

Evolutionary algorithm and parameters extraction for dye-sensitised solar cells one-diode equivalent circuit model

Wei Peng, Yun Zeng, Hao Gong, Yong-qing Leng, Yong-hong Yan, Wei Hu

College of Physics and Microelectronics Sciences, Hunan University, Changsha, People's Republic of China
E-mail: huwei@hnu.edu.cn

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With the aim of improving energy conversion efficiency of dye-sensitised solar cells (DSCs), three evolutionary algorithms (EAs), namely genetic algorithm, particle swarm optimisation (PSO) and differential evolution, are investigated the first time to extract the DSCs parameters based on the single-diode photovoltaic (PV) equivalent circuit model. By comparing the accuracy, calculation speed and anti-noise ability of the three EA techniques, PSO shows the highest accuracy and the best anti-noise property. To evaluate the parameters, especially the series-internal resistance (R_s) that is important for DSCs energy conversion efficiency, a batch of DSCs devices were made and the R_s obtained by changing the series resistance value connected with the DSCs. The two methods give the R_s approximately equal value, and almost same current–voltage figures based on PSO simulation with measured characteristics, which prove PSO is an efficient computational method and can be used to extract the parameters for the DSCs PV model.

1. Introduction: In the last decade, much attention has been paid to the development of dye-sensitised solar cells (DSCs), which are widely viewed as a potential third generation photovoltaic (PV) technology, because of their low cost and high-energy conversion efficiency [1, 2]. In general, DSCs are comprised of a bandgap mesoporous metal oxide layer bounded with organic or organometallic dye as photoanode (such as titanium dioxide, TiO_2 bounded with ruthenium complexes coded as N719 or N3), a high work function cathode (for example platinum, Pt) and a liquid electrolyte redox couple (such as iodide/tri-iodide, I^-/I_3^-). The DSCs are photoelectrochemical devices and the operational principles are different from conventional solar cells. Photoexcitation of the monolayer dye results in the electron injection into the conduction band of TiO_2 , and leaving the oxidised state dye that is regenerated by the electron donation I^- from the electrolyte. The I^- can be regenerated by the reduction of I_3^- at the counter Pt electrode, with the circuit being completed through electron migration through the external load [3]. In order to improve the energy conversion efficiency and realise widely commercial application of DSCs-based PV modules, it is necessary to analyse the critical parameters and obtain their accurate values by using the proper PV models and simulation methods, then we can understand their affect on the DSCs' performance [4, 5]. There are several techniques, such as electrochemical impedance spectroscopy (EIS), which have been performed to analyse internal resistance in DSCs based on the equivalent circuit [6, 7]. We introduce the evolutionary algorithm (EA) technique, for the first time in this Letter, to extract these parameters based on the DSCs PV equivalent circuit model. EA techniques have been widely used to handle nonlinear functions without requiring derivatives information. In the general PV cell model based on silicon, three most popular EAs, namely genetic algorithm (GA) [8, 9], particle swarm optimisation (PSO) [10, 11] and differential evolution (DE) [12] are employed for the parameter extraction. Since the efficient and accurate PV simulator is the fundamental requirement for the EA technique, we compare the accuracy, calculation speed and anti-noise ability for the three techniques, and find PSO has the highest accuracy and the best anti-noise property. To evaluate the EA techniques and extract the series-internal resistance (R_s) value, which is one of the most complicated and important parameters for PV energy conversion efficiency, we made a batch DSCs devices and measured the current–voltage (I – V) characteristics under standard

AM 1.5 sunlight with series resistance connected, then estimated the R_s value when the series resistance value was close to 0. We found the R_s of the two methods approximately equal in value. The results prove the PSO technique is an efficient and accurate computational method to extract the DSCs parameters.

2. Parameters extraction and comparison: The well-known single-diode PV model is depicted in Fig. 1 which well describes the characteristics of various solar cells [13]. The I – V characteristic of DSCs also can be given by the following equation based on this model

$$I = I_{\text{ph}} - I_0 \left[\exp \left(q \frac{V + IR_s}{nKT} \right) - 1 \right] - \frac{V + IR_s}{R_{\text{sh}}} \quad (1)$$

where I_0 is the saturation current, I_{ph} the photocurrent, R_s the series resistance, R_{sh} the shunt resistance, n the ideality factor, q the electron charge, K the Boltzmann constant, and T the thermodynamic temperature. Two types of approach, namely the analytical and numerical extraction methods, are used to obtain the five unknown parameters of I_0 , I_{ph} , n , R_s and R_{sh} . Generally, more accurate parameters can be achieved by the numerical method because of all of the points on the curve would be utilised, but its accuracy and calculation speed strongly depend on the fitting algorithm type. The EA is a generic population-based metaheuristic optimisation algorithm in which nonlinear function fitting can be well-handled without requiring derivatives information. We introduce three EAs in this Letter to extract the parameters based on the DSCs equivalent circuit. To compare the three EA techniques, we adopt the standard algorithm fitness procedure. For the DSCs parameters'

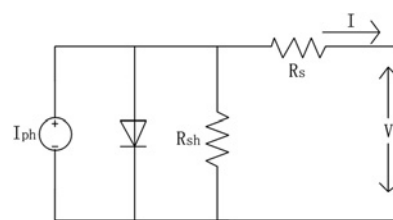


Figure 1 Single-diode equivalent circuit for DSCs

extraction routine, the fitness function is defined by the following equation

$$F = \sqrt{\frac{1}{N} \sum_{i=1}^N (I_i - I_{ci})^2} \quad (2)$$

where N is the number of data, I_i is the measured current and I_{ci} is the computed current given by (1).

The EA flowage structure is shown in Fig. 2. The procedure of the GA starts from a seed and generates a set of individuals. Each of these individuals can extract a group of parameters, the best fitted parameters are selected to form the new population when the process has been repeated 50 000 times till this iterations procedure been accomplished. In our works, the population size (NP) and mutation rate is 100 and 0.2, respectively. The one point crossover method has been used and the crossover rate is 0.8 in our calculation. Each particle in PSO moves with an adaptable velocity, which depends on its own flying experience and other particles in the swarm. The particle position is given by

$$x_i(j+1) = x_i(j) + v_i(j+1) \quad (3)$$

where v_i represents the velocity calculated by

$$v_i(j+1) = wv_i(j) + c_1r_1(xbest - x_i(j)) + c_2r_2(gbest - x_i(j)) \quad (4)$$

w is the inertia weight, c_1 and c_2 are acceleration coefficients that we set as 2.05, r_1 and r_2 are two random functions that yield two real numbers in the range $[0, 1]$, $xbest$ is the particle i best position and $gbest$ is the global one. w is a random quantity by making $w = (1 - r_1)r_2$, so that the number of algorithm control constants is 3 (NP, c_1 and c_2). For the DE algorithm, an initial population of NP parameter vectors $X_{i,G}$ is created. For a given parameter vector $X_{i,G}$, three vectors ($X_{r1,G}$, $X_{r2,G}$, $X_{r3,G}$) are randomly selected in the range $[1, NP]$, and the indices i , r_1 , r_2 and r_3 are distinct. A

donor vector $V_{i,G}$ is created by adding the weighted difference between the two vectors to the third vector as

$$V_{i,G} = X_{r1,G} + M(X_{r2,G} - X_{r3,G}) \quad (5)$$

where M , which is mutation scaling factor, is 0.8. The donor vector $V_{i,G}$ and the target vector $X_{i,G}$ are mixed to yield the trial vector

$$U_{ji,G} = \begin{cases} V_{ji,G} & (\text{rand} \leq \text{CR or } j = j_{\text{rand}}) \\ X_{ji,G} & \text{otherwise} \end{cases} \quad (6)$$

where $j = 1, 2, \dots, D$, $i = 1, 2, \dots, NP$ and CR (crossover rate) is 0.8. And j_{rand} is a randomly chosen index, which ensures that $U_{ji,G}$ attains at least one element from $V_{i,G}$. The selection operation is described as

$$X_{i,G+1} = \begin{cases} U_{i,G} & F(U_{i,G}) < F(X_{i,G}) \\ X_{i,G} & \text{otherwise} \end{cases} \quad (7)$$

where $i = 1, 2, \dots, NP$ and $F(x)$ is the fitness function. When the new trial vector acquires a lower value, it swaps the corresponding target vector in the next generation; otherwise the target is preserved in the population.

The three techniques for DSCs parameter extraction are carried out using synthetic data obtained from Murayama and Mori [4]. The values of synthetic data for DSCs are as follows: $I_{ph} = 0.0024 \text{ A}$, $I_0 = 5.05 \times 10^{-8} \text{ A}$, $n = 2.5$, $R_s = 38.1 \Omega$ and $R_{sh} = 3683 \Omega$. The $I - V$ curve is obtained and fitted by using the synthetic values by the GA, PSO and DE. In our calculations, the search ranges are set as follows: $I_{ph} \in [0, 0.01]$, $I_0 \in [0, 1 \times 10^{-6}]$, $n \in [1, 5]$, $R_s \in [0, 100]$ and $R_{sh} \in [0, 1 \times 10^6]$. Based on the convergence performance results, the three techniques all exhibit low root-mean-square error (RMSE). The RMSE of the GA, PSO and DE are 2.6965×10^{-6} , 3.1539×10^{-6} and 2.6957×10^{-6} , respectively. The DE technique has the highest convergence speed compared with the GA and PSO techniques. The relative error (e) for parameters are shown in Table 1. Compared with I_{ph} , n and R_s , the relative error of I_0 and R_{sh} are larger. This is because the parameters are extracted by minimising the fitness value.

To evaluate the three EA methods further and gain more accurate parameters under the noisy environment, we add random noise with relative intensity 2.5% to the synthetic data and then the current is written as

$$I_{\text{noise}} = I_{\text{synthetic}}[1 + 0.25 \text{rand}(-1, 1)] \quad (8)$$

The device parameters with noise are listed in Table 2. We can see from this Table that PSO has the highest accuracy among the three techniques, and five parameters extracted by PSO have the lowest relative error. These results show that the PSO has a better anti-noise ability because of its mechanism of memory and one-way information sharing. We believe that PSO is a more suitable algorithm for DSCs parameter extraction under the real environment rather than the other two.

3. Experiment and parameter extraction for DSCs: The DSCs with an active area of 0.16 cm^2 are assembled as follows [14–16]. The FTO glass photoelectrodes with TiO_2 are immersed in the dye N719 solution with a concentration of $4 \times 10^{-4} \text{ mol/l}$ in dry ethanol for 24 h. Then they are rinsed with anhydrous ethanol and dried again. The counter electrodes are prepared by spin coating 4 wt% H_2PtCl_6 isopropanol solution onto the FTO glass. All cells are sealed by using 25 μm Surlyn (Du Pont) polymer film. A hole of 1 mm diameter is made on the counter electrode and the electrolyte is injected into the spacer between the two electrodes by the vacuum reverse pressure perfusion method from this hole. Finally, the hole is completely resealed using a

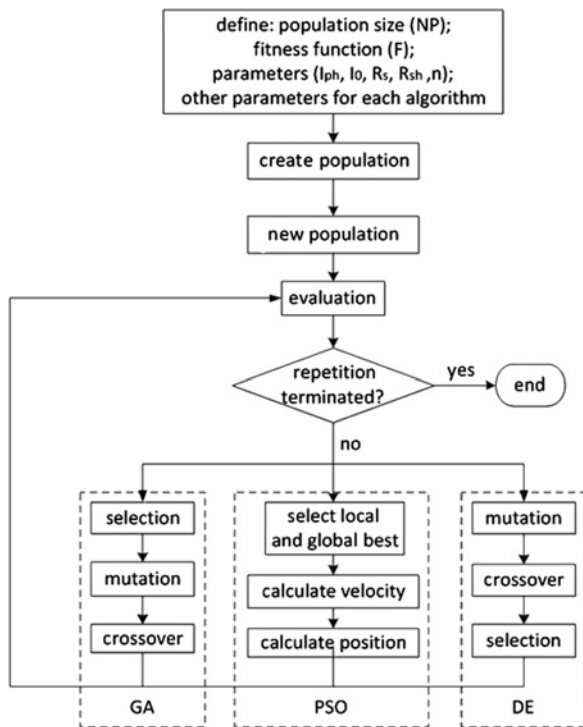


Figure 2 Flow chart of GA, PSO and DE

Table 1 Extracted parameters and relative error with the pure synthetic data

Parameters	Synthetic value	GA		PSO		DE	
		Value	<i>e</i> , %	Value	<i>e</i> , %	Value	<i>e</i> , %
I_{ph} , mA	2.4	2.3982	0.08	2.3921	0.33	2.3985	0.06
I_0 , $A \times 10^{-8}$	5.05	4.9524	1.93	7.1022	40.64	4.8753	3.45
N	2.5	2.4952	0.19	2.6307	5.23	2.4917	0.33
R_s , Ω	38.1	38.262	0.43	36.953	3.01	38.308	0.55
R_{sh} , Ω	3683	3764	2.20	4158	12.90	3752	1.87

Table 2 Extracted DSCs parameters and relative error with 2.5% intensity noise

Parameters	Synthetic value	GA		PSO		DE	
		Value	<i>e</i> , %	Value	<i>e</i> , %	Value	<i>e</i> , %
I_{ph} , mA	2.4	2.4048	0.20	2.4002	0.01	2.4050	0.21
I_0 , $A \times 10^{-8}$	5.05	3.9660	21.47	5.5966	10.82	3.8984	22.80
N	2.5	2.4467	2.13	2.5250	1.00	2.4429	2.28
R_s , Ω	38.1	39.478	3.62	38.217	0.31	39.539	3.78
R_{sh} , Ω	3683	3317	9.94	3539	3.91	3307	10.21

thickness of 60 μm Surlyn film. An AM 1.5 G solar simulator with a 300 W xenon lamp (Newport) is used to illuminate the DSCs, and the incident light power is 100 mW/cm^2 . The I - V curve is obtained using a digital source-meter (Keithley 2400) under an atmosphere environment. We measured the DSCs I - V curve and obtained the equivalent circuit parameters by the PSO algorithm. R_s , which is determined by the carrier transport resistance, the thickness of the electrolyte layer and the sheet resistance of the FTO layer [17], is the key factor for PV devices and has a strong influence on the DSCs-performance. To verify this important parameter, the following works were performed. A group additional resistance, whose values are 12, 20, 32.8, 47, 62.9 and 75.7 Ω , were series connected with DSCs and the cells' I - V curve were measured in turn. We also obtained the total series resistance $R_{s,\text{all}}$ by PSO again, in which the $R_{s,\text{all}}$ is the sum of the internal series resistance R_s and the external additional resistance $R_{s,\text{external}}$ ($R_{s,\text{all}} = R_s + R_{s,\text{external}}$).

The measured I - V curves changing with the series resistance are shown in Fig. 3, and the fitness I - V curves by the PSO algorithm are shown in Fig. 4. We can see the fitness I - V curves quite match up with the experimental curves. It means the extraction parameters are in agreement with the real process parameters in the PV model. Based on the PV model and the PSO algorithm, the extracted parameters for DSCs with additional external resistance are shown in

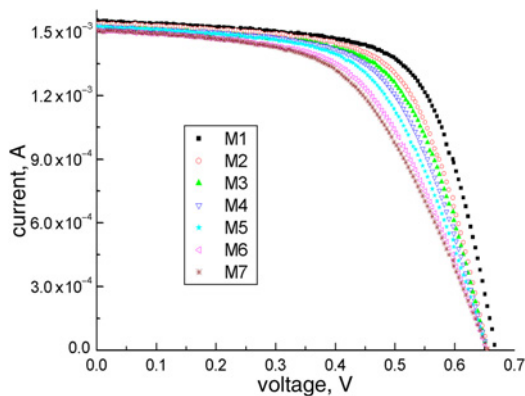
Figure 3 Measured I - V curves of DSCs without (M1) and with (M2-7) a group changing series resistance

Table 3. $R_{s,\text{all}}$ changing with the external series connection resistance $R_{s,\text{external}}$ and a linear relationship between the $R_{s,\text{all}}$ and $R_{s,\text{external}}$ is found in Fig. 5. Estimated from the linear fit line, the $R_{s,\text{all}}$ is equal to the R_s when the $R_{s,\text{external}}$ is close to 0, which is about 32.40 Ω . This R_s value is quite close to the PSO result 32.86 Ω that is much higher than the value of the traditional Si solar cell. That means it is a potential way to improve the energy conversion efficiency by

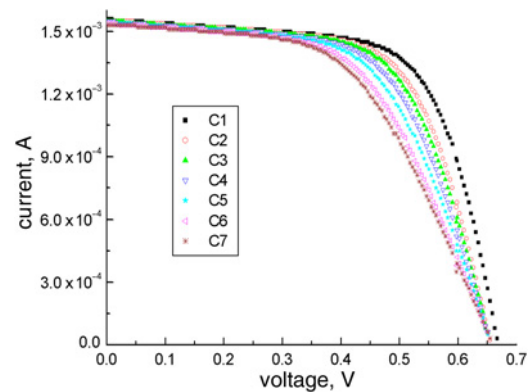
Figure 4 Fitness I - V curves of DSCs by PSO without (C1) and with (C2-7) a group changing series resistance

Table 3 Extracted parameters using PSO algorithm for the DSCs connecting a group series resistance

Additional $R_{s,\text{external}}$, Ω	Extracted parameters						R_s , Ω
	I_{ph} , mA	I_0 , $A \times 10^{-10}$	n	$R_{s,\text{all}}$, Ω	R_{sh} , Ω		
M1	0	1.567	3.55	1.70	32.86	5190	32.86
M2	12.0	1.567	3.55	1.67	44.52	5190	32.52
M3	20.0	1.567	3.55	1.67	54.12	5190	34.12
M4	32.8	1.567	3.55	1.67	66.45	5190	33.65
M5	47.0	1.567	3.55	1.67	80.52	5190	33.52
M5	62.9	1.567	3.55	1.67	98.64	5190	35.74
M7	75.7	1.567	3.55	1.67	111.23	5190	35.53

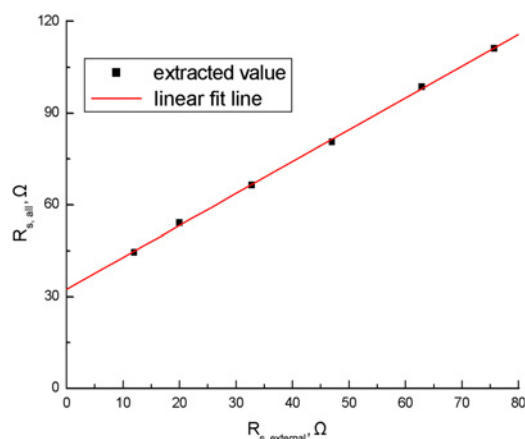


Figure 5 $R_{s,all}$ value changing with the external series resistance $R_{s,external}$ for DSCs

reducing the series internal resistance of DSCs, and we can estimate the series internal resistance value easily by our PSO technique.

4. Conclusion: In this work, the parameters for the DSCs one-diode PV model are extracted using three evolutionary algorithms, namely GA, PSO and DE. By comparing the accuracy, calculation speed, anti-noise ability, especially the relative errors of the extracted parameters based on three techniques under a noise condition, we find PSO shows the highest accuracy and excellent anti-noise ability, which means PSO is the best computational method to evaluate and extract DSCs parameters. In order to verify the technique and parameter accuracy, we also made batch devices and measured the I - V data under AM 1.5 G sunlight. By comparing the I - V curves and internal resistance value, we find the PSO is an efficient and accurate computational method to extract the parameters of the DSCs PV model.

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