A differential evolution approach for parameter extraction of solar cell from current-voltage characteristics

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This letter presents an approach based on differential evolution (DE) algorithm for determining the solar cell model parameters from current-voltage ($I-V$) characteristics. The validity of this approach has been confirmed with experimental and simulated $I-V$ data. It was demonstrated that the $I-V$ curve derived from the parameters extracted by the DE approach is in good agreement with the experimental or simulated $I-V$ data. A low objective function value as well as a high parameter precision can be obtained by the DE algorithm.

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The high growth rate of photovoltaic energy systems has led to an increase in research projects on various aspects of photovoltaic systems, from the development of novel solar cells to the performance analysis, sizing, performance estimation and optimization of photovoltaic energy systems[1−3]. One of these issues, the modeling of solar cells is an essential topic of research. The use of equivalent circuit models is a convenient and widely used method for simulating solar cell performance. In order to achieve an equivalent circuit model of a power source, we need generally to extract the model parameters by means of some techniques according to the measured data.

The single diode equivalent circuit model of illuminated solar cells may be expressed as

$$I = I_{\rm ph} - I_{\rm SD}\{\exp[q(V+IR_{\rm s})/nk_{\rm B}T]-1\} - (V+IR_{\rm s})/R_{\rm sh}, \quad (1)$$

where $R_{\rm s}$, $R_{\rm sh}$, $I_{\rm ph}$, $I_{\rm SD}$, n, $k_{\rm B}$, q, and T are the series resistances, the shunt resistances, the cell-generated photocurrent, the diode saturation current, the diode ideality factor, the Boltzmann constant, the electronic charge, and the temperature in Kelvin, respectively. The knowledge of the parameters of solar cells is necessary for cell array simulation and process optimization[4]. Over the years, many methods have been proposed to extract the solar cell model parameters. Among these methods, the direct approaches are based on the use of the $I-V$ curve features, such as the axis intercepts and the gradients at selected points, to determine some cell parameters. The accuracy of these techniques is limited by the measured $I-V$ data, whose errors are introduced by the numerical differentiation or the simplified formulas used in parameter extraction. Over the past decades, several different traditional nonlinear optimization algorithms, such as the quasi-Newton method and its variations, have been proposed to solve solar cell parameters extraction problem. The drawback of traditional optimization techniques is mostly that they need prior knowledge of the parameters of interest, i.e. initial guesses[5,6]. In recent years, the methods based on intelligent optimization algorithms have attracted much attention. For example, the simulated annealing (SA)[7], genetic algorithm (GA)[8−11] and particle swarm optimization (PSO)[12] were proposed so as to improve the accuracy of the extracted parameters. Among intelligent optimization algorithms, the GA is one of the most popular algorithms in applied physics[13−25]. However, GA has two drawbacks: premature convergence and lack of good local search ability[26,27]. In order to overcome the disadvantages of GA, differential evolution (DE) algorithm has been proposed[28] as an alternative to GA for solving optimization problems. The DE's advantages are easy to implement, require a few control parameters tuning and exhibit fast convergence. Also, the DE can cope very well with local optima, which is a known weakness of traditional nonlinear optimization algorithms. DE has consistently ranked as one of the best search algorithm[29]. In this letter we explore an additional possibility; the parameter extraction of a solar cell equivalent circuit model is carried out with the help of the DE algorithm.

Consider the solar cell model described by the Eq. (1) as well as following the approach recently proposed in Ref. [8], the objective function can be given by

$$\varepsilon = \sqrt{\frac{1}{N}\sum_{k=1}^{N}[I_k - (I_{\rm ph} - I_{{\rm D}_k} - I_{{\rm sh}_k})]^2}, \quad (2)$$

$$I_{{\rm D}_k} = I_{\rm SD}\{\exp[q(V_k + I_k R_{\rm s})/(nk_{\rm B}T)] - 1\},$$

$$I_{{\rm sh}_k} = (V_k + I_k R_{\rm s})/R_{\rm sh},$$

where $R_{\rm s}, R_{\rm sh}, I_{\rm ph}, I_{\rm SD}$, and n are the model parameters as defined before, which are unknown for real cases, to be determined as accurately as possible; I_k and V_k denote an experimental data pair at the kth point of an $I-V$ curve; N is the number of the experimental data pairs. In this case, the Eq. (2) implies the current error of the equivalent circuit model.

It is well known that Eq. (1) is an implicit transcendental equation and may not be solved explicitly in general for current and voltage using common elementary

functions. With the help of the objective function described by Eq. (2), the optimization procedure has the advantage of no requirement of solving numerically the implicit equation.

Obviously, the Eq. (2) is nonlinear. This means that the objective function is not quadratic, possessing a single global minimum. For traditional optimization algorithms, this will result in local minima, which in turn might attract the solution into one of them depending on the starting position. Although the GA is effective at finding relatively good neighborhoods of solution in a complex search space, they may have premature convergence towards a local minimum. The population in a GA reaches a state such that the genetic operators can no longer produce offsprings that outperform their parents. In this case, the algorithm will lose its capability of finding better solutions in the multi-modal error surface of objective function due to the existence of numerous local optima. Therefore, in this work we try applying the DE algorithm to the extraction of solar cell equivalent circuit model parameters.

For the DE algorithm, in the initialization phase, a population of NP trial solutions is randomly generated. In the iteration process, the ith individual of the population at the jth iteration is indicated by $\theta_j(i) = (R_{\rm s}, R_{\rm sh}, I_{\rm ph}, I_{\rm SD}, n)$, $i = 1, 2, \cdots, NP$. The population evolves iteratively by means of some reproduction rules reported in details in Ref. [30]. These rules are governed by some control parameters, i.e., a scaling factor F and a crossover constant CR, which control the amplification of the differential variation and the diversity of the population, respectively. CR and F should be chosen in order to avoid a premature convergence to local minima or a slow convergence rate. Some criterions for the choice of these parameters, together with a discussion about the main features of the DE, can be found in Ref. [30]. Finally, the iterative algorithm stops if a maximum number of iterations, $j_{\max}$, is reached.

In basic DE, the mutant vector $V_i = [v_{i1}, v_{i2}, \cdots, v_{id}]$ for the ith parent X_i is generated, by combining three random and distinct population members X_{r1}, X_{r2}, and X_{r3}, as follows:

$$V_i(j+1) = X_{r1}(j) + F \cdot [X_{r2}(j) - X_{r3}(j)], \qquad (3)$$

Following the mutation operation, the crossover operator is applied to increase the diversity of the population. Thus, for each target individual X_i, a trial vector $U_i = [u_{i1}, u_{i2}, \cdots, u_{id}]$ is generated by the following equation:

$$u_{ik}(j+1) = \begin{cases} v_{ik}(j+1), & \text{if rand}(k) \leqslant CR \text{ or } k = \text{randn}(i), \\ x_{ik}(j), & \text{otherwise}, \end{cases}$$
$$k = 1, \quad 2, \cdots, d, \qquad (4)$$

where rand(k) is the kth independent random number uniformly distributed in the range of [0, 1]. randn(i) is a randomly chosen index from the set $\{1, 2, \cdots, d\}$.

Therefore, there are significant differences between the DE and GA in the follows:

(1) In GA, two parents are selected for crossover and the child is a recombination of the parents. In DE, three parents are selected for crossover and the child is a perturbation of one of them.

(2) The new child in DE replaces a randomly selected vector from the population only if it is better than it. In conventional GA, children replace the parents with some probability regardless of their fitness.

To illustrate the proposed approach, we used experimental and simulated $I - V$ data as evaluation of the extracting power of the DE. We considered the number of maximal iteration $j_{\max} = 2000$, the population size NP= 50, the scaling factor $F = 0.5$, and the crossover constant CR= 0.6. For the sake of comparison, we also implemented the parameter extraction of a solar cell model using the GA. In this case, we used real-value GA algorithm with the function 'ga' available in the Genetic Method and Direct Search Toolbox of the MATLAB software, running with the same objective function, maximal iteration index, population size and search range as the DE approach. The following real-value GA controlling parameters have been used: the crossover rate was 0.8, the mutation rate 0.2, and the elite strategy was used, where the best individual in each iteration was copied into the succeeding iteration in order to speed convergence. Both approaches run with the same objective function, maximal iteration index, population size and search ranges.

The experimental data from a commercial solar cell were first used to extract the parameters of model with an operating temperature of 328 K. The results of parameter extraction by using DE and GA with experimental data are summarized in Table 1. In the case of GA, the best value in all objective function values obtained is listed over 10 runs. Examination of Table 1, it is clear that the objective function value obtained by DE is lower than that obtained by GA. The result obtained by DE is reasonable to the solar cell model and outperforms that obtained by GA. The initial ranges of all parameters are listed in the second column of Table 1. We can observe

Table 1. Parameter Extraction Results of Solar Cell Model by Using DE and GA with Experimental Data

	Search Range	Extracted Parameter	
		DE	GA
$R_{\rm s}(\Omega)$	[0, 5×10^{-2}]	2.3316×10^{-2}	2.3680×10^{-2}
$R_{\rm sh}(\Omega)$	[10, 500]	104.27	78.133
$I_{\rm ph}$(A)	[1.5, 1.6]	1.5401	1.5402
$I_{\rm SD}$(A)	[1×10^{-10}, 1×10^{-4}]	5.6773×10^{-5}	5.1361×10^{-5}
n	[1, 5]	1.6940	1.6792
ε	—	1.26×10^{-4}	3.97×10^{-4}

Table 2. Parameter Extraction Results of Solar Cell Model by Using DE and GA with Simulated Data

	Search Range	True Parameter	Extracted Parameter	
			DE	GA
$R_s(\Omega)$	$[0, 5\times10^{-2}]$	2.3316×10^{-2}	2.3316×10^{-2}	2.3429×10^{-2}
$R_{sh}(\Omega)$	[10, 500]	104.27	104.27	102.69
I_{ph}(A)	[1.5, 1.6]	1.5401	1.5401	1.5402
I_{SD}(A)	$[1\times10^{-10}, 1\times10^{-4}]$	5.6773×10^{-5}	5.6773×10^{-5}	5.5555×10^{-5}
n	[1, 5]	1.6940	1.6940	1.6907
ε	—	—	3.57×10^{-16}	1.67×10^{-4}

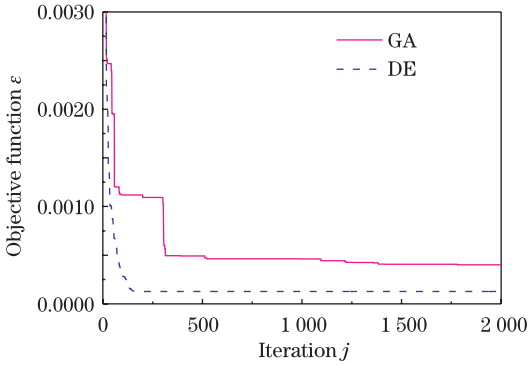

Fig. 1. Evolving processes of the objective function values of the DE and GA methods with experimental data.

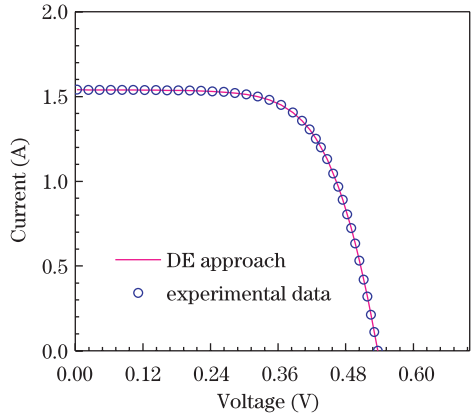

Fig. 2. Experimental data and the curve processed by DE with experimental data.

that the DE does not particularly necessitate initial guesses as close as possible to the solutions for the parameters of a solar cell model to be extracted. Required only is a very broad range specified for each of the parameters. Figure 1 shows the evolving processes of two methods with experimental data. Obviously, in this case the DE approach has a lower objective function values than the GA approach, since the local search ability of DE is better than that of GA. In order to attest the quality of the parameter extraction, the obtained parameter values can be fed back to solar cell model to achieve $I-V$ curve as soon as the optimal operation of DE is finished. Figure 2 shows a comparison between the experimental $I-V$ data of the solar cell and the curve processed by the DE approach. From Fig. 2, the experimental data and the curve show very close agreement, which means the proposed parameter extraction approach is feasible.

Note that there is no way to know the true values of the extracted parameters due to using the experimental data. Therefore, in order to validate the accuracy of the extracted parameters, the parameter values obtained by DE approach with experimental data were used as true values and fed back to solar cell model to produce a set of simulated data. With these simulated data, a new set of parameter values was obtained by DE and GA approaches and listed in Table 2. As shown in the table, the proposed approach yields the same parameter values as the true values when we only take five significant figures. Note that in this case the objective function achieved by DE is very small, but cannot be zero due to the accumulation of errors in the numerical calculations. Compared with GA, DE has much more precision for the parameter extraction of solar cell model. The evolving processes of two methods with simulated data are illustrated in Fig. 3. GA still is difficult in converging to the global optimal solution due to premature phenomenon. This drawback of GA can lead to poor performance regarding the accuracy of the extracted parameters. It is clear that the DE has much lower objective function value than the GA when the maximum iteration number is reached, so the DE can generate higher quality solutions than GA. Figure 4 shows a comparison between the simulated $I-V$ data and the curve derived from the parameters extracted by the DE approach. The comparison results indicate that the curve is in good agreement with the simulated data throughout the voltage range used.

In conclusion, the test results with experimental and simulated $I-V$ data indicate that a satisfying extraction performance can be achieved by the DE approach. The DE outperforms the GA with whether experimental data or simulated data. Also, the proposed method does not

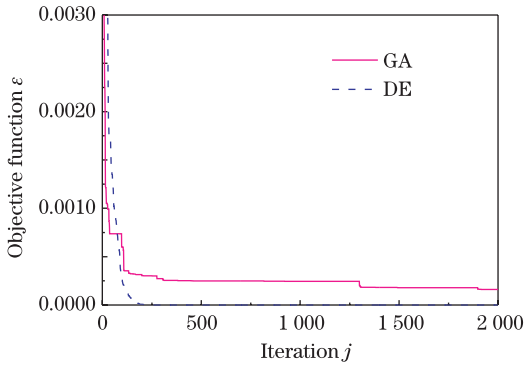

Fig. 3. Evolving processes of the objective function values of the DE and GA methods with simulated data.

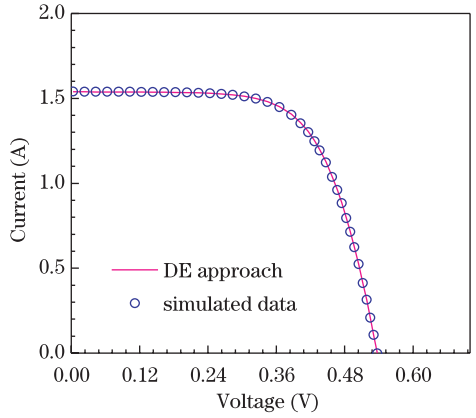

Fig. 4. Simulated data and the curve processed by DE with simulated data.

particularly necessitate initial guesses as close as possible to the solutions, which is different from traditional optimization approaches.

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