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Short note

A novel Elite Opposition-based Jaya algorithm for parameter estimation of photovoltaic cell models

Long Wang [a,b,c], Chao Huang [c,*]

[a] School of Computer and Communication Engineering, University of Science and Technology Beijing (USTB), Beijing 100083, China
[b] Beijing Key Laboratory of Knowledge Engineering for Materials Science, Beijing 100083, China
[c] Department of Systems Engineering and Engineering Management, City University of Hong Kong, 83 Tat Chee Ave, Kowloon, Hong Kong

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ABSTRACT

Parameter estimation of photovoltaic (PV) cell models using a novel Elite Opposition-based Jaya (EO-Jaya) algorithm is studied in this letter. The EO-Jaya is a swarm intelligence algorithm without algorithm specific parameters. Compared with the generic Jaya algorithm, the Elite Opposition Learning strategy is incorporated into the solution updating phase, which increases the solution diversity. The effectiveness of the EO-Jaya algorithm is validated via estimating model parameters of a real PV cell. The computational results prove the superiority of the proposed algorithm compared to newly published estimation methods.

1. Introduction

Accurate modeling of photovoltaic (PV) cells plays a vital role in performance evaluation, control scheme design and condition monitoring of PV systems. Two basic steps are often considered for modeling the PV cells: (1) the mathematical model formulation and (2) the accurate estimation of model parameters. Various mathematical models have been developed to depict the nonlinear relationship between the Current and Voltage of a PV cell, among which the single diode (SD) model and the double diode (DD) model are widely employed in both theoretical analyses and practical applications. Five and seven model parameters are required to estimate in the SD and DD models respectively and the estimation accuracy directly affects the performance of these models. In literature, two main classes of estimation methodologies, deterministic and heuristic, have been adopted for parameter identification of PV cell models. The heuristic approaches have achieved generally better performance than the deterministic methods considering the robustness and accuracy [1]. The heuristic approaches, including Genetic Algorithms (GA) [1], Particle Swarm Optimization (PSO) [2], Artificial Bee Swarm Optimization (ABSO) [3], Artificial Bee Colony (ABC) [4], and Teaching-learning Based Optimization (TLBO) [5] have been explored for estimating model parameters of PV cells in previous studies. However, the performance of conventional heuristic algorithms highly depends on the settings of algorithm-specific parameters, such as the mutation probability, crossover probability, and selection operator in GA as well as the inertia weight, social and cognitive parameters in PSO. Therefore, tuning these algorithm-specific parameters needs to be considered, which introduces extra computational cost.

In this letter, a novel Elite Opposition-based Jaya (EO-Jaya) algorithm is proposed for parameter estimation of PV cell models. Similar to the generic Jaya algorithm [6], the proposed EO-Jaya algorithm is also free of algorithm-specific parameters. Meanwhile, in the proposed algorithm, an Elite Opposition-based Learning mechanism is incorporated into the updating

* Corresponding author.
E-mail addresses: lwang@ustb.edu.cn, chao.huang@my.cityu.edu.hk (C. Huang).

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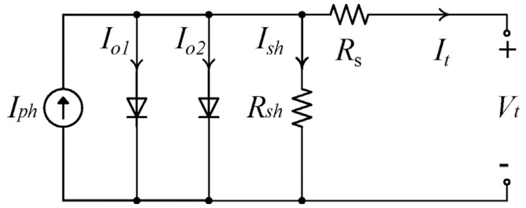

Fig. 1. Equivalent circuit of the double diode model.

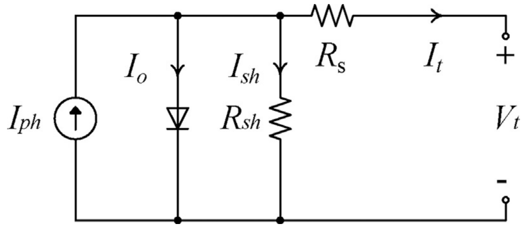

Fig. 2. Equivalent circuit of the single diode model.

of solutions in the Jaya algorithm. By transforming solutions in current search space into a opposite search space, the Elite Opposition-based Learning offers a higher probability of finding solutions closer to the global optimum. To validate the proposed algorithm, model parameters are estimated based on collected experimental data from a real PV cell and its performance is compared with newly published estimation methods.

2. Photovoltaic cell models and problem formulation

This section presents mathematical descriptions of the two widely utilized PV cell models, the SD and DD models.

Fig. 1 demonstrates the equivalent circuit of the DD model. According to the circuit, the current of the cell is computed in (1).

$$I_t = I_{ph} - I_{o1} - I_{o2} - I_{sh} \tag{1}$$

where I_t is the terminal current, I_{ph} is the photo-generated current, I_{o1}, I_{o2} are the first and second diode currents separately, and I_{sh} is the shunt resistor current. In the DD model, the PV cell acts as a p-n junction and Eq. (2) is obtained based on the Shockley diode equation.

$$I_t = I_{ph} - I_{o1}[\exp(\frac{q(V_t + R_s \cdot I_t)}{a_1 \cdot k \cdot T}) - 1] - I_{o2}[\exp(\frac{q(V_t + R_s \cdot I_t)}{a_2 \cdot k \cdot T}) - 1] - \frac{V_t + R_s \cdot I_t}{R_{sh}} \tag{2}$$

where V_t is the terminal voltage, R_s and R_{sh} are the series and shunt resistances repetitively, q is the electric charge of an electron, k is the Boltzmann constant, T is the temperature of the cell in Kelvin, and a_1 and a_2 represent the diffusion and recombination diode ideality factors. In the DD model, seven parameters (I_{ph}, I_{o1}, I_{o2}, R_s, R_{sh}, a_1 and a_2) need to be derived from I–V data of a PV cell.

The equivalent circuit of the SD model is shown in Fig. 2 and the corresponding current of the cell is computed in (3).

$$I_t = I_{ph} - I_o \left[\exp\left(\frac{q(V_t + R_s \cdot I_t)}{a \cdot k \cdot T}\right) - 1\right] - \frac{V_t + R_s \cdot I_t}{R_{sh}} \tag{3}$$

where I_o is reverse saturation current of the diode and a is the diode ideality factor. Thus, five parameters (I_{ph}, I_o, R_s, R_{sh}, and a) need to be estimated in the SD model.

In order to estimate model parameters of the PV cell, an optimization problem is formulated to minimize the deviation between the measured current and modeled current and the root mean squared error (RMSE) is utilized as the objective function, described in (4).

$$\mathrm{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}[I_{t,i}(\boldsymbol{x}) - I_{m,i}]^2} \tag{4}$$

where $I_{t,i}$ and $I_{m,i}$ are computed and measured PV cell currents respectively, $\boldsymbol{x}$ denotes the model parameters, and N is the number of experimental data.

3. Elite Opposition-based Jaya algorithm

Jaya algorithm [6–8] is a swarm based stochastic optimization algorithm and the solution updating procedure is presented in (5).

$$x'_{j,k,i} = x_{j,k,i} + r_{1,j,i}(x_{j,best,i} - |x_{j,k,i}|) - r_{2,j,i}(x_{j,worst,i} - |x_{j,k,i}|) \tag{5}$$

where $x_{i,k,j}$ is the value of the jth element of the kth candidate at iteration i, $x_{i,best,j}$ is the value of the jth element of the best candidate, $x_{i,worst,j}$ is the value of the jth element of the worst candidate, and $r_{1,j,i}$ and $r_{2,j,i}$ are two independent random number generated from a uniform distribution, $U(0, 1)$.

Elite Opposition-based Learning [9] is a newly emerging technique in the heuristic search domain. In this learning scheme, both original solutions and opposite solutions are evaluated and better solutions are retained for the next generation. Given the solution $\boldsymbol{x}_{best}$ with the best fitness value, the elite opposition-based solution of the individual solution $\boldsymbol{x}_k$ is define as (6).

$$x^*_{j,k,i} = r \cdot (da_j + db_j) - x_{j,best,i} \tag{6}$$

where da_j and db_j is the dynamic bound of the jth element, defined in (7).

$$da_j = \min(x_{j,k,i}), da_j = \max(x_{j,k,i}) \tag{7}$$

da_j and db_j are updated every 50 generations and the following rule is utilized to ensure solution within the bound.

$$x^*_{j,k,i} = rand(da_j, db_j), \text{if} x^*_{j,k,i} < da_j \text{or} db_j > x^*_{j,k,i} \tag{8}$$

Thus, in the EO-Jaya algorithm, a better solution between $\boldsymbol{x}$ and $\boldsymbol{x}^*$ is selected for the updating procedure described in (5). Accordingly, the EO-Jaya algorithm is demonstrated in Algorithm 1.

Algorithm 1. EO-Jaya algorithm

Input: Population size: n;
Output: Solution: $\boldsymbol{x}$;
for $k := 1$ *to* n **do**
  Initialize $\boldsymbol{x}_{k,1}$;
end
Get $\boldsymbol{x}_{best,1}, \boldsymbol{x}_{worst,1}$;
Set $i = 1$;
repeat
  for $k := 1$ *to* n **do**
    Generate $\boldsymbol{x}^*_{k,i}$ according to (6);
    if *solution* $\boldsymbol{x}^*_{k,i}$ *better than* $\boldsymbol{x}_{k,i}$ **then**
      Set $\boldsymbol{x}_{k,i} = \boldsymbol{x}^*_{k,i}$
    end
    for $j := 1$ *to* d **do**
      Set $r_{1,j,i}$ = a random number from $[0, 1]$;
      Set $r_{2,j,i}$ = a random number from $[0, 1]$;
      Set
      $x'_{j,k,i} = x_{j,k,i} + r_{1,j,i}(x_{j,best,i} - |x_{j,k,i}|) - r_{2,i}(x_{j,worst,i} - |x_{j,k,i}|)$;
    end
    if *solution* $\boldsymbol{x}'_{k,i}$ *better than* $\boldsymbol{x}_{k,i}$ **then**
      Set $\boldsymbol{x}_{k,i+1} = \boldsymbol{x}'_{k,i}$;
    else
      Set $\boldsymbol{x}_{k,i+1} = \boldsymbol{x}_{k,i}$;
    end
  end
  Set $i = i + 1$;
  Update $\boldsymbol{x}_{best,i}, \boldsymbol{x}_{worst,i}$;
until *termination criterion satisfied*;

4. Case study

To evaluate the performance of the proposed algorithm for estimating parameters of PV cell models, experimental *I–V* data collected from a 57 mm diameter commercial (R.T.C France) silicon PV cell under standard test conditions are utilized. Parameters of the SD and DD models are identified based the collected data using the proposed algorithm. The population size is set to 150 and the maximum iteration number is 10,000. The algorithm is run 50 times and the best results are presented. A PC with a Intel Core i5@3.2GHz CPU and 8GB memory is employed to perform the estimation. The boundaries of each parameter is shown in Table 1.

Six parameters are estimated with the EO-Jaya and the yielded RMSE is shown in Table 2. In order to compare the EO-Jaya algorithm with the newly published methods, the RMSE values of four other algorithms, MABC [10], GOTLBO [5], ABSO [3], and ABC [4], are also included in Table 2.

Table 1
The boundaries of PV model parameters.

Parameter	Lower bound	Upper bound
R_s (Ω)	0	1
R_{sh} (Ω)	0	100
I_{ph} (A)	0	1
I_o (μA)	0	1
I_{o1} (μA)	0	1
(I_{o2} (μA)	0	1
a	1	2
a_1	1	2
a_2	1	2

Table 2
RMSEs of different algorithms for the SD model.

Algorithm	RMSE (10^{-4})
MABC	9.8610
GOTLBO	9.8744
ABSO	9.9124
ABC	9.8620
EO-Jaya	**9.8603**

Table 3
RMSEs of different algorithms for the DD model.

Algorithm	RMSE (10^{-4})
MABC	9.8276
GOTLBO	9.8318
ABSO	9.8344
ABC	9.8610
EO-Jaya	**9.8262**

It is observable that the EO-Jaya dominates all the algorithms with the lowest RMSE, and the MABC has the second best RMSE. The worst result (RMSE = 9.9124×10^{-4}) is obtained using the ABSO algorithm. Seven parameters are extracted for the DD model and RMSE values of different algorithms are summarized in Table 3.

Table 3 shows that the EO-Jaya has best performance over all five algorithms for the DD model. Therefore, the EO-Jaya has the ability to accurately estimate parameters of PV cell models.

5. Conclusions

A novel EO-Jaya algorithm for estimating model parameters of PV cells was presented in this letter. Similar to the generic Jaya algorithm, the EO-Jaya algorithm was free of algorithm-specific parameters. In the EO-Jaya, the Elite Opposition-based Learning was incorporated into the solution updating phase. The effectiveness of the proposed algorithm was validated with I–V data collected from a real PV cell and parameters of two PV cell models, the SD and DD models, were estimated.

In the comparative analysis of five different estimation methods, the EO-Jaya yielded the best results for the two models. Computational studies confirmed the propose algorithm was applicable to parameter estimation of PV cell models.

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