

Research Article

Parameter Estimation of Photovoltaic Models via Cuckoo Search

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Since conventional methods are incapable of estimating the parameters of Photovoltaic (PV) models with high accuracy, bioinspired algorithms have attracted significant attention in the last decade. Cuckoo Search (CS) is invented based on the inspiration of brood parasitic behavior of some cuckoo species in combination with the Lévy flight behavior. In this paper, a CS-based parameter estimation method is proposed to extract the parameters of single-diode models for commercial PV generators. Simulation results and experimental data show that the CS algorithm is capable of obtaining all the parameters with extremely high accuracy, depicted by a low Root-Mean-Squared-Error (RMSE) value. The proposed method outperforms other algorithms applied in this study.

1. Introduction

Photovoltaic (PV) cells, normally assembled into modules or arrays on mounting systems, are capable of producing electrons when photons strike its surface. Taking the advantages of many promising features like renewability, less pollution, and ease of installation, PV generators are envisaged to be an important energy source for the future.

Due to the high initial cost of a PV-supplied system, predictive performance tools are widely used by engineers to optimize the system performance [1, 2]. PV manufacturers normally provide limited tabular data measured under the Standard Test Conditions (STCs), which correspond to a cell temperature of 25°C and an irradiance of 1000 W/m² at 1.5 air mass spectral distributions. As reported in [3], PV generators always operate under environments far from the STCs. Due to this reason, the data available in the datasheet usually fail to fulfill the engineering requirements.

PV model, with the ability to predict I - V characteristics of PV generators under an operating environment other than the STCs, is a predictive performance tool that allows consumers to maximize the cost effectiveness of the system before installation [2]. They are generally analytical equations based on a physical description that formulate PV generated current (I) with the most crucial technical characteristics

and the environmental variables, such as the operating voltage (V), the ambient temperature (T), and the irradiance (G). Over the years, significant research efforts have been contributing to the development of the behavioral models [4–8]. Among numerous modeling approaches, the Single-Diode Model (SDM) is the most widely utilized PV model in the literature. A general SDM includes five parameters, namely, photocurrent (I_{pv}), saturation current (I_o), diode ideality constant (n), series resistance (R_s), and shunt resistance (R_p). In order to adapt PV model behavior to different operating conditions, de Blas et al. [9] suggested to apply the procedure described in the International Standard IEC 891 that relates current and voltage of the PV characteristics at given values of T and G with the corresponding values at different operating environments. The Improved Single Diode Model (ISDM) presented by De Soto et al. [5] includes the dependence of the PV parameters on operating conditions. The normal parameters at the STCs are necessary to be determined in this model. Both SDM and ISDM are adopted in this study of parameter estimation.

Analytical methods [5, 10–12] are common approaches in estimating the parameters by mathematical equations. Although having the merit of simplicity, it is hard to further reduce the errors of the estimated values. Furthermore, analytical methods utilize the I - V curve features or

semiconductor parameters that are unavailable in the datasheet. This problem often reduces its feasibility. Recently, PV parameter estimation is deemed as a multidimensional optimization problem. Several computational intelligence methods, such as Genetic Algorithms (GA) [13], Chaos Particle Swarm Optimization (CPSO) [14], Firefly [15], and Pattern Search (PS) [16], were proposed in the literature. These algorithms usually extract relevant parameters by minimizing the Root Mean Square Error (RMSE) as the objective function in the optimization process. Askarzadeh and Rezazadeh [17] reported that the optimization methods produce better results than analytical methods.

Cuckoo Search (CS) is a nature-inspired optimization algorithm based on the fascinating breeding behavior such as brood parasitism of certain species of cuckoos. In [18, 19], Yang and Deb reported that the CS algorithm outperforms Particle Swarm Optimization (PSO) and GA algorithms for various standard test functions. In this paper, a CS-based parameter estimation method for the SDM and ISDM is presented. Simulation and experimental results show superior accuracy and feasibility of the proposed parameter estimation method.

The rest of the paper is organized as follows. Section 2 explains both PV models (SDM and ISDM) used in this work. The objective function formulation is given in Section 3. This is followed by results and discussions in Section 4. The results comparison is also available here, and finally the conclusions are derived in Section 5.

2. PV Modeling

2.1. Single Diode PV Model (SDM). PV cells are made of a variety of semiconductor materials using different manufacturing processes. The working principle of PV cells is essentially on the basis of the PV effect, which refers to the generation of a potential difference at the P - N junction in response to visible or other radiation. When a PV cell is exposed to light, the semiconductor materials absorb photons, and accordingly charged carriers are generated. Potential difference and current in the external circuit lead to the separation of carriers in the internal electric field created by the P - N junction and collection at the electrodes. The photogenerated charge carriers can be subsequently captured in the form of an electric current, that is, electricity I_{pv} . Eliminated the PV effect, a PV cell behaves like a conventional diode that does not depend on any light parameters. The Shockley diode equation is generally used to describe the current flowing through the diode (I_d):

$$I_d = I_o \left(e^{V_d/nV_t} - 1 \right). \quad (1)$$

In (1), I_o is the normal diode current, and V_d represents the electrical potential difference between the two ends of the diode. The ideality factor n is assumed to be independent of the environment variables T and G . V_t denotes the thermal voltage of the PV, and its value can be written as a function of T :

$$V_t = \frac{kT}{q}, \quad (2)$$

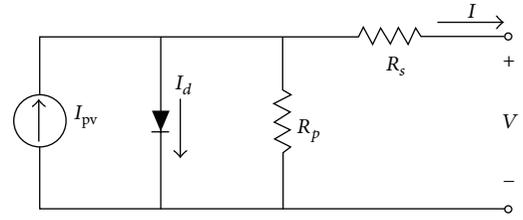


FIGURE 1: The equivalent circuit of the SDM.

where k and q represent the Boltzmann constant (1.380650×10^{-23} J/K) and the electron charge (1.602176×10^{-19} C), respectively.

SDM assumes that the superposition principle holds; that is, the total characteristic is the sum of the dark and illuminated characteristics [3–5]. As expressed in (3) below, the terminal current I is therefore equal to I_{pv} subtracting the current diverting through the diode and R_s . The equivalent circuit of the SDM is shown in Figure 1.

$$I = I_{pv} - I_o \left(e^{(V+IR_s)/nV_t} - 1 \right) - \frac{V + IR_s}{R_p}. \quad (3)$$

PV module is a particular case of the PV cells connected in series. If the number of the connected cells is up to N_s , V_t is scaled to N_s times. The model equation is then rewritten as

$$I = I_{pv} - I_o \left(e^{(V+IR_s)/nN_sV_t} - 1 \right) - \frac{V + IR_s}{R_p}. \quad (4)$$

In this sense, I_{pv} , I_o , R_s , and R_p are the corresponding parameters of a PV module.

2.2. Improved Single Diode Model (ISDM). The traditional SDM ignores the operating conditions effect on these parameters. However, some studies have shown that the parameters, such as I_{pv} and I_o , vary under different environmental conditions. These are due to changes of temperature T and irradiance G . Aiming to evaluate the PV behavior at environmental conditions other than the normal values T_n and G_n , the relations between the operating parameters and the normal parameters are studied by numerous researchers.

In [4], the value of light-generated I_{pv} is reported to be linearly dependent on the solar irradiation under the influence of temperature:

$$I_{pv} = \frac{G}{G_n} \left(I_{pv_n} - K_i \Delta T \right), \quad (5)$$

where I_{pv_n} is the light-generated current at the STCs. K_i , the short-circuit current coefficient, is one of the ISDM parameters. The difference between the standard test temperature T_n and T is denoted by ΔT .

Based on the diode theory, Messenger and Ventre [20] presented an approximate linear expression for the diode saturation current I_o , which can be expressed as

$$I_o = I_{on} \left(\frac{T}{T_n} \right) e^{[(qE_g/nk)(1/T_n - 1/T)]}, \quad (6)$$

where E_g is the material band gap. Usually, E_g is set at a reasonable level depending on the semiconductor materials (1.12 eV for crystalline silicon and 1.75 eV for amorphous silicon) in simulation and design tools [21]. De Soto et al. [5] present an estimation method for E_g in a wide temperature range:

$$E_g = E_{gn} (1 - 0.0002677\Delta T), \quad (7)$$

where E_{gn} is a normal value at the STCs ($E_{gn} = 1.12$ eV for silicon cells and $E_{gn} = 1.6$ eV for the triple junction amorphous cells).

In [3], Lo Brano et al. study how the series and shunt resistances are affected by the solar irradiance. On the basis of the experimental data, the values of R_s and R_p are observed varying in inverse linear modes with G :

$$R_s = \frac{G_n}{G} R_{sn}, \quad (8)$$

$$R_p = \frac{G_n}{G} R_{pn},$$

where the values of the resistances R_{sn} and R_{pn} are evaluated under the STCs.

By using the aforementioned relations, the ISDM described in [5] is able to analytically describe the I - V characteristic of a PV generator for each generic condition of operative temperature and solar irradiance.

3. Parameter Estimation

3.1. Formulation of Parameter Estimation Problem. PV parameter estimation is a process that minimizes the difference between the measured data and the calculated current by adjusting the normal PV parameters. When the number of experimental data is up to N , the objective function can be formulated by RMSE as

$$\text{RMSE} = \sqrt{\frac{1}{N} \sum_{i=1}^N (f_i(V, I, x))^2}, \quad (9)$$

where $x = [I_{pv}, I_o, n, R_s, R_p]$ for SDM and $x = [I_{pvn}, I_{on}, n, R_{sn}, R_{pn}, K_i, E_g]$ for ISDM. $f(V, I, x)$ is the homogeneous form of (4) which expresses the I - V characteristics of the SDM:

$$f(V, I, x) = I_{pv} - I_o \left(e^{(V+IR_s)/nN_sV_t} - 1 \right) - \frac{V + IR_s}{R_p} - I. \quad (10)$$

For the case of ISDM, I_{pv} , I_o , n , R , and R_p satisfy the relational expressions discussed in the previous subsection, namely, (5)–(8).

3.2. Cuckoo Search. The CS algorithm [18, 19], proposed by Yang and Deb, is a nature-inspired stochastic global search algorithm that follows three idealized behavior rules.

- (i) A cuckoo lays an egg and dumps it randomly into other bird species' nests.

Cuckoo Search via Lévy Flights

Initialization of n host nests (population)

while within the stopping criterion,

Choose a cuckoo egg by Lévy flights and evaluate its fitness (F_i);

Choose an egg in other's nest randomly and calculate its fitness (F_j);

If $F_i > F_j$, replace j th egg by i th egg;

A fraction (p_a) of worse nests are demolished and replaced by new ones;

Preserve good nests (best solutions).

end while

PSEUDOCODE 1: Pseudocode of the Cuckoo Search (CS) [19].

- (ii) The best nests with high quality eggs will be carried forward to the next generation.
- (iii) There are a fixed number of available host nests. If a host bird discovers that the eggs are not its own, it will either throw these alien eggs away, or it may abandon the nest and build a brand new nest at a nearby location.

Based on the three rules, the basic steps of CS can be summarized by the pseudocode shown in Pseudocode 1. In the CS algorithm, a pattern corresponds to a nest while each individual attribute of the pattern corresponds to an egg laid by the cuckoo. On the basis of random-walk algorithms, the general system equation of the CS algorithm is given in:

$$X_{g+1,i} = X_{g,i} + \alpha \otimes \text{Lévy}(\beta), \quad (11)$$

where g and i denote the generation number ($g = 1, 2, 3, \dots, \text{MaxGen}$) and the pattern number ($i = 1, 2, \dots, n$), respectively. The product \otimes means entry-wise multiplications. Here $\alpha > 0$ is the step size scaling factor which should be related to the scales of the problem of interest [19]. The j th attributes of the i th pattern is initiated by using (12),

$$X_{g=0;j,i} = \text{rand} \cdot (Ub_i - Lb_i) + Lb_i, \quad (12)$$

where Ub_i and Lb_i are the upper and lower bounds of the j th attributes, respectively. In each computation step, the CS algorithm checks whether the value of an attribute exceeds the allowed search range. If this happens, the value of the related attribute will be updated with the corresponding boundary value.

Before the searching process, the CS algorithm detects the most successful pattern as x_{best} pattern. Among the existing algorithms exist for generating Lévy flights in the literature, Yang and Deb [18, 19] reported that Mantegna's algorithm [22] works well in most of the optimization problems. Accordingly the evolution phase of the pattern initialized with the detection step of ϕ , which is given by (13) [23]:

$$\phi = \left(\frac{\Gamma(1 + \beta) \cdot \sin(\pi \cdot \beta/2)}{\Gamma(((1 + \beta)/2) \cdot \beta \cdot 2^{(\beta-1)/2})} \right)^{1/\beta}, \quad (13)$$

where β is 1.5 in the standard software implementation of the CS algorithm [30]. Γ denotes the gamma function.

After initialization, the evolution phase of the x_i pattern starts by defining the donor vector v , where $v = x_i$. The required step size of the j th attributes can be calculated by the following equation:

$$s_j = 0.01 \cdot \left(\frac{u_j}{v_j} \right)^{1/\beta} \cdot (v - x_{\text{best}}), \quad (14)$$

where $u = \phi \cdot \text{randn}[D]$ and $v = \text{randn}[D]$. The $\text{randn}[D]$ function generates a uniform integer between $[1, D]$ [25]. The donor pattern v is then randomly adjusted by

$$v = v + s_j \cdot \text{randn}[D]. \quad (15)$$

The CS algorithm will evaluate the fitness of the random pattern. If a better solution is caught, the x_{best} pattern will be updated. The unfeasible patterns are revised by the crossover operator given in (16) as follows:

$$v_i = \begin{cases} x_i + \text{rand} \cdot (x_{r1} - x_{r2}), & \text{rand}_i > p_0, \\ x_i, & \text{others,} \end{cases} \quad (16)$$

where p_0 is the mutation probability value ($p_0 = 0.25$ in the standard software implementation [30]). The final step of a generation is to check if the revised infeasible patterns deliver a better solution.

4. Results and Discussions

With the aim of providing a thorough evaluation of the CS algorithm in estimating the PV parameters, both SDM and ISDM are considered in this paper. Two case studies are designed to estimate the CS algorithm in model parameters estimation:

- (i) a commercial 57 mm diameter solar cell (R.T.C. France [26]) operating at the standard irradiance level;
- (ii) a PV module (KC200GT Multicrystal Photovoltaic Module) operating under varied environment conditions.

During the parameter extraction process, the objective function $f(V, I, x)$ is minimized with respect to the parameters range. In theory, the value of I_{pvn} is slightly larger than that of I_{scn} . E_{gn} is in a loose range from 1 eV to 2 eV. K_i is around the value provided by the datasheet (normally less than 0.02%/°C). The I_{on} is usually less than 50 μA . As stated in [27], the ideality factor ranges between 1 and 2. PV modules produced by most manufacturers have R_s less than 0.5 Ω and R_p between 5 and 170 Ω [8, 28]. As for PV cell, the ranges of R_s and R_p can be scaled by simply dividing N_s [29].

Statistical analysis is performed to evaluate the quality of the fitted models to the experimental data. Besides RMSE, other two fundamental measures, namely, Individual Absolute Error (IAE) and the Mean Absolute Error (MAE), are

TABLE 1: A comparison between the parameter results obtained by the CS algorithm and that of other algorithms from the SDM.

	CS	CPSO [14]	GA [13]	PS [16]
I_{pv}	0.7608	0.7607	0.7619	0.7617
I_o	3.23E-07	4.00E-07	8.09E-07	9.98E-07
n	1.4812	1.5033	1.5751	1.6
R_s	0.0364	0.0354	0.0299	0.0313
R_p	53.7185	59.012	42.3729	61.1026
RMSE	0.0010	0.0014	0.0191	0.0149

applied to evaluate in this paper. Equations (17) and (18) preset the IAE and MAE, respectively:

$$\text{IAE} = |I_{\text{calculated}} - I_{\text{measured}}|, \quad (17)$$

$$\text{MAE} = \frac{1}{N} \sum_{i=1}^N \text{IAE}_i. \quad (18)$$

The optimization algorithms applied in this paper are programmed in MATLAB. Similar simulation conditions, including population size, maximum generation number, and search ranges, are set to ensure a fair evaluation (population size = 25; maximum generation number = 5000).

4.1. Case Study 1: Parameter Estimation for a PV Cell at the Certain Irradiance Level. Table 1 lists the model parameters of the R.T.C France PV cell at 33°C, which are extracted from the experimental data in [26]. The parameters obtained from the CS algorithm are compared with three different parameter estimation approaches: CPSO [14], GA [13], and PS [16]. From the RMSEs of these methods, which are listed in the last row of Table 1, the CS algorithm [30] outperforms the other three optimization methods. CS obtained slightly lower RMSE, recording 0.0010 in numerical value.

During the parameter estimation process for the SDM, the values of the objective function in different optimization algorithms are shown in Figure 2. The function “ga” in MATLAB [31], whose crossover rate $P_c = 0.8$ and mutation rate $P_m = 0.2$, is utilized for the convergence process test. As for PSO implementation [24], the algorithm parameters are set as learning factors $c_1 = c_2 = 2$, inertia factors $w_{\text{max}} = 0.9$, $w_{\text{min}} = 0.4$, and velocity clamping factor $V_{\text{max}} = 0.5$. In Figure 2, no further improvement by GA is observed after 500 iterations. On the contrary, the CS algorithm showed continuous improvement until the maximum generation. The CS algorithm, whose convergence speed is slightly faster than PSO, shows the best accuracy result in the minimization task after 5000 iterations.

Table 2 lists the parameters of the ISDM obtained by the CS algorithm. In order to evaluate the accuracy of the CS-based estimation, these parameters are substituted into the ISDM. Since the I - V demonstrates nonlinear characteristics, the PV terminal current I is solved by the Newton-Raphson method [32] in this paper. In Table 3, the calculated results I_{ISDM} are compared with the experimental data I_{measured} to observe the agreement between them. The notations IAE_{SDM} and IAE_{ISDM} denote the IAE for SDM and ISDM, respectively.

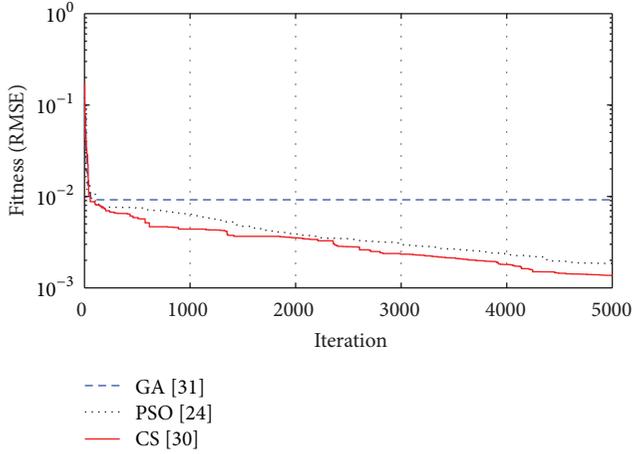


FIGURE 2: Convergence process of different optimization algorithms during the parameter estimation process of the SDM.

TABLE 2: Parameters of the ISDM obtained by the CS algorithm.

I_{pvn}	I_{on}	n	R_{sn}	R_{pn}	K_i	E_{gn}
0.7361	1.84E-07	1.5009	0.0355	57.8394	0.0031	1.0020

Although the RMSE of the ISDM is less than that of CPSO, GA, and PS, it is similar to the RMSE of the conventional SDM under a certain environmental condition.

4.2. Case Study 2: Parameter Estimation for a PV Module under Different Environment Conditions. In this section, the validity of the CS algorithm is evaluated using KC200GT PV module operating under different environment conditions. The estimated parameters, both in the SDM and ISDM, are shown in Table 4. As illustrated in Section 1, the main application of the parameter extraction is to predict the I - V characteristics for design purpose. It is worth pointing out that the SDM parameters can only be extracted by the experimental data measured under a certain test condition. Significant errors may occur as the experimental data are measured under varying operating conditions. In the commercial simulation tool like PSIM [21], the PV parameters of the SDM are firstly estimated at the STCs, then the equations (given in the appendix) are applied to calculate the electrical characteristics of different operating conditions. The ISDM-based parameter estimation, however, can be performed by the data measured under any conditions.

Figure 3 shows the I - V curves generated using the parameters obtained by the CS algorithm. The simulated results are compared with the experimental data, which are collected at five different irradiance levels (1000 W/m^2 , 800 W/m^2 , 600 W/m^2 , 400 W/m^2 , and 200 W/m^2) and three different temperature levels (25°C , 50°C , and 75°C). It can be seen that the I - V curves of the ISDM fit the whole range of the experimental dataset. On the other hand, the errors of SDM seem larger at lower irradiance and higher temperature levels. With the experimental data, the RMSE of the current I in

TABLE 3: A comparison between the errors of ISDM and SDM. The parameters are extracted by the CS algorithm.

No	V_{measured}	I_{measured}	I_{ISDM}	IAE_{ISDM}	IAE_{SDM}
1	-0.2057	0.7640	0.7639	0.0001	0.0001
2	-0.1291	0.7620	0.7626	0.0006	0.0007
3	-0.0588	0.7605	0.7614	0.0009	0.0009
4	0.0057	0.7605	0.7602	0.0003	0.0003
5	0.0646	0.7600	0.7592	0.0008	0.0009
6	0.1185	0.7590	0.7583	0.0007	0.0010
7	0.1678	0.7570	0.7574	0.0004	0.0001
8	0.2132	0.7570	0.7565	0.0005	0.0009
9	0.2545	0.7555	0.7555	0.0000	0.0004
10	0.2924	0.7540	0.7540	0.0000	0.0003
11	0.3269	0.7505	0.7517	0.0012	0.0009
12	0.3585	0.7465	0.7476	0.0011	0.0009
13	0.3873	0.7385	0.7402	0.0017	0.0016
14	0.4137	0.7280	0.7273	0.0007	0.0006
15	0.4373	0.7065	0.7066	0.0001	0.0005
16	0.4590	0.6755	0.6748	0.0007	0.0002
17	0.4784	0.6320	0.6304	0.0016	0.0011
18	0.4960	0.5730	0.5717	0.0013	0.0009
19	0.5119	0.4990	0.4994	0.0004	0.0005
20	0.5265	0.4130	0.4137	0.0007	0.0005
21	0.5398	0.3165	0.3176	0.0011	0.0007
22	0.5521	0.2120	0.2127	0.0007	0.0001
23	0.5633	0.1035	0.1033	0.0002	0.0008
24	0.5736	-0.0100	-0.0089	0.0011	0.0008
25	0.5833	-0.1230	-0.1244	0.0014	0.0014
26	0.5900	-0.2100	-0.2095	0.0005	0.0009
MAE				0.0007	0.0007
RMSE				0.0010	0.0010

TABLE 4: Parameters of the KC200GT PV module obtained by the CS algorithm.

(a) SDM parameters (extracted by the CS algorithm)						
I_{pv}	I_o	n	R_s	R_p		
8.1729	4.23E-10	1.0090	0.2665	140.4875		
(b) ISDM parameters (extracted by the CS algorithm)						
I_{pvn}	I_{on}	n	R_{sn}	R_{pn}	K_i	E_{gn}
8.1847	5.12E-10	1.0170	0.2574	117.9224	0.0028	1.2474

SDM is calculated as 0.2837, while the RMSE of I in ISDM is only 0.0776.

Figure 4 shows the absolute current errors of different performance predicting methods under different operating conditions. The curves denoted by the label ‘‘analytical SDM’’ are obtained from the analytical SDM model [4]. Ignoring the effect of incidence angle and air mass, the curves labeled by ‘‘analytical ISDM’’ denote the I - V curves from De Soto’s

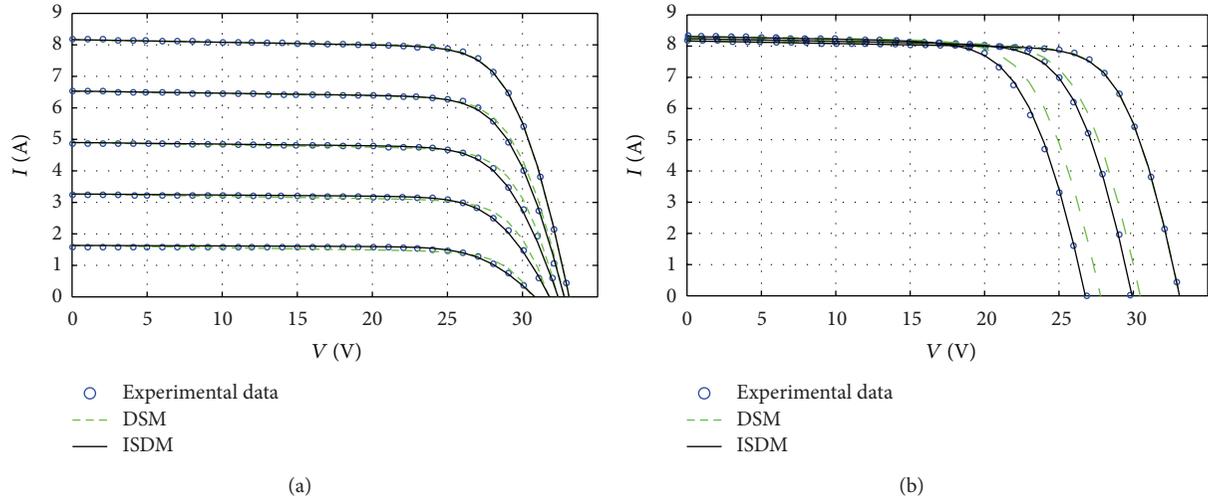


FIGURE 3: The simulated I - V characteristic curves of the KC200GT PV module: (a) under different irradiance levels; (b) under different temperature levels.

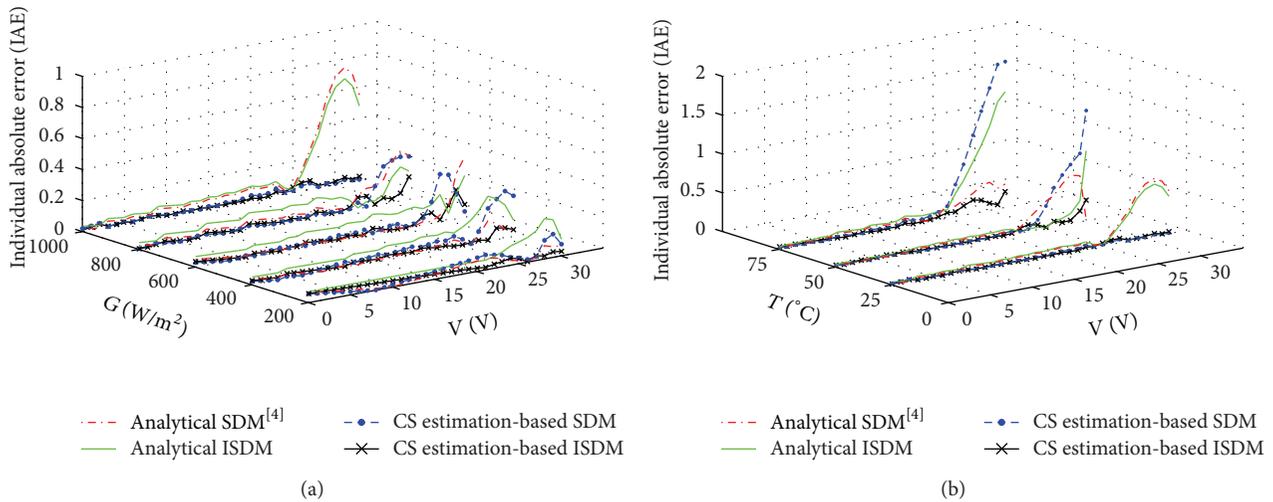


FIGURE 4: A comparison of the individual absolute errors among different PV modeling methods: (a) under different irradiance levels; (b) under different temperature levels.

analytical ISDM model [5]. It is evident the ISDM with the parameters extracted by the CS algorithm is more accurate than the analytical model. As for the SDM, the CS algorithm is capable of extracting a set of PV parameters with a good fit for the experimental data at the STCs. However, the SDM with the equations in the appendix does not exhibit a good prediction performance under other operating conditions.

To further validate the accuracy of the CS algorithm, the extracted parameters are compared to the ones obtained using GA in Figure 5. In general, the CS algorithm gives the better performance than GA for all cases. The Maximum Power Point (MPP), usually locating around 74% of the open circuit voltage, is an important technical data in PV modeling. However, a negative point of the GA-based ISDM is that the errors in the high voltage range are relatively high.

The maximum absolute error of the GA-based ISDM is up to about 0.8 A, while the absolute error of the CS is kept below 0.2 A.

5. Conclusion

In this work, the Cuckoo Search (CS) algorithm is applied to estimate the parameters of two PV models, namely, Single Diode Model (SDM) and its improved version (ISDM). The feasibility of the proposed method has been validated by estimating the parameters of two commercial PV generators. The simulation and experimental results showed that the CS algorithm is capable of not only extracting all the parameters of the SDM under a certain condition but also successfully

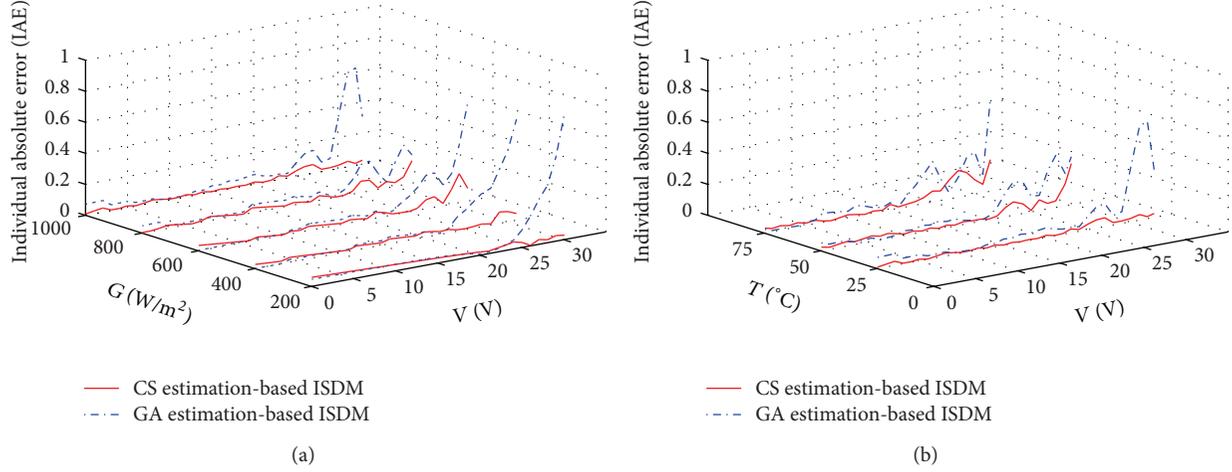


FIGURE 5: A comparison of the individual absolute errors between CS- and GA- based ISDM: (a) under different irradiance levels; (b) under different temperature levels.

estimating all the parameters of ISDM under different operating conditions. In statistical analysis, CS algorithm recorded the lowest RMSE value compared to other algorithms such as GA, PSO and PS.

Appendix

PV Physical Model Adopted in PSIM

By using the parameters extracted at the STCs, the I - V characteristics of a PV generator under nonstandard operating conditions can be calculated via the following equations:

$$\begin{aligned}
 I &= I_{pv} - I_d - I_R, \\
 I_{pv} &= I_{scn} \cdot \frac{G}{G_n} - K_i \cdot (T - T_n), \\
 I_d &= I_o \cdot \left(e^{qV_d/nkT} - 1 \right), \\
 I_o &= I_{cn} \cdot \left(\frac{G}{G_n} \right)^3 \cdot e^{(qE_g/nk) \cdot (1/T - 1/T_n)}, \\
 I_R &= \frac{V_d}{R_p}, \\
 V_d &= \frac{V}{N_s} + I \cdot R_s.
 \end{aligned} \tag{A.1}$$

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