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Parameter extraction of PV models using an enhanced shuffled complex evolution algorithm improved by opposition-based learning

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Abstract

Accurate and efficient parameter extraction of PV models from I-V characteristic curves is significant for modeling, evaluation and fault diagnosis of PV modules/arrays. Recently, a large number of algorithms are proposed for this problem, but there are still some issues like premature convergence, low accurate and instability. In this paper, a new improved shuffled complex evolution algorithm enhanced by the opposition-based learning strategy (ESCE-OBL) is proposed. The proposed algorithm improves the quality of the candidate solution by the opposition-based learning strategy. Moreover, the basic SCE algorithm evolves with the traditional competition complex evolution (CCE) strategy, but it converges slowly and is prone to be trapped in local optima. In order to improve the exploration capability, the complex in the basic SCE is evolved by a new enhanced CCE. The ESCE-OBL algorithm is compared with some state-of-the-art algorithms on the single diode model (SDM) and double diode model (DDM) using benchmark I-V curves data. The comparison results demonstrate that the proposed ESCE-OBL algorithm can achieve faster convergence, stronger robustness and higher efficiency.

Keywords: Parameters extraction; Opposition-based learning (OBL); Enhanced shuffled complex evolution (ESCE)

1. Introduction

The environment pollution and energy shortage issues make the renewable and broadly available solar energy become more and more attractive. During the design and optimization of PV systems, it is important to establish an

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accurate PV model for the DC side PV modules/arrays, and the change of their models is significant for the status evaluation and fault diagnosis [1-3]. In addition, the accuracy of PV models greatly relies on the parameters of model structures [4]. Therefore, parameter extraction is important for PV modelling, which is often regarded as a non-linear optimization problem. In order to improve the accuracy, many metaheuristics methods (i.e. R_{cr}-IJADE [5], JAYA [4], GOFPANM [6], ABC-NMS[7] and so on) have been proposed to obtain the global optimal solution, among which the shuffled complex evolution (SCE) is a robust, accurate and efficient algorithm[8]. However, the basic SCE algorithm will converge slowly when the initial value is far away from the optimal solution. In this paper, we propose the new ESCE-OBL algorithm using the opposition-based learning strategy and enhanced CCE strategy to improve basic SCE algorithm for the higher convergence speed and accuracy. The opposition-based learning strategy can increase the diversity of the population and the enhanced CCE strategy improves the speed of convergence. To verify the robustness, convergence and accuracy, the proposed ESCE-OBL algorithm is used to extract the parameters of the SDM and DDM models using the benchmark I-V data of a PV module and a solar cell.

2. Parameter extraction problem of PV models

2.1. Single-diode model (SDM)

The SDM is the most commonly used PV model, the schematic of which is depicted in Fig. 1. The expression of its output current-voltage relationship is given by Eq. (1) [9]. There are five unknown parameters (I_{pv}, I_o, a, R_s, and R_{sh}) to be extracted for SDM, where I_{pv} is the photo-generated current, I_0 is the saturation current, a is the diode ideal factor. R_s represents series resistance and R_{sh} is the shunt resistance. K is the Boltzmann constant (1.380653×10^{-23} J/K), T is the temperature of the junction in Kelvin and q is the absolute value of electron charge (1.60217646×10^{-19} C).

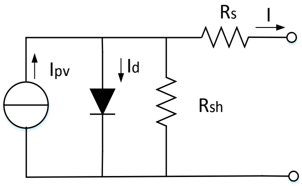

Fig. 1. SDM circuit model

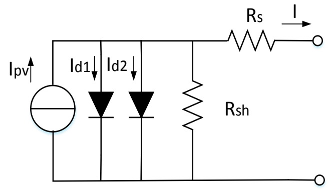

Fig. 2. DDM circuit model

$$I = I_{pv} - I_o\left(\exp\left(\frac{q(V+IR_s)}{\alpha KT}\right)-1\right)-\frac{V+IR_s}{R_{sh}} \tag{1}$$

2.2. Double-diode model (DDM)

The DDM has the higher accuracy but larger computation compared to the SDM. The DDM model is shown in Fig. 2. The expression of its output current-voltage relationship is given by Eq. (2), and there are seven unknown parameters (I_{PV}, I_{o1}, a_1, I_{o2}, a_2, R_s, and R_{sh}).

$$I = I_{pv} - I_{o1}\left(\exp\left(\frac{q(V+IR_s)}{\alpha_1 KT}\right)-1\right) - I_{o2}\left(\exp\left(\frac{q(V+IR_s)}{\alpha_2 KT}\right)-1\right)-\frac{V+IR_s}{R_{sh}} \tag{2}$$

2.3. Objective function

The problem of the parameter extraction is to extract the unknown model parameters based on the selected model and the measured I-V curve. The goal is to minimize deviation between the experimental data and the simulated data with the extracted parameters. The error function for the deviation between the measured and simulated data is defined as Eq. (3) and Eq. (4) for the SDM and DDM respectively. The root mean square error (RMSE) is used as the objective function as given in Eq. (5) where the X is the unknown parameters of the different models, N is the number of the data points, V and I represent the voltage and current of the measure data.

$$f(V,I,X)=I_{pv}-I_o\left(\exp\left(\frac{q(V+IR_s)}{aKT}\right)-1\right)-\frac{V+IR_s}{R_{sh}}-I \tag{3}$$

$$f(V,I,X)=I_{pv}-I_{o1}\left(\exp\left(\frac{q(V+IR_s)}{a_1KT}\right)-1\right)-I_{o2}\left(\exp\left(\frac{q(V+IR_s)}{a_2KT}\right)-1\right)-\frac{V+IR_s}{R_{sh}}-I \tag{4}$$

$$RMSE(x)=\sqrt{\frac{1}{N}\sum_{i=1}^{N}f(V,I,X)^2} \tag{5}$$

3. The proposed ESCE-OBL algorithm

3.1. The basic SCE improved by the opposition-based learning

The basic shuffled complex evolution algorithm (SCE) is firstly proposed in [10]. The main structure of the SCE is population, complex and sub-complex. If the optimization problem has many local optima, the SCE is prone to lose the balance between the exploration and exploitation [11]. Compared with the SCE, the proposed algorithm utilizes the OBL strategy in the initialization stage to improve the quality of the initial population and the ECCE further improve the convergence of the CCE strategy. The process of the ESCE-OBL is introduced as follows.

Step 1: Initialize parameters. Set up the $nps \geq 1$ and $npg \geq nopt + 1$, where the nps is the number of complex, npg is the number of population in the each complex and the $nopt$ is the dimension of the fitness function. The total number of the population is $npt = nps * npg$.

Step 2: Generate population. The npt initial population is generated by the Eq. (6), where the BU and BL are the upper and lower bound of each points, the *rand* is a random number in [-1, 1].

$$x_i = BL + rand * (BU - BL), i = 1,2,...,npt \tag{6}$$

Step 3: Apply opposition-based learning strategy. The opposition-based learning (OBL), which has chance to create opposite candidates solution to be closer to the global optimum solution than then random initialization by Eq. (7) [12], is used to improve the quality of the initial population.

$$x^o = BL + BU - x \tag{7}$$

Step 4: Sort points. The initial points are sorted in ascending order according to the objective function values. Store the better npt points of the initial points in an array $D = \{x_i, f_i, i = 1, 2, \dots \dots, npt\}$. The x_1 is the best point, while the npt is the worst.

Step 5: Partition the population into complexes. The npt points in D are partitioned into npg complex A^k.

Step 6: Evolve each complex. The ECCE is used to evolve the complex.

Step 7: Shuffle complexes. Each evolved complex replaces the original complex $A^1, A^2, \dots, A^{nps}$ in D. Sort the D like the Step 3.

Step 8: Check convergence. If the convergence condition is satisfied, the algorithm stops. Else, go to Step 3.

3.2. The enhanced competitive complex evolution strategy

The competitive complex evolution strategy (CCE) is enhanced by a new update strategy for the worst point, which consists of the following steps:

Step 1: Initialize parameters. Set up controlling parameters: q, α, β, m, n, where $2 \le q \le ngs, \alpha \ge 1, \beta \ge 0, \gamma \ge 1, m \ge 1, n \ge 1$.

Step 2: Select parents. The q sub-complex is chosen by Eq. (8). Then q points and their fitness values are stored in $B = \{u_i, v_i \mid i = 1, 2, \ldots, q\}$, where the $floor(\cdot)$ is the round down function in the Matlab, $rand$ is a number between [0, 1] and Idx is the index of the individuals in the complex. u_i is the points in the k complex and the v_i is the fitness value of u_i.

$$Idx = 1 + floor(npg + 0.5 - \sqrt{(npg + 0.5)^2 - rand * npg(npg + 1)}) \tag{8}$$

Step 3: Generate the offspring. The process of the evolution is shown as follows. The u_b and the u_q is the best and worst one in the complex respectively. Then the new u_x will be judged whether it is in the flexible space.

(a) Calculate the centroid point ce in the B by the Eq. (9) where q is the number of sub-complex.

$$ce = \frac{1}{q-1} \sum_{i=1}^{q-1} u_j, i = 1, 2, \ldots, q \tag{9}$$

(b) Compute the new reflection points u_r by Eq. (10).

$$u_r = ce + \alpha(ce - u_q) \tag{10}$$

(c) If the $F_r < F_1$ or $F_r < F_{q-1}$, the u_r will be calculated by (e) and go to the step (f). Or else, the points are updated by the Eq. (11) where u_g and u_b are the best point in the all population and current complex respectively. Then calculate F_c and go to (e).

$$u_c = \begin{cases} u_r + \beta\left(u_g - u_r\right) & if\ F_{q-1} < F_r < F_q \\ u_q + \beta\left(ce - u_q\right) & if\ F_r > F_q \end{cases} \tag{11}$$

(d) If the $F_c > F_q$, the worst point will be updated by the new strategy in Eq. (12), which updates the worst points by both global best points u_g and local best points u_b , rather than generating the new points randomly as the basic CCE. Then, the F_z is calculated. If the $F_z < F_q$, go to the step (f). Or else, recreate the u' randomly, where the r is a random number in range [-1, 1]. Theoretically, this new strategy has better capability to approach the global optimum than the random updated process.

$$u_z = u_q + \beta(u_g - u_q) + \gamma \cdot r(u_b - u_q), r \in (-1, 1) \tag{12}$$

(e) The expansion point u_e is produced by the Eq. (13) and the fitness value is calculated. The better one between u_r and u_e will be chosen to replace the u_q and go to the step (f).

$$u_e = ce + \gamma(ce - u_q) \tag{13}$$

(f) Choose the u_x to update the u_q and repeat the steps (a) to (f) for n times.

Step 4: Iterate. Repeat Steps (1) to (4) for m times.

4. Experiments and result comparison

4.1. Evaluation result on the benchmark problems

In this section, the ESCE-OBL algorithm is used to extract the parameters from three benchmark I-V data that are from a silicon solar cell of 57 mm diameter operating at 33℃ from R.T.C France and a PV module named Photowatt-PWP201 operating at 45 °C [5]. In order to validate the superior performance of the proposed ESCE-OBL, the RMSE is used to measure the accuracy and the maximum number of fitness function evaluations (MNFES) is selected to represent the convergence. Some state-of-the-art algorithms are used to make a comparison, including R_{cr}-IJADE [5], SCE and GOFPANM [6]. The results of the parameters extraction for SDM and DDM are shown in Table 1 and Table 2, from which it can be observed that the ESCE-OBL algorithm achieves the least RMSE value with the least MNFES number. The comparison on the I-V curve between measured and simulated data obtained by ESCE-OBL is shown in Fig. 3 and Table 3. There are only tiny errors between measured and simulated curves in three benchmark problems, which validates that the parameters extracted by ESCE-OBL are accurate.

Table 1. Comparison among the state-of-the-art algorithms on benchmark problems

Item	Solar Cells				PV module			
	GOFPANM	Rcr-IJADE	**SCE**	**ESCE-OBL**	GOFPANM	R_{cr}-IJADE	**SCE**	**ESCE-OBL**
Ipv (A)	0.76077	0.76078	**0.76078**	**0.76078**	1.030514	1.0305143	**1.03051**	**1.03051**
Io (uA)	0.32021	0.32302	**0.32302**	**0.32302**	3.482263	3.4822631	**3.48226**	**3.48226**
Rs (Ω)	0.03637	0.03638	**0.03638**	**0.03638**	1.201271	1.2012710	**1.20127**	**1.20127**
Rsh(Ω)	53.7185	53.7185	**53.7185**	**53.7185**	981.9823	981.98233	**981.982**	**981.982**
N	1.48118	1.48118	**1.48118**	**1.48118**	48.64284	48.642835	**48.6428**	**48.6428**
RMSE	9.8602E-4	9.8602E-4	**9.8602E-4**	**9.8602E-4**	0.02425	0.02425	**0.02425**	**0.02425**
MNFES	10,000	10,000	**5,000**	**5,000**	10,000	10,000	**5,000**	**5,000**

Table 2. Comparison among the state-of-the-art algorithms for DDM of the solar cell

Item	ABC	STLBO	GOTLBO	GOFPANM	Rcr-IJADE	SCE	**ESCE-OBL**
Ipv (A)	0.7608	0.76078	0.760752	0.760781	0.760781	0.760781	**0.760781**
Io1 (uA)	0.0407	0.22566	0.800195	0.749348	0.225974	0.225964	**0.225974**
Io2 (uA)	0.2874	0.75217	0.220462	0.225974	0.749347	0.749460	**0.749349**
Rs (Ω)	0.0364	0.03674	0.036783	0.036740	0.036740	0.036740	**0.036740**
Rsh(Ω)	53.780	55.4920	56.0753	55.48544	55.48544	55.48604	**55.48544**
n1	1.4495	1.45085	1.999973	2.000000	1.451017	1.451013	**1.451017**
n2	1.4885	2.00000	1.448974	1.451017	2.000000	2.000000	**2.000000**
RMSE	9.861E-04	**9.8248E-04**	9.8318E-04	**9.8248E-04**	**9.8248E-4**	**9.8248E-4**	**9.824848E-4**
MNFES	1,500,000	50,000	20,000	20,000	20,000	12,000	**10,000**

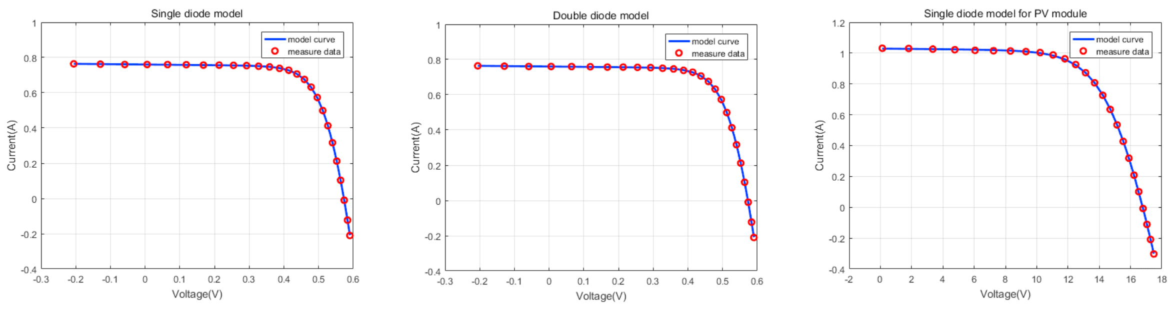

Fig. 3. The comparison on the I-V curves between measured data and simulated data obtained by ESCE-OBL

Table 3. The simulated result of ESCE-OBL for three benchmark problems

	Solar Cell				PV module		
	Measured data		Fit Data (SDM)	Fit Data (DDM)	Measured data		Fit Data (SDM)
Item	$V_{measured}$ (V)	$I_{measured}$ (A)	$I_{calculated}$(A)	$I_{calculated}$(A)	$V_{measured}$ (V)	$I_{measured}$ (A)	$I_{calculated}$(A)
1	-0.20570	0.76400	0.76408770	0.76399853	0.12480	1.03150	1.02911914
2	-0.12910	0.76200	0.76266308	0.76261279	1.80930	1.03000	1.02738106
3	-0.05880	0.76050	0.76135530	0.76134052	3.35110	1.02600	1.02574179
4	0.00570	0.76050	0.76015399	0.76017130	4.76220	1.02200	1.02410716
5	0.06460	0.76000	0.75905520	0.75910054	6.05380	1.01800	1.02229181
6	0.11850	0.75900	0.75804234	0.75811046	7.23640	1.01550	1.01993069
7	0.16780	0.75700	0.75709165	0.75717503	8.31890	1.01400	1.01636312
8	0.21320	0.75700	0.75614136	0.75622912	9.30970	1.01000	1.01049617
9	0.25450	0.75550	0.75508687	0.75516426	10.2163	1.00350	1.00062899
10	0.29240	0.75400	0.75366387	0.75371356	11.0449	0.98800	0.98454839
11	0.32690	0.75050	0.75139096	0.75139721	11.8018	0.96300	0.95952169
12	0.35850	0.74650	0.74735385	0.74730796	12.4929	0.92550	0.92283883
13	0.38730	0.73850	0.74011722	0.74002494	13.1231	0.87250	0.87259967
14	0.41370	0.72800	0.72738222	0.72726569	13.6983	0.80750	0.80727426
15	0.43730	0.70650	0.70697265	0.70686785	14.2221	0.72650	0.72833648
16	0.45900	0.67550	0.67528015	0.67522132	14.6995	0.63450	0.63713800
17	0.47840	0.63200	0.63075827	0.63076181	15.1346	0.53450	0.53621307
18	0.49600	0.57300	0.57192835	0.57198680	15.5311	0.42750	0.42951133
19	0.51190	0.49900	0.49960701	0.49969317	15.8929	0.31850	0.31877450
20	0.52650	0.41300	0.41364879	0.41372192	16.2229	0.20850	0.20738952
21	0.53980	0.31650	0.31751010	0.31754043	16.5241	0.10100	0.09616719
22	0.55210	0.21200	0.21215493	0.21212605	16.7987	-0.0080	-0.0083253
23	0.56330	0.10350	0.10225131	0.10217389	17.0499	-0.1110	-0.1109364
24	0.57360	-0.01000	-0.0087175	-0.0087825	17.2793	-0.2090	-0.2092472
25	0.58330	-0.12300	-0.1255074	-0.1255386	17.4885	-0.3030	-0.3008635
26	0.59000	-0.21000	-0.2084723	-0.2083844			

4.2. Robustness and Convergence

For validating the improvement of the ESCE-OBL in terms of convergence and robustness, the basic SCE is used for further comparison. The $NFES^*$ is the number of the objective function evaluations when the fitness value is less than the threshold value V_{th} firstly. The statistical results of the RMSE and $NFES^*$ are shown in Table 4. It can be observed that the ESCE-OBL has lower standard deviation and mean value of RMSE and $NFES^*$ for both SDM and DDM problems. From the average convergence graph as shown in Fig. 4, it can be observed obviously that the curve of the proposed algorithm has a faster decreased speed than the basic SCE. Therefore, the ESCE-OBL features better convergence and robustness than the basic SCE in parameters extraction.

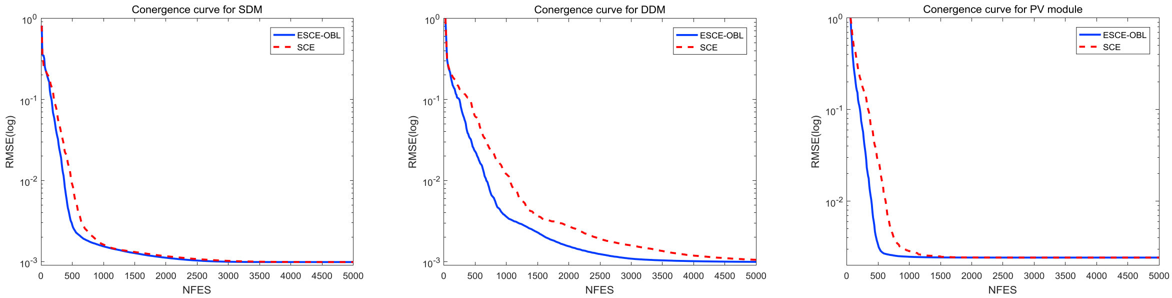

Fig. 4. Average convergence of the SCE and ESCE-OBL for three problems

Table 4. Statistical comparison for SDM and DDM of the solar cell

Algorithm	RMSE (SDM)		NFES* (Vth = 0.001)		RMSE (DDM)		NFES* (Vth = 0.001)	
	Mean(E-04)	Std	Mean	Std	Mean(E-04)	Mean(E-04)	Mean	Std
SCE	9.860236	1.64 E-08	2680	818	9.849378467	9.849378467	4828.6	1336.70
ESCE-OBL	**9.860218**	**3.15 E-14**	**2453**	**648**	**9.836941429**	**9.836941429**	**3342.3**	**887.8**

5. Conclusion

In this paper, a new improved algorithm ESCE-OBL is proposed to extract the unknown parameters of the PV SDM and DDM models. It improves the diversity and quality of the candidate solutions by the OBL and CCE enhanced with a new strategy to update the worst points. In order to verify the advantages of the proposed algorithm, some recent algorithms are used for the comparison, such as the GOFPANM and R_{cr}-IJADE algorithms. The comparison result shows that the proposed algorithm can achieve the best accuracy as other algorithms. In terms of the convergence, the ESCE-OBL can find the global best points with the least MNFES number. For validating the improvement of the ESCE-OBL in terms of convergence and robustness, the basic SCE is used for comparison. The result indicates that the ESCE-OBL is more stable and has faster convergence in the three benchmark problems. Therefore, the proposed ESCE-OBL algorithm is an effective alternative for solving the parameter extraction problem for PV modules/arrays.

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