Extracting Solar Cell Model Parameters Based on Chaos Particle Swarm Alogorithm

Huang Wei, Jiang Cong, Xue Lingyun*
School of Automation
Hangzhou Dianzi University
Hangzhou, China
hw@hdu.edu.cn

Song Deyun
Department of Research and Development
Hangzhou Yuhang Electric Apparatus Ltd.
Hangzhou, China
songdy@yeah.ne

Abstract**—**Utilizing the numerical analysis and optimization method for extracting solar cells model parameters, one recurrent issue refers to the difficulty in initializing the parameters. Moreover, those methods using solar cells exponential model are sensible to small changes in the data measured. A chaotic particle swarm optimization algorithm (CPSO) was presented for extracting solar cell model parameters, in which the global search performance and local convergence of particle swarm optimization (PSO) were improved by introducing a chaos search. The CPSO searched for optimal parameters without strict limitation on the search ranges. The procedure is illustrated by applying it to parameters extraction using the current-voltage data measured from a silicon cell and a solar module. The results demonstrate that the method can reduce the influence of experimental data measurement accuracy, and the statistical analysis data of fitting (*I-V*) characteristics curves are better than that of other published methods.

Keywords- solar cells model; parameter extraction; particle swarm optimization; chaotic search

I. INTRODUCTION

The five-parameter exponential model of solar cells, as a well known model applied in many fields of solar energy research, is derived from the equivalent circuit based on the internal physical mechanisms acting within solar cells. The parameters (series resistance R_s , shunt resistance R_{sh} , photo-current I_{ph} , reverse saturation current I_0 , and diode quality factor A) have specific meaning which contains abundant information of solar cells performance. Due to the complexity of the model, which is defined as a transcendental nonlinear exponential equation, direct method to measure the parameters is lacked. For quality control and performance evaluation of the solar cells, it is required to extract the accurate parameters from the current-voltage (*I-V*) characteristics curves measured under different conditions of temperature and illumination [1].

Over the years, several methods have been suggested for fitting *I–V* characteristics curve [1-4]. Taylor polynomial fitting method has high computational accuracy, but accompanied with high complicacy. The parameters extracted can not be directly used to evaluate the performance of solar cells. Analytical method for single or double exponential model introduces an iterative procedure for solving solar cells *I-V* transcendental equations, but the results will be various choosing different measurement point in the *I-V* curve. Quasi-Monte Carlo method is the cross-product of number theory and approximate analysis. The algorithms have no restrictions on fitting model, and its calculation accuracy can be arbitrarily controlled within a certain range. But the convergence speed is low, and the computational cost, to approach the model parameters in high precision, is excessive. Otherwise the fitting precision is sensitive to the initial values of parameters. In practice, it is difficult to predict the intrinsic PN junction features characterized by the quality factor and the reverse saturation current, especially in case of that the solar cells parameters is deviated from normal values.

Gradient-based Numerical analysis and optimization methods need a continuously differentiable objective function, and may converge on local optimal solution easily. Direct optimization approaches such as the Simplex Method only use the value of objective function, but the start point and the step length of iterations are embarrassed for solving complex optimization problems. Genetic algorithm (GA) gets the global optimal solution by onerous evolutionary computation without gradient information [5]. But the contradiction of premature convergence and slowness of local convergence makes GA difficult to solve complex optimization problems as well. Particle swarm optimization (PSO) is drawn attention widely because of the features: the method can find global optimal solution in high probability with a few parameters, eases to program and has no limit on optimization problem model. However, the standard PSO presents precocity and stagnation, and has low precision for complex problems due to the inherent convergent character of PSO [6].

A chaos particle swarm optimization algorithm (CPSO) is presented for extracting the five parameters of solar cells. Firstly, using the morphological characters in restricted regions (in the vicinity of open circuit voltage and short circuit current point) of the *I-V* curve, the formulas are obtained to specify the lower and upper bounds of parameters. Secondly, a chaotic search is embedded into original PSO optimizer to enhance the global and local searching performance of PSO.

II. SOLAR CELLS I-V EXPLICIT EQUATION

Figure 1 shows the equivalent circuit of the five-parameter solar cells model. This circuit includes a series resistance and a diode in parallel with a shunt resistance. The *I-V* relationship at

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a fixed cell temperature and solar radiation is expressed as (1). Five parameters must be known in order to determine the current and voltage, and thus the power deliver to the load.

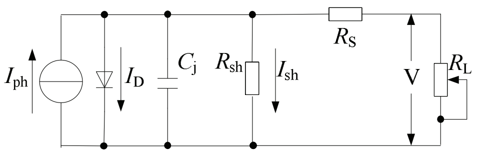


Figure 1. Five-parameter solar cells model equivalent circuit

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

Where, K is Boltzmann's constant, q is the electronic charge, T is the cell temperature in Kelvin.

In theory, the five parameters can be extracted from solving five simultaneous equations, but the above transcendental equation can not be solved directly by using common elementary functions in general. Through introducing the Lambert W function, exact explicit analytical solutions to obtain solar cells model parameters is already exist [7-8]. The equivalent explicit expression of (1) is given below:

$$I = \frac{R_{sh}(I_{ph} + I_0) - V}{R_s + R_{sh}} - \frac{AV_{th}}{R_s} W(x) \quad (2)$$

where, $x = \frac{R_s R_{sh} I_0}{AV_{th}(R_s + R_{sh})} \exp\left(\frac{R_{sh}(R_s I_{ph} + R_s I_0 + V)}{AV_{th}(R_s + R_{sh})}\right)$, $V_{th} = kT/q$. "W" represents the usual short-hand notation for the principal branch of Lambert W function. Utilizing the mathematical characteristics of W function, the above explicit representations provide convenience for model parameter estimation and optimization. The (2) is a good computational alternative to using iterative solution of the original transcendental equation (1), although it still remains unsuitable issues for the purpose of extracting the model parameters directly by using numerical fitting method [7-8].

III. CHAOTIC PSO OPTIMIZATION ALGORITHM

A. Classical PSO

In classical PSO, the candidate solution of the problem is corresponding to the position of particle. Each particle is associated with a velocity, and swarm is an apparently disorganized population of moving particles. Particle has a fitness value determined by the objective function of the problem, and the velocity is constantly adjusted according to the best fitness value of itself and the swarm's ones.

Suppose a PSO search space is N−dimensional, and the population size is M, the position of particle i is expressed as $x_i = (x_{i1}, x_{i2}, ..., x_{iN})$, it's velocity is $v_i = (v_{i1}, v_{i2}, ..., v_{iN})$, p_i is the best one of particle historic positions (Pbest), p_g is the best one of swarm's historic positions (Gbest). Particle position and velocity are updated by (3), (4) in each iteration.

$$v_{id}^{k+1} = w \cdot v_{id}^k + c_1 \cdot r_1\left(p_{id} - x_{id}^k\right) + c_2 \cdot r_2\left(p_{gd} - x_{id}^k\right) \quad (3)$$

$$x_{id}^{k+1} = x_{id}^k + r \cdot v_{id}^{k+1} \quad (4)$$

Here, x_{id}^k 、 v_{id}^k are respectively the d^{th} vector component of position and velocity of particle i at the k^{th} iteration; p_{gd} , p_{id} are the d^{th} vector component of the Gbest and the Pbest; c_1 , c_2 are the learning factor of individual and population respectively; w is the inertia weight; r_1 , r_2 , r are random values between [0, 1]. The first part on left side of (3) shows the 'inertia' that the particle will remain the previous velocity; the second part shows the 'individual cognizance' that the particle will move toward Pbest; the third part reflects the 'social behavior' which is motivated by knowledge updating and co-operation between particles, and the particles will approach to Gbest.

B. Chaos PSO

In (3-4), the modified velocity and position of each particle are calculated using the current velocity and the distance from Pbest to Gbest, and the learning factors (c_1 , c_2) adjust the maximal flying step length that pull each particle toward Pbest and Gbest, and thus, appropriate c_1 and c_2 can accelerate convergence. But in late stage of the iteration, x_{id}^k , p_{gd} , p_{id} are clustered together, the action of particles appears inertia, which result in insufficient PSO search capacity. Over recent years, much research is still in progress for proving the potential of the PSO in solving complex optimization problems, which are mainly focused on initialization, search strategy, control parameter selection of PSO algorithm, and the adaptive techniques introduced into PSO. In [9], a control strategy, the inertia weight linearly decreased within iterative procedure, was proposed to improve the global and local search capacity of PSO. In [10], control parameters, which could reflect the evolution speed and aggregation degree of particles, were employed to adjust the inertia weight dynamically during a run. An adaptive method was suggested in [11] by using the fitness difference between particles to evaluate the degree of population convergence, and adjust the inertia weight in whole evolutionary process adaptively.

Due to the randomicity of particles initialization and evolution executed thereupon, it is difficult to provide a balance between global and local explorations. In this work, a chaotic search strategy-based Particle Swarm Optimization (CPSO) was put forward. Chaos is a familiar nonlinear phenomenon in natural world. Chaotic variable possesses the characteristic, such as randomicity, ergodicity and non-repeatability. It was developed as an effective search approach by using chaotic variable to traverse all status changing in a certain area (search space) [12]. CPSO introduces a logistic equation (5) to generate chaotic sequence.

$$z_{n,d} = \mu z_{n-1,d}\left(1 - z_{n-1,d}\right) \quad (5)$$

When the control parameter μ is ascertained, arbitrary initial value of $z_0 \in [0,1]$ to (5) can generate a certain chaotic sequence $[z_1, z_2, ..., z_D]$, $n = 1,2,...,D$. CPSO chaotic search is described as following:

While particle (i) represents stagnation, CPSO generates a N -dimensional random initial vector $z_0=\lfloor z_{0,1},z_{0,2},...,z_{0,N}\rfloor$, where, $z_{0,N}\in[0,1]$. Using (5), D neighborhood points of the particle can be produced, and the chaotic variable is transformed to optimizing variable $z'_{n,k}$ by (6):

$$z'_{n,k}=x_{i,k}+R_{i,k}(2z_{n,k}-1). \tag{6}$$

Here, $R_{i,k}$ is the radius of chaotic search, which is assured by the initial range of the particle (i), and then the range of $z'_{n,k}$ is $\lfloor x_{i,k}-R_{i,k}, x_{i,k}+R_{i,k}\rfloor$, $k=1,2,...,D$.

To solve the fitness function of optimization problem thus, the fitness values $f(z'_{n,k})$ of these chaotic sequence are obtained. f^* is the fitness value at optimal position x_i^* generated by chaotic search. Comparing with the fitness value F_{id} , which is corresponding to the particle historic optimal position p_{id} , if f^* is better than F_{id} , replace the particle current position with x_i^* , then v_i^* is updated by (7):

$$v_i^*=(x_i^*-x_i)/\|x_i^*-x_i\|. \tag{7}$$

During the chaotic search run, CPSO only re-initiates the considered 'inertia' particle, and the current structure of PSO is unchanged. Thus the features of PSO, simplicity in structure and computation, are remained. The inertia weight in CPSO decreased linearly as (17):

$$w=Maxw+cur\_i*(Maxw-Minw)/G \tag{8}$$

$Maxw$ is the maximum of inertia weight; $Minw$ is the minimum; G is the maximum number of iterations; Cur_i is the current number of iterations.

IV. Solar Cell Parameter Extraction

Note that the drawback of the optimization method based on numerical analysis is that they need prior knowledge of the parameters of solar cells, i.e. initial value estimates. The CPSO proposed in this work searches for the optimum parameters in a approximate parameter scope.

A. Objective function

By fitting the *I-V* curve to the measured data, the solar cells parameters extraction involves minimizing the objective function H with respect to the five parameters X_i :

$$H(X)=\sum_{i=1}^{N}(I_c-I_m)^2 \tag{9}$$

$X_i=(I_{ph},I_0,A,R_{sh},R_s)$, is a set of unknown parameters, and (I_{mi} , V_{mi}) are respectively the measured current and voltage at the i^{th} point among N data points. I_{ci} is a calculated value by substitution V_{mi} in (2).

B. Parameters Estimation

In general, solar cell satisfies:

$$\frac{I_D}{I_{ph}}=\frac{I_0\left\{\exp\left[\frac{q(V+IR_s)}{KAT}\right]-1\right\}}{I_{ph}}\le 1 \tag{10}$$

$$R_s<<R_{sh}. \tag{11}$$

While $V\to 0$, the (8) can be simplified as the (9), and the *I-V* curves represent good linear relationship.

$$I\approx I_{ph}-\frac{V+IR_s}{R_{sh}}\approx I_{ph}-\frac{V}{R_{sh}}. \tag{12}$$

$\because I_{ph}\approx I_{sh}$, $\therefore I\approx I_{sc}-V/R_{sh}$. The above equation is differentiated to yield:

$$R_{sh}=\left|\left(\frac{dI}{dV}\right)^{-1}_{V=0}\right|=\left|\frac{dV}{dI}\right|_{I=I_{SC}}. \tag{13}$$

Thus, the R_{sh} can be estimated approximately by measuring the slope of I-V curve while $V\to 0$.

The estimation of R_s is similar to the R_{sh} . While $V\to V_{OC}$, $I\to 0$, based on the Taylor series extension, the eq. (1) can be written as:

$$I=I_{ph}\frac{KAT}{qI_0R_s}-\frac{V}{R_S}. \tag{14}$$

The above equation is differentiated to yield:

$$R_s=\left|\left(\frac{dI}{dV}\right)^{-1}_{V=V_{OC}}\right|=\left|\frac{dV}{dI}\right|_{I=0}. \tag{15}$$

The approximate value of R_s can be extracted from (12).

The determination of search ranges in the CPSO, based on the estimation of the five parameters, is summarized as:

(1) Photo-current (I_{ph}): I_{ph} is very close to the solar cells short circuit current I_{SC} . The search range is ±1% - ±5% of the I_{SC} ;

(2) Reverse saturation current (I_0): The search range is 0 - ±10% of the I_{SC} ;

(3) Diode quality factor (A): For solar cells with good performance, the A value is close to 1, and if cells with a higher junction voltage, the value scope lies between 1.1 - 1.3, while lower junction voltage lies between 1.6 - 1.8. The search range (0.5 - 2.0) is recommended;

(4) Shunt resistance (R_{sh}): The search range is ±1% - ±5% of the K_1 , which is the slope of *I-V* curve measured when $I\to I_{SC}$;

(5) The series resistance (R_s): The search range is ±1% - ±5% of the K_2 , which is the slope of I-V curve measured when $V\to V_{OC}$.

C. Searching Procedures

The searching procedures of CPSO were shown as below:

Step 1. Initialization: Set the particles population size m , the maximum number of iterations G , the fitness threshold ξ , the stagnation criterion δ, the stagnation-occurred times N_c, the maximum of inertia weight $Maxw$, the minimum one $Minw$, and the learning factor c_1, c_2; specify the lower and upper bounds of the solar cells parameters; and then initialize randomly each particle of the swarm including searching points, velocities, Pbests, and Gbest.

Step 2. Substitute each particles into the formula (2), and calculate the evaluation value of each particle using the fitness function $H(X)$ defined as (9).

Step 3. Compare each particle's fitness value with its Pbest. The best fitness value among the Pbests is denoted as Gbest, and the corresponding fitness value is named as F_{id}, F_{gd} respectively.

Step 4. Use formulas $\Delta F_i = |F_i - F_{id}|/F_i$ and $\Delta F_i < \delta$ to detect whether particle is in stagnation state. If the continuous times exceed N_c, call the chaotic searching subprogram as fellow, otherwise turn to step 5.

1) Initialize the chaotic iteration counter $G_c = 1$ and maximum iterations $G_{c\max}$;

2) Generate a chaotic sequence by (5) and transform to the optimizing variable by (6);

3) Calculate the fitness value of chaotic sequence $f(z'_{n,k})$ and update the best fitness value f^*, the position x_i^*, and the velocity v_i^*;

4) Set $G_c = G_c + 1$, go to step ②, until $G_c \geq N_{\max}$;

5) Compare f^* with F_{id}, if f^* is better than F_{id}, update the particle position and velocity with x_i^*, v_i^*, else, turn to step 6.

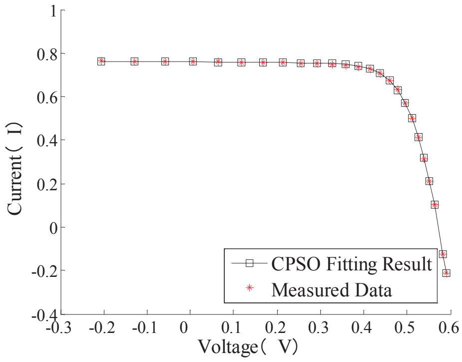
Step 5. Update the particle position and velocity by (3-4);

Step 6. Repeat step 2-6 until the threshold ξ or the number G is satisfied, the last Gbest is the optimal parameters.

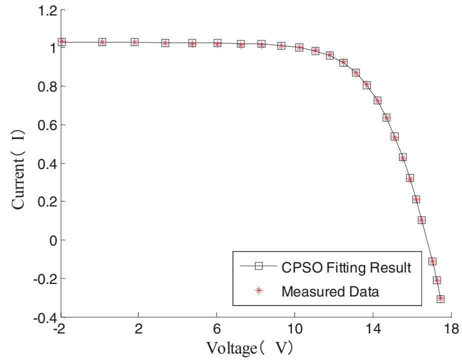
V. EXPERIMENT RESULT AND ANALYSIS

Five parameters extraction experiments for the given solar cell have been performed to check the performance of the CPSO method, and the experimental *I-V* data were taken from the literature [13], which is obtained from a commercial silicon solar cell at 33℃ and a solar module at 45℃. The following PSO parameters are used for searching the parameters: $m = 150$, $Maxw = 0.94$, $Minw = 0.4$, $\xi = 10^{-6}$, $\delta = 10^{-1}$, $N_c = 3$, $G = 300$, c_1 and c_2 are assigned to 2.

Figure 2 shows the I-V experimental characteristics plots and the fitted curve derived from (2) with the parameters obtained by using the CPSO, the calculated values are accordance with the measured data observably. The extracted parameters and the comparison with that from other different method based on the same *I-V* data, which were published previously [13-16], are given in Table I. It shows good agreement for most of the extracted parameters.



(a) Single solar cell



(b) Solar module

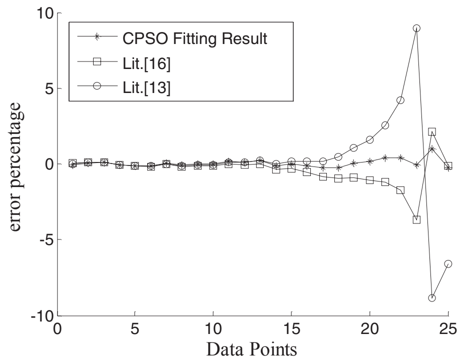
Figure 2. Experimental data and fitted curve based on CPSO

TABLE I. THE COMPARISON OF PARAMETERS EXTRACTION

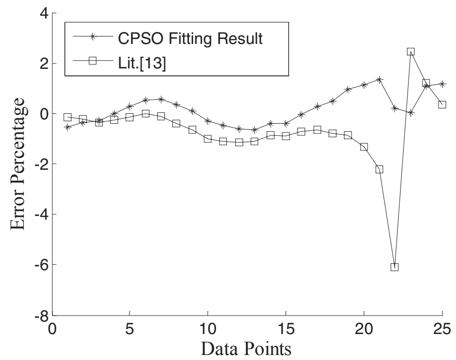
	Lit.[13]	Lit.[14]	Lit.[15]	Lit.[16]	CPSO
Single solar cell					
$R_{sh}(\Omega)$	53.7634	48.7805	41.9111	49.5049	59.012
$R_s(\Omega)$	0.0364	0.0078	0.0385	0.0364	0.0354
A	1.4837	1.4616	1.456	1.5039	1.5033
$I_0(\mu A)$	0.3223	0.7231	0.46	0.4039	0.4000
$I_{ph}(A)$	0.7608	0.7600	0.7603	0.7608	0.7607
Solar module					
$R_{sh}(\Omega)$	549.45	689.66	689.66	200	1850.1
$R_s(\Omega)$	1.2057	1.092	1.2293	1.146	1.0755
A	48.45	48.93	48.93	51.32	52.243
$I_0(\mu A)$	3.2876	3.8236	46	6.77	8.301
$I_{ph}(A)$	1.0318	1.0310	1.030	1.035	1.0286

In order to test the fitting quality of the experimental data, the error percentage, $(I_i - I_{ical})(100/I_i)$, is calculated, where I_{ical} is the current calculated for each V_i, by solving the explicit equation (2) with the determined set of parameters: $X_i = (I_{ph}, I_0, A, R_{sh}, R_s)$. (I_i, V_i) are respectively the measured current and voltage at the i^{th} point among the measurement points.

According to the trials, the error distribution curves are shown in fig.3. Comparing the CPSO method with the control groups, the fitting error of each measured point is small and uniformly distributed in whole range of *I-V* curve, which demonstrate that the calculated values can approach to the measured data preferably. The maximum of error percentage is less than 2%. The statistical analysis results using the fundamental measures of accuracy, such as the root mean square error (RMSE), the mean bias error (MBE) and the mean absolute error (MAE) are given in Table II. The statistical data of CPSO are obviously better than that of the control groups.



(a) Single solar cell



(b) Solar cell module

Figure 3. Error distribution curves of data fitting

TABLE II. STATISTICAL INDICATORS OF FITTING ACCURACY

	RMSE (%)	MBE (%)	MAE (%)
Single solar cell			
Lit. [13]	3.037	0.1682	1.444
Lit.[14]	0.525	-0.102	0.433
Lit.[16]	1.034	-0.403	0.598
CPSO	0.265	0.061	0.168
Solar cell module			
Lit.[13]	1.5610	-0.6820	1.0021
Lit.[14]	0.767	-0.238	0.567
Lit.[16]	13.7663	-4.0677	9.1761
CPSO	0.6244	0.1819	0.5067

VI. CONCLUTION

One recurrent issue using numerical analysis methods is referred to the difficulty in initializing the parameter of solar cells. It is due to the fact that the parameters of exponential model are correlative strongly, and the extracted parameter is extremely sensible to small changes in the measured data. Applying those methods will probably result in bigger errors and uncertainties in the presence of considerable parasitic series and shunt resistance. A CPSO algorithm is presented for improving the extracting accuracy of the solar cells parameters. The method is based on formulating the parameter extraction problem as a search and optimization one. The chaotic searching embedded in CPSO is used to overcome the particle's 'inertia', and improve the global search performance and local convergence. As the result shown, the influence of the measuring error of experimental data is reduced observably. In addition, the proposed method needs no prior knowledge of the parameters of interest, and the search range estimation associated is straightforward and easy to use.

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