

Parameters Extraction of single Diode Model of Photovoltaic Cell using Improved Firefly Algorithm

Yong Wu¹, Qian Xia², Richard Blanchard³

1 School of Automation, Wuhan University of Technology, Wuhan Hubei Province China, Yong Wu wuyong@whut.edu.cn 2 School of Automation, Wuhan University of Technology, Wuhan Hubei Province China, Qian Xia 945155836@qq.com 3 Centre for Renewable Energy Systems Technology, Loughborough University UK, Richard Blanchard r.e.blanchard@lboro.ac.uk

Abstract: Models of photovoltaic (PV) are significant in the design, study and control of renewable energy system. In these models, equivalent diode circuit model is widely researched and used because of its high precision. In diode circuit model, usually there are several parameters to be determined. To improve the performance of PV models, it is important to extract their unknown parameters exactly and quickly. However, because of the nonlinear of the V-I characteristic output of PV, it is difficult to obtain the parameters accurately. In this paper, a self-adaptive firefly algorithm is proposed to extract the parameters of single diode circuit model. Through introducing an adaptive mutation factor into the evolution process of a firefly algorithm, it improves the precision and stability of the solution. The proposed adaptive firefly algorithm is used to extract the parameters of single diode current data of PV, the proposed algorithm can extract parameters exactly and quickly. The proposed algorithm is compared with classic firefly algorithms and other algorithms in the paper. The results show that the effectiveness of the proposed algorithm.

Keywords: parameters extraction; PV model; adaptive firefly algorithm;

1. INTRODUCTION

To solve the energy crisis and environmental pollution, renewable energy offers broader energy resources, enhances energy security and provides an effective route to reducing atmospheric pollution and carbon dioxide (CO₂) emissions. Among renewable energy sources, solar energy has been widely concerned duo to its many advantages such as no pollution, easy access and low cost ^[1,2]. As the key component, photovoltaic (PV) cell plays important role in converting solar energy into electrical energy and is widely used in solar photovoltaic power generation. Every PV cell has low output current and low output voltage. So in practice, many PV cells are connect in series and in parallel to form PV panel which has higher output power. To study PV cell, appropriate model should be established and the parameters of the model should be obtained accurately. Studying the nonlinear output characteristic of PV cell based on its model is an important foundation of management, optimization and design of PV panel.

There are two types of models to study PV cell, namely equivalent circuit model and engineering model. Equivalent circuit model of PV cell uses photo-generate effect and diode circuit equation. This model has a high precision and can well simulate I-V output characteristic of PV cell. The equivalent circuit model includes single diode model and double diode model which have 5 and 7 parameters respectively. Usually, these parameters are not given by manufacturers of PV panels and the mathematic models are nonlinear and transcendental equation. Furthermore, the I-V output characteristic of PV cell are affected by radiation intensity, shaded illuminate, ambient temperature and other factors. It is difficult to calculate and extract the parameters of PV cells.

In order to obtain parameters of equivalent circuit model, the traditional method is derived from mathematical analysis ^[3,4]. This method obtains the parameters by simplifying the characteristic equation and weakening the associated parameters ^[5,6]. The results are usually approximate and have some error. To overcome these

deficiencies, intelligent evolutionary algorithms (IEAs) have been used to solve the parameters extraction problem.

IEAs simulate natural biological characteristics to solve problem and are widely used in many fields. IEAs do not require objective function to be linear, continuous and derivable. IEAs are essentially multi dimension parallelism and are suitable for solving the problems which are nonlinear and complex. It can get exact solution and has robustness in solving complex problems. Intelligent optimization algorithms are widely used in extracting parameters of PV cell ^[6~10].

Firefly algorithm (FA) was first proposed by Xinshe Yang in 2008 ^[11-13]. It used the characteristics of firefly to transmit information through flashing patterns and behavior of firefly. It makes use of luminescence intensity and distance among fireflies to define the attractiveness and generate new generation of population. FA has simple structure and is easy to realize. It has good ability in optimization and has been successfully used in solving many complex problems.

This paper is passed introducing an adaptive mutation factor into the evolution process of a firefly algorithm. When used in single diode parameters extraction, it improves the precision and stability of the solution. Compared with the classic firefly algorithm and differential evolution algorithm, the adaptive firefly algorithm can extract parameters more accurately and quickly. The main contents of this paper include the following aspects: section 2 describes the problem formulation of parameter extraction with single diode model. Section 3 describes the classic firefly algorithm and adaptive firefly algorithm. Section 4 explains the simulation and experimental results. Finally, the final conclusions are discussed in section 5.

2. PROBLEM FORMULATION

Photovoltaic cell current-voltage curve is nonlinear, it changes with temperature and light intensity. Usually PV cell can be equivalent to two circuit models (single diode model and double diode model). The following is a brief introduction to the physical model and mathematical description of the single diode model.

2.1. Single diode model of PV cell

PV cell can directly transform solar energy into electrical energy by using the photovoltaic effect of semiconductor. Based on this principle, equivalent diode circuit model of a PV cell is established. Diode model can exactly simulate the output of PV cell. There are two circuit models, single diode model and double diode model which have 5 and 7 parameters respectively. The single diode model of PV cell is shown in Fig. 1.



Figure 1 Single diode model of PV cell

From the fig.1 above, the 5 parameters are I_{ph} , I_d , I_{sh} , R_{sh} and R_s . The meaning of the parameters are:

- I_{ph} = current created by solar energy
- Id = current through the diode
- R_{sh} = shunt resistor
- I_{sh} = current flowing through the shunt resistor R_{sh}
- R_s = serial resistor

From single diode model of PV cell, output current-voltage characteristic can be deduced:

The model output current is It, Its expression is:

$$I_t = I_{ph} - I_d - I_{sh} \tag{1}$$

Id is derived from the Shockley formula:

$$I_d = I_{sd} \left\{ exp\left[\frac{q(U_t + R_s I_t)}{nkT} \right] - 1 \right\}$$
(2)

In (1) and (2), U_t is output voltage of PV cell which is described in fig.1, I_{sd} is the current flowing through the diode, T is operating temperature of PV cell, q is elementary charge, k is Boltzmann constant and n is ideal constant of the diode which is generally between 1 and 2.

The formula for current lsh is:
$$I_{sh} = \frac{U_t + I_t R_s}{R_{sh}}$$
(3)

The specific values of q, k and T are listed in Table 1:

Table 1: Constant values of q, k and T		
Items	ems value	
q(C)	1.63*10^-19	
k(J/K)	1.38*10^-23	
T(K)	300	

Synchronous (2) ~ (3) is substituted into (1) to obtain the outpu $I_t = I_{ph} - I_{sd} \left\{ \exp\left[\frac{q(U_t + R_s I_t)}{nkT}\right] - 1 \right\} - \frac{U_t + R_s I_s}{R_{sh}}$ (4)

2.2. PV cell model parameters extraction problem

When use IEAs to extract 5 parameters of single diode model, the real output I-V data of PV cell can be used. The objective of parameters extraction problem is to minimize the difference between real and estimated based on (4). The parameter estimation using optimization technique is implemented in the following approach:

•a set of real data of I-V for a PV cell or a PV module is measured.

•an objective function is defined for minimizing the difference between the real data and measured values.

•the parameters are tuned by applying an optimization algorithm until the best objective function is obtained.

•after completing the optimization algorithm, the optimal value is extracted from the solution obtained by the optimization algorithm.

The parameters vector for the single diode model is defined as: e = [Rs, Rsh, Ish, Isd, n]; The unknown vector is determined by the I-V curve of the photovoltaic cell and the objective function;

The objective function determined by equations (1) to (4) above
$$z(U_t, I_t, e) = I_t - I_{ph} + I_{sd} \left\{ exp \left[\frac{q(U_t + R_s I_t)}{nkT} \right] - 1 + \frac{U_t + R_s I_t}{R_{sh}} \right\}$$
(5)

The data on the vector e and I-V curves are brought into equation (5) to obtain multiple sets of objective function values. In order to obtain the optimal solution, the square root error is selected, and the formula is as follows:

the square root formula

$$\text{RMSE} = \sqrt{\frac{1}{n} \sum_{i=1}^{n} z(U_t, I_t, e)} \qquad (6)$$

The objective of optimization is to minimize of formula (6).

3. IMPROVED FIREFLY ALGORITHM 3.1. Overview of Firefly algorithm

Firefly algorithm is a new type of natural heuristic optimization algorithm proposed by the scholar Xueshe Yang of Cambridge University in 2008^[12]. The algorithm simulates the luminescence mechanism and behavior mechanism of the fireflies in the natural world. It refers to a random search algorithm based on swarm

intelligence^[13]. This algorithm discards the biological characteristics of fireflies and uses the luminescence properties of fireflies to search for companions and to move to the strongest light in the area for optimization.

The most important factor in the firefly algorithm is in two factors: brightness and attractiveness. Brightness determines the fineness of the firefly, movement and the direction of movement. In optimization problem, brightness is related to the objective function. The attraction is determined by the brightness. The greater the brightness, the stronger its attraction to other fireflies. The attraction determines the distance traveled by the fireflies.

As mentioned above, the firefly algorithm mathematical expression is described as:

Definition 1: Relative brightness

$$\mathbf{I} = I_0 \times e^{-\gamma r_{ij}^2} \tag{7}$$

 $\beta = \beta_0 \times e^{-\gamma r_{ij}^2}$

(8)

Where:

- l₀ = the maximum brightness of the firefly, that is brightness when r = 0, related to the value of the objective function. The better the objective function value is, the higher the firefly brightness is.
- γ = light absorption coefficient. Because the fluorescence brightness gradually decreases with distance and the absorption of the propagation medium, the light intensity absorption coefficient is set to reflect this characteristic.
- r_{ij} = spatial distance between fireflies i and j.

Definition two: The relative attraction degree of fireflies

where:

- β_0 = the maximum degree of attraction, that is, the degree of attraction at the light source.

Definition 3: Location Update
$$x_i = x_i + \beta \times (x_i - x_j) + \alpha \times (rand - \frac{1}{2})$$
 (9)

Where:

- x_i, x_i = spatial positions of the fireflies i and j;
- $-\alpha$ = step length factor, which is a uniform distribution constant on [0, 1]. Rand is a uniformly distributed random factor on the [0,1] port.

3.2. Improved Firefly Algorithm

The step length factor and displacement distance in the FA are the key factors that determine the convergence speed and accuracy of the algorithm. In the basic FA, the step length factor is a fixed value, the accuracy and convergence speed are poor in the calculation process, and it is easy to fall into partial optimal situation. Location update in FA (formula 9) cannot satisfy the accuracy and searching effect throughout iterations. In view of considerations above, this paper proposes that the adaptive step size factor and introduces the inertia weight to change the displacement distance, named adaptive firefly algorithm (AFA). AFA Introduces Inertia Weights to Equation (8):

 $\beta = \beta_0 \times e^{-\gamma r_{ij}^2} \times \omega \quad (10)$

At the beginning of firefly algorithm, ω is large, a wide range of search can be performed and the light intensity of a wider range of fireflies can be observed. The smaller ω in the late search can greatly improve the accuracy of small-scale search. In order to achieve this goal, the degressive inertia weight controlled by the number of iterations is defined as:

inertia weight

$$\omega = \omega_{max} - (\omega_{max} - \omega_{min}) \times \frac{i}{MaxGeneration} (11)$$

Where:

ωmax,ωmin = maximum, minimum inertia weight.

- k= current number of iterations.
- MaxGeneration= the maximum number of iterations.

In AFA, step size factor controls the global search ability and local search ability. In the beginning of the iteration, larger value of step size factor will be helpful to have stronger global searching ability and this will improve the convergence speed. When at the later stage of iteration, smaller value of step size factor is help have stronger local searching ability and this will improve the accuracy of solution.

As described above, in AFA, the step factor is designed to decrease with the increase of the number of iterations. So AFA has a faster convergence speed at the beginning of algorithm. As the number of iterations continues to increase, the step factor decreases and the local searching ability increases. To evaluate the solution, an adaptive step size factor that controls the number of iterations for the step size factor is introduced:

adaptive step size factor $\alpha = \alpha - \text{RMSE}(k) \times \frac{k}{MaxGeneration} \times \alpha$ (12)

Where:

- a= the initial step size factor;
- RMSE(k) = the square root error when the number of iterations is k;
- k= the current number of iterations;
- MaxGeneration = the maximum number of iterations;

The new displacement formula can be gotten:

new displacement formula

$$x_{i} = x_{i} \times \beta_{0} \times e^{-\gamma r_{ij}^{2}} \times (x_{i} - x_{j}) + (\alpha - RMSE(k) \times \frac{k}{MaxGeneration} \times \alpha) \times (rand - \frac{1}{2})$$
(13)

3.3. PV cell parameters extract procedure based on AFA

Firstly, the objective function is determined by the single-diode photovoltaic model based on (4). Then, multiple sets of photovoltaic parameter values (Iph, Isd, Rs, n, Rsh) within the range are randomly generated. The parameters and the data on the existing I-V curve are brought into the objective function (5), then the adaptation value (square root error) of the objective function is obtained through (6), and other parameters are moved to the set of photovoltaic parameter values with the best adaptation value by formula (13).Obtain multiple sets of new parameter values, and then perform the process of solving the objective function and the fitness value again, and solve the optimal value; after many iterations to obtain the final optimal value, the extracted optimal photovoltaic parameter value. The following are the specific algorithm steps:

- 1) Define the objective function f(x), x=(x1,x2,x3...xt) by the equation(5)
- 2) Set the algorithm parameters β0, α0, γ, n (number of fireflies), MaxGeneration (maximum number of iterations) by formula(7) and (10);
- 3) Initialize the firefly population x_i,i=1,2,3...n
- 4) Determine the absolute brightness based on the objective function at x_i
- 5) For w=1:MaxGeneration
- 6)For i=1:n; fireflies population
- 7) For j=1:b; number of sampling points
- 8) Calculate the objective function
- 9)End for j
- 10) Calculate square root error through (6)
- 11)End for i
 10) Find the summation of a shafting
- 12) Find the current optimal solution
- 13) lf (lj>li)
- 14) Change position by displacement formula (13)
- 15)End for w
- 16) Output optimal solution

4. SIMULATION EXPERIMENTS AND RESULTS

In this section, simulation experiments to extract parameters of single diode model by basic firefly algorithm, the improved firefly algorithm and DE algorithm and the results are compared . The basic parameters of the

algorithm are set as follows: the firefly population is 50, and the number of fireflies inside the population is 5, the sampling point data obtained by the algorithm is 26, and the maximum number of iterations is 1000;

The 26 sampling points	obtained by the algorithn	n are list in Table 2:
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Table2:26 sampling points				
Ut(V)	lt(A)			
-0.2057	0.764			
-0.1291	0.762			
-0.0588	0.7605			
0.0057	0.7605			
0.0646	0.76			
0.1185	0.759			
0.1678	0.757			
0.2132	0.757			
0.2545	0.7555			
0.2924	0.754			
0.3269	0.7505			
0.3585	0.7465			
0.3873	0.7385			
0.4137	0.728			
0.4373	0.7065			
0.459	0.6755			
0.4784	0.632			
0.496	0.573			
0.5119	0.499			
0.5265	0.413			
0.5398	0.3165			
0.5521	0.212			
0.5633	0.1035			
0.5736	-0.01			
0.5833	-0.132			
0.59	-0.21			
	Table2:26 sampling points Ut(V) -0.2057 -0.1291 -0.0588 0.0057 0.0646 0.1185 0.1678 0.2132 0.2545 0.2924 0.3269 0.3585 0.3873 0.4137 0.4373 0.459 0.4784 0.496 0.5119 0.5265 0.5398 0.5521 0.5633 0.5736 0.5833 0.59			

According to the above, using the data in Table 2 for DE, basic firefly, and self-adaptive firefly algorithms for single-diode photovoltaic cell parameter identification, five optimal parameters and corresponding evaluation functions (RMSE) are shown in the following table:

Table3: Single-diode photovoltaic cell model parameter identification and comparison

PARAMETER	DE	FA	AFA
IPH (A)	0.794677	0.7437177	0.752757
ISD(MA)	0.1	0.18251	0.23434
RS(Ω)	0.0108647	0.0552238	0.056614
Ν	1.4381	1.5871	1.310267
RSH(Ω)	52.280197	63.057952	53.40467
RMSE	0.0894002	0.0190773	0.014961

Figure 2 compares the fitness values of the three algorithms. Because the DE mutation process will exceed the upper and lower limits, make data reset. The reset data group may be enlarged during the hybridization process, resulting in the local algorithm being liable to fall into place when the DE algorithm has too many iterations.



Figure2 finesse curve

From Table 4 and Figure 2 above, compared with basic firefly algorithm and DE algorithm, adaptive firefly algorithm has better convergence speed and more accurate convergence value. The results shows that compared with FA and DE algorithm, the improved firefly algorithm is more suitable for extracting parameters of single-diode PV cell.

5. CONCLUSION

In this paper, adaptive optimization is embedded into the firefly algorithm, and an excellent firefly algorithm is constructed with increasing number of iterations. The algorithm fully utilizes adaptive optimization to overcome the poor accuracy and convergence speed of the firefly algorithm iteration process. In a local optimal situation, this algorithm has been successfully applied to the nonlinear optimization problem of photovoltaic cell module parameter identification with multiple local extremum. Simulation test and comparison results show that the algorithm has high recognition accuracy, good simulation effect, and can be more effective.

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