.51E−09	5.13E−05
Double diode model	Mean	1.0080E−03	**9.9613E−04**	1.0054E−03	9.9821E−04
	STD	8.44E−05	4.88E−05	6.31E−05	**2.71E−05**

values of *CDC* result in the decreasing performance of CSO. When *CDC* = 0.2, which means the number of mutated dimensions is equal to one, CSO gives the best performance.

6.3. Effect of seeking memory pool (SMP)

Table 8 shows the results for the variation of *SMP*. The values of *SMP* are adopted as 4, 8, 12 and 16. We can find that the larger the value of *SMP* is, the better the performance of CSO obtained. The larger values of *SMP* increase the probability of finding the global optimal solution for CSO. However, it should be noted that larger value of *SMP* also leads to a increase in the use of the memory and computation time. Therefore, in this paper, we set *SMP* = 4 although the obtained results is slightly worse than comparative results.

6.4. Effect of mixture ratio (MR)

The effect of *MR* on the performance of CSO is studied in this experiment and results are summarized in Table 9. It can be seen that the setting of *MR* has little impact on the performance of CSO. For single diode model, the best result is obtained when *MR* value is set as 0.5. For double diode model, although the STD value for 0.5 is slightly worse than that for 0.9, the mean value for 0.5 is slightly better than that for 0.9. We should also note that larger value of *MR* increases the number of cats that undertake the seeking mode. This results in the increase of computation time of CSO. Thus, the *MR* value is set as 0.5 in this paper.

Consequently, the experimental results in above subsections infer that the parameter setting of CSO in this paper is reasonable.

7. Conclusions

In this paper, the CSO algorithm based optimization technique is applied to estimate the unknown parameters of solar cell models. The results have been compared with reported results by other methods. Comparisons show that proposed technique has the capability to find global optimal solution and provides a high performance in terms of consistency and convergence. Furthermore, presented statistic analysis demonstrates the high quality of obtained solutions. Results show that there has a good agreement between calculated and experimental *I–V* curve when CSO obtained solutions are used to simulate the performance of single and double diode solar cell models. In addition, the effect of control parameters on the performance of CSO has also been studied. Results show that when small step and one-dimension mutation strategy are adopted, the better performance of CSO can be obtained. In summary, the proposed CSO algorithm can be an effective tool to solve the optimization problem of parameter identification of solar cell models.

References

[1] Navabi R, Abedi S, Hosseinian SH, Pal R. On the fast convergence modeling and accurate calculation of PV output energy for operation and planning studies. Energy Convers Manage 2015;89:497–506.
[2] Charalambous PG, Kalogirou SA, Maidment GG, Yiakoumetti K. Optimization of the photovoltaic thermal (PV/T) collector absorber. Sol Energy 2011;85:871–80.
[3] Agrawal S, Tiwari GN. Energy and exergy analysis of hybrid micro-channel photovoltaic thermal module. Sol Energy 2011;85:356–70.
[4] Sobhnamayan F, Sarhaddi F, Alavi MA, Farahat S, Yazdanpanahi J. Optimization of a solar photovoltaic thermal (PV/T) water collector based on exergy concept. Renew Energy 2014;68:356–65.
[5] Singh S, Agarwal S, Tiwari GN, Chauhan D. Application of genetic algorithm with multi-objective function to improve the efficiency of glazed photovoltaic thermal system for New Delhi (India) climatic condition. Sol Energy 2015;117:153–66.
[6] Singh S, Agrawal S, Gadh R. Optimization of single channel glazed photovoltaic thermal (PVT) array using Evolutionary Algorithm (EA) and carbon credit earned by the optimized array. Energy Convers Manage 2015;105:303–12.
[7] Kahoul N, Houabes M, Sadok M. Assessing the early degradation of photovoltaic modules performance in the Saharan region. Energy Convers Manage 2014;82:320–6.
[8] Rus-Casas C, Aguilar JD, Rodrigo P, Almonacid F, Pérez-Higueras PJ. Classification of methods for annual energy harvesting calculations of photovoltaic generators. Energy Convers Manage 2014;78:527–36.
[9] Tadj M, Benmouiza K, Cheknane A, Silvestre S. Improving the performance of PV systems by faults detection using GISTEL approach. Energy Convers Manage 2014;80:298–304.
[10] Chan DSH, Phang JCH. Analytical methods for the extraction of solar-cell single- and double-diode model parameters from *I–V* characteristics. IEEE Trans Electron Dev 1987;34:286–93.
[11] Khan F, Baek SH, Park Y, Kim JH. Extraction of diode parameters of silicon solar cells under high illumination conditions. Energy Convers Manage 2013;76:421–9.
[12] Bai JB, Liu S, Hao YZ, Zhang Z, Jiang M, Zhang Y. Development of a new compound method to extract the five parameters of PV modules. Energy Convers Manage 2014;79:294–303.
[13] Easwarakhanthan T, Bottin J, Bouhouch I, Boutrit C. Nonlinear minimization algorithm for determining the solar cell parameters with microcomputers. Int J Sol Energy 1986;4:1–12.
[14] Zagrouba M, Sellami A, Bouaïcha M, Ksouri M. Identification of PV solar cells and modules parameters using the genetic algorithms: application to maximum power extraction. Sol Energy 2010;84:860–6.
[15] AlRashidi MR, AlHajri MF, El-Naggar KM, Al-Othman AK. A new estimation approach for determining the *I–V* characteristics of solar cells. Sol Energy 2011;85:1543–50.

[16] Wei H, Cong J, Lingyun X, Deyun S. Extracting solar cell model parameters based on chaos particle swarm algorithm. In: International conference on electric information and control engineering (ICEICE); 2011. p. 398–402.
[17] Khanna V, Das BK, Bisht D, Vandana, Singh PK. A three diode model for industrial solar cells and estimation of solar cell parameters using PSO algorithm. Renew Energy 2015;78:105–13.
[18] El-Naggar KM, AlRashidi MR, AlHajri MF, Al-Othman AK. Simulated annealing algorithm for photovoltaic parameters identification. Sol Energy 2012;86:266–74.
[19] Askarzadeh A, Rezazadeh A. Parameter identification for solar cell models using harmony search-based algorithms. Sol Energy 2012;86:3241–9.
[20] AlHajri MF, El-Naggar KM, AlRashidi MR, Al-Othman AK. Optimal extraction of solar cell parameters using pattern search. Renew Energy 2012;44:238–45.
[21] Oliva D, Cuevas E, Pajares G. Parameter identification of solar cells using artificial bee colony optimization. Energy 2014;72:93–102.
[22] Askarzadeh A, Rezazadeh A. Artificial bee swarm optimization algorithm for parameters identification of solar cell models. Appl Energy 2013;102:943–9.
[23] Hachana O, Hemsas K, Tina G, Ventura C. Comparison of different metaheuristic algorithms for parameter identification of photovoltaic cell/module. J Renew Sust Energy 2013;5:053122.
[24] Dkhichi F, Oukarfi B, Fakkar A, Belbounaguia N. Parameter identification of solar cell model using Levenberg–Marquardt algorithm combined with simulated annealing. Sol Energy 2014;110:781–8.
[25] Shieh HL, Kuo CC, Chiang CM. Modified particle swarm optimization algorithm with simulated annealing behavior and its numerical verification. Appl Math Comput 2011;218:4365–83.
[26] Raaymakers WHM, Hoogeveen JA. Scheduling multipurpose batch process industries with no-wait restrictions by simulated annealing. Eur J Oper Res 2000;126:131–51.
[27] Mahdavi M, Fesanghary M, Damangir E. An improved harmony search algorithm for solving optimization problems. Appl Math Comput 2007;188:1567–79.
[28] Basu M. Improved differential evolution for economic dispatch. Int J Electr Power Energy Syst 2014;63:855–61.
[29] Cuevas E, Cienfuegos M. A new algorithm inspired in the behavior of the social-spider for constrained optimization. Expert Syst Appl 2014;41:412–25.
[30] Panda S, Kiran H, Dash SS, Subramani C. A PD-type multi input single output SSSC damping controller design employing hybrid improved differential evolution-pattern search approach. Appl Soft Comput 2015;32:532–43.
[31] Chu SC, Tsai PW. Computational intelligence based on the behavior of cats. Int J Innov Comput 2007;I(3):163–73.
[32] Pradhan PM, Panda G. Solving multiobjective problems using cat swarm optimization. Expert Syst Appl 2012;39:2956–64.
[33] Saha SK, Ghoshal SP, Kar R, Mandal D. Cat Swarm Optimization algorithm for optimal linear phase FIR filter design. ISA T 2013;52:781–94.
[34] Rahman MM, Hasanuzzaman M, Rahim NA. Effects of various parameters on PV-module power and efficiency. Energy Convers Manage 2015;103:348–58.
[35] Sharma V, Chandel SS. Performance and degradation analysis for long term reliability of solar photovoltaic systems: a review. Renew Sust Energy Rev 2013;27:753–67.