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Simulated Annealing algorithm for photovoltaic parameters identification

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Abstract

A Simulated Annealing based approach is proposed in this paper for optimal estimation of solar cell model parameters. Different solar cell models, namely single diode, double diode, and photovoltaic module, are used in this study to verify the proposed approach outcomes. The developed technique is used to solve a transcendental function that governs the current–voltage relationship of a solar cell, as no direct general analytical solution exists. Several cases were investigated to test and validate the consistency of accurately estimating various parameters of different solar cell models. Comparative study among different parameter estimation techniques is presented to show the effectiveness of the developed approach. Furthermore, statistical analyses are carried out to measure the accuracy of the estimated parameters and model suitability.

Keywords: Photovoltaic; Solar cell; Simulated Annealing; Parameter estimation

1. Introduction

Emerging involvement of environmental friendly energy sources in producing electricity is being sought by many nations due to possible depletion and price increase of fossil based fuels, global warming, air pollution, and strict environmental laws. Solar energy is one of the most promising renewable sources that is currently being used worldwide to contribute to meeting rising demands of electric power. It has been reported that solar photovoltaic (PV) is the fastest growing power-generation technology in the world, with an annual average increase of 60% between 2004 and 2009 (Global Status Report, 2010). PV is not only capable of directly converting solar energy to electricity, but also is an emission-free distributed generation unit that would supply power at the load site.

PV systems comprise different parts centered around a solar panel that typically has arrays of interconnected solar cells. Several models have been proposed to describe the current–voltage relationship (*I*–*V*) in solar cells (Xiao et al., 2006; Chegaar et al., 2003; Ye et al., 2009). The *I*–*V* curve of a solar cell exhibits non-linear characteristics determined by the solar cell parameters that describe its model. To gain better understanding of the solar cell physics, a lumped parameter equivalent circuit model is commonly used to simulate its behavior under different operating conditions. In practice, there are two main equivalent circuit models used to describe the non-linear *I*–*V* relationship: single and double diode models. The key parameters that describe solar cell models behavior are the generated photocurrent, saturation current, series resistance, shunt resistance, and ideality factor. Accurate estimation of these parameters is always required to provide precise modeling and accurate performance evaluation of a given solar system.

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Various techniques have been reported to approximate different parameters of solar cells. Reference Easwarakhanthan et al. (1986) proposed a modified non-linear least error squares estimation approach based on Newton's method to calculate solar cell parameters. A major drawback of this approach is its dependency on the initial values used in the proposed iterative technique. In addition, this type of optimization method is local in nature and may reach a local solution rather than a global one if multiple solutions exist. A new analytical solution technique, using the so called "Co-content function" which is based on Lambert function, has been proposed in reference Ortiz-Conde et al. (2006) to extract the solar cell parameters. A comparative study of three different methods, namely curve-fitting method, iterative 5-point method, and analytical 5-point method, for extracting solar cell parameters is presented in reference Chan et al. (1986). Similar analytical solution methods are presented in references Jain and Kapoor (2004), Chan and Phang (1987), Saleem and Karmalkar (2009). However, these techniques, that necessitate certain modeling conditions to make it applicable such as continuity, convexity and differentiability, involve heavy computations, tedious algebraic manipulation, and finally curve fitting. The Genetic Algorithm (GA) based approach is introduced as a new evolutionary tool for extracting the solar cell parameters in reference Jervase et al. (2001). Shortcomings of reported results are the relatively high percentage of errors associated with the extracted parameters and the binary conversion pertaining to GA implementation. Particle swarm optimization (PSO) is introduced in references Ye et al. (2009), Munji et al. (2010) as a different population based optimizer for solar cell parameters extraction. A comparative study illustrated that PSO outperformed GA in extracting more accurate parameters of solar cells. Reference proposes a robust Pattern Search (PS) technique for extracting the solar cell parameters as it introduces a new objective to this estimation problem.

This paper presents a Simulated Annealing (SA) based approach for estimating solar cell parameters. Section 2 discusses the solar cell modeling and mathematical formulation of the estimation problem along with the proposed approach. Section 3 presents testing and simulation results. The paper is then concluded in Section 4.

2. Modeling and estimation by Simulated Annealing

Before proceeding to the estimation phase, it is essential to have a mathematical model that accurately represents the electrical characteristics of the solar cell and the PV module. Despite the fact that many equivalent circuit models have been developed and proposed over the past four decades to describe the solar cell's behavior, only two models are used practically. In this section the two common models are briefly presented.

2.1. Double diode model

The solar cell is ideally modeled as a current source connected in parallel with a rectifying diode. However, in practice the current source is also shunted by another diode that models the space charge recombination current and a shunt leakage resistor to account for the partial short circuit current path near the cell's edges due to the semiconductor impurities and non-idealities. In addition, the solar cell metal contacts and the semiconductor material bulk resistance are represented by a resistor connected in series with the cell shunt elements (Wolf et al., 1977). The equivalent circuit for this model is shown in Fig. 1.

In this double-diode model, the cell terminal current is calculated as follows:

$$I_L = I_{ph} - I_{D1} - I_{D2} - I_{sh} \tag{1}$$

where, I_L is the terminal current, I_{ph} the cell-generated photocurrent, I_{D1}, I_{D2} is the first and second diode currents, I_{sh} is the shunt resistor current.

The two diodes currents are expressed by Shockley equation as illustrated respectively in Eqs (2) and (3), while the leakage resistor current I_{sh} is formulated as shown in Eq. (4):

$$I_{D1} = I_{SD1}\left[\exp\left(\frac{q(V_L + I_L R_s)}{n_1 kT}\right) - 1\right] \tag{2}$$

$$I_{D2} = I_{SD2}\left[\exp\left(\frac{q(V_L + I_L R_s)}{n_2 kT}\right) - 1\right] \tag{3}$$

$$I_{sh} = \frac{V_L + I_L R_s}{R_{sh}} \tag{4}$$

where R_s and R_{sh} are the series and shunt resistances respectively; I_{SD1} and I_{SD2} are the diffusion and saturation currents respectively; V_L is the terminal voltage; n_1 and n_2 are the diffusion and recombination diode ideality factors; k is Boltzmann's constant; q is the electronic charge and T is the cell absolute temperature in Kelvin. Substituting Eqs. (2)–(4) into Eq. (1), the cell terminal current is now rewritten as shown in the following equation:

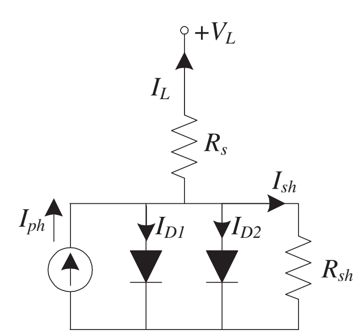

Fig. 1. Equivalent circuit of a double diode model.

$$I_L = I_{ph} - I_{SD1}\left[\exp\left(\frac{q(V_L + I_L R_s)}{n_1 kT}\right) - 1\right] - I_{SD2}\left[\exp\left(\frac{q(V_L + I_L R_s)}{n_2 kT}\right) - 1\right] - \left[\frac{(V_L + I_L R_s)}{R_{sh}}\right] \tag{5}$$

Given a measured set of I–V data for the solar cell, it is clear that for such a model there are seven parameters to be estimated, namely: R_s, R_{sh}, I_{ph}, I_{SD1}, I_{SD2}, n_1, and n_2.

2.2. Single diode model

Even though the diffusion and recombination currents are linearly independent, both currents are often combined together under the introduction of a non-physical diode ideality factor n. This concept is also known as single diode model. Recently, the use of this model to describe the static I–V characteristic has been considered widely, and it has been used successfully to fit experimental data. The single diode model equivalent circuit is shown in Fig. 2.

In this model, Eq. (5) is reduced to the following equation:

$$I_L = I_{ph} - I_{SD}\left[\exp\left(\frac{q(V_L + I_L R_s)}{nkT}\right) - 1\right] - \left[\frac{V_L + I_L R_s}{R_{sh}}\right] \tag{6}$$

Consequently, the parameters to be estimated are R_s, R_{sh}, I_{ph}, I_{SD} and n.

2.3. PV module model

The PV module comprises of series and parallel solar cell combinations; that is, series strings are connected in parallel with each other. A blocking diode is connected in series with each PV string to prevent excess current produced by other strings from flowing back in the string should a string fail. In series strings, a bypass diode is connected across individual PV cell, or number cells, to divert the power output flow or the current through the shunt diode in case one or more of the string's cells failed or are shaded. A typical model configuration of a PV module (using single diode model) is shown in Fig. 3, and the terminal equation that relates the currents and voltages of a PV module arranged in N_P parallel strings and N_S series cells is mathematically expressed as in the following equation:

$$I_L = I_{ph}N_p - I_{SD}N_p\left[\exp\left(\frac{q\frac{V_L}{N_s} + I_L\frac{R_s}{N_p}}{nkT}\right) - 1\right] - \left[\frac{\frac{V_L N_p}{N_s} + I_L R_s}{R_{sh}}\right] \tag{7}$$

2.4. Problem formulation

It is noted that Eqs. (5)–(7) are implicit nonlinear transcendental functions that involve the overall output current produced by the PV cell in both sides of the equation. Furthermore, the parameters R_s, R_{sh}, I_{ph}, I_{SD} and n vary with temperature, irradiance and depend on manufacturing tolerance. Such functions have no explicit analytical solutions for either I_L or V_L. Instead, numerical methods, curve fitting techniques, and optimization methods are often utilized to solve such functions. In this paper the estimation problem is formulated as a nonlinear optimization one. The SA optimization technique is employed to estimate the parameters by minimizing a pre-selected objective function.

2.5. Objective function

Before proceeding to the optimization stage, a performance criterion or an objective function should be first defined. In this work, the proposed objective function to be minimized the summation of the individual absolute errors (IAE). In order to form the objective function, the

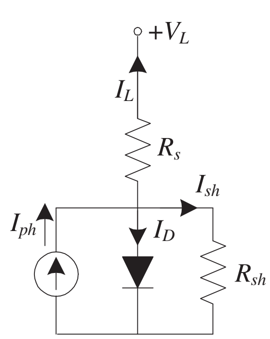

Fig. 2. Equivalent circuit of a single diode model.

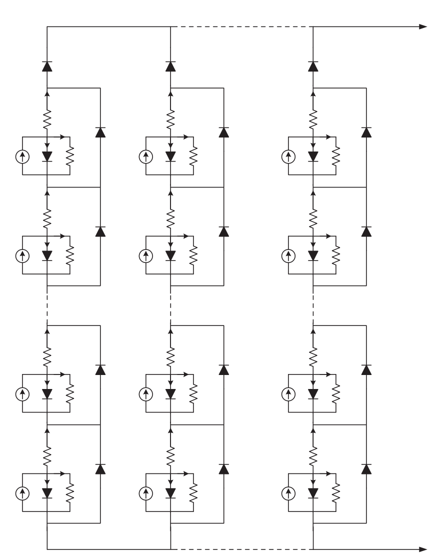

Fig. 3. Equivalent circuit model of a PV module.

I–V relationships given in any of Eqs. (5)–(7) are rewritten in the following homogeneous equations:

$f_i(V_L, I_L, I_{ph}, I_{SD1}, I_{SD2}, R_s, R_{sh}, n_1, n_2) = 0$ for the double diode model
$f_i(V_L, I_L, I_{ph}, I_{SD}, R_s, R_{sh}, n) = 0$ for the single diode model

In general we can write

$$f_i(V_L I_L, x) = 0 \tag{8}$$

where x is the parameters vector to be estimated (5 or 7 based on the selected model). The new objective function that sums IAEs for any given set of measurements is defined as:

$$F = \sum_{i=1}^{N} |f_i(V_{Li}, I_{Li}, R_s, R_{sh}, \ldots)| \tag{9}$$

or

$$F = \sum_{i=1}^{N} |f_i(V_{Li}, I_{Li}, x)| = 0 \tag{10}$$

where N is the number of data points, I_{Li} and V_{Li} are ith measured current and voltage pair values, respectively.

During the SA optimization process, the objective function is to be minimized with respect to the parameter set. Theoretically, the objective function should have zero value when the parameters' exact values are obtained. In other words, the objective function should be zero for any experimental set of I–V data when the exact value has been determined for each parameter. However, it is expected to obtain a very small non zero value due to the presence of measuring noise errors. Moreover the smaller the objective function, the better the solution obtained.

2.6. Parameter estimation by Simulated Annealing

SA emulates the physical gradual cooling process (called annealing) that produces high quality crystals, i.e. better strength properties, in metals. The two major steps in SA are the transition mechanism between states and the cooling schedule with the objective being finding the state with minimum energy. Forming a perfect crystal is simply done by properly controlling temperature in the annealing process. In SA, a new solution candidate is randomly generated at each iteration. A probability distribution with a scale proportional to the control parameter, i.e. temperature, governs the distance of the new solution candidate from the existing solution. Measure of solutions' goodness is made by computing and comparing the objective function values. The temperature parameter decreases based on a cooling schedule as the algorithm converges to the optimal solution.

This optimization technique was proposed independently by Kirkpatrick et al(1983) and by Cerny(1985). They have noted that alternative physical states of the matter resemble the solution space of an optimization problem and the objective function of an optimization problem corresponds to the free energy of the material. Forming a perfect crystal corresponds to finding the optimal solution whereas a crystal with defects corresponds to finding a local solution. In both papers, SA was introduced to solve combinatorial problems by adapting the crystallization process model developed by Lee and El-Sharkawi (2008), Metropolis et al. (1953). This model generates a sequence of states of a solid and assumes that the probability for a physical system to have a certain energy level E is proportional to Boltzmann factor $e^{\frac{-E}{k_B^* T}}$, where k_B denotes the Boltzmann constant, when the thermodynamic equilibrium is reached at a given temperature T. Assuming a solid in initial state x_i with energy level E_i and the next state x_j with energy E_j, if the difference between the two energy levels is less than or equal to zero, the new state x_j is accepted. Otherwise, if the difference is greater than zero, the new state is accepted with probability:

$$P(E, T) = e^{\left(\frac{E_i - E_j}{k_B^* T}\right)} \tag{11}$$

The general proposed SA estimator used in this work can be summarized as follows:

Step 0: Initialize the temperature, T_{initial}.
Step 1: Generate some initial random solution, x_i (at step i).
Step 2: Evaluate the objective function, F_i (in our case $F_i = E_i$).
Step 3: After certain amount of iterations, the temperature is reduced. If the temperature criterion is satisfied go to step 10

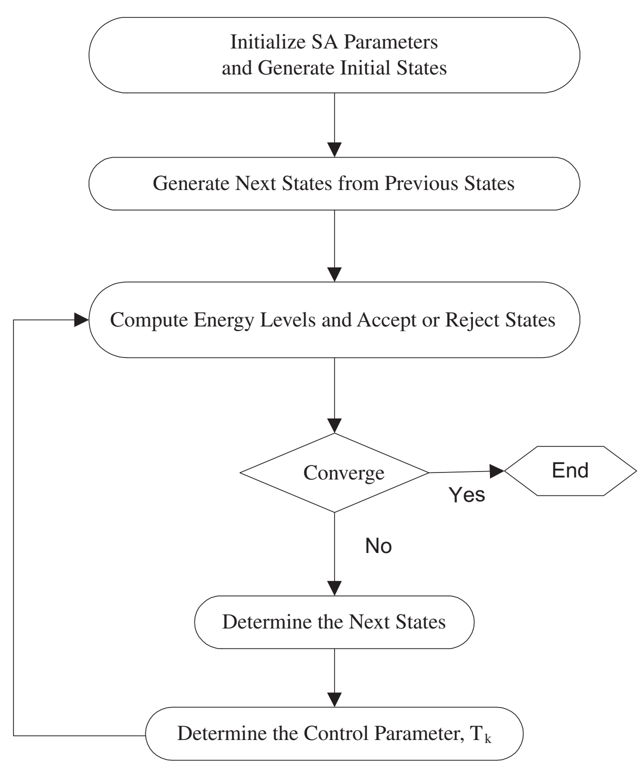

Fig. 4. Flow chart of SA algorithm.

Step 4: If the iteration is satisfied go to step 9.
Step 5: Generate a new solution, x_j.
Step 6: Evaluate the objective function E_i.
Step 7: Acceptance test: if $E_j–E_i < 0$, then store the new solution. Otherwise, accept the new solution with a probability, $P(E,T)$.
Step 8: If the objective function remains the same consecutive times, go to step 9 else go to step 4.
Step 9: Reduce the temperature and go to step 3.
Step 10: Stop if termination criterion is met.

Fig. 4 simply summarizes these steps.

3. Simulation results

The proposed SA technique is used in this section to estimate the solar cell model parameters. Real measured I–V data of solar cell and solar module are considered in this testing. A 57 mm diameter commercial silicon solar cell as well as a solar module in which 36 polycrystalline silicon cells are connected in series are taken from reference (AlRashidi et al., 2011). Table 1 shows the experimental data obtained for a silicon solar cell and a module at 33°C and 45°C, respectively.

Table 1
Experimental recorded data.

Measurement	Solar cell		Solar module	
	V_a (V)	I_a (A)	V_a (V)	I_a (A)
1	−0.2057	0.7640	−1.9426	1.0345
2	−0.1291	0.7620	0.1248	1.0315
3	−0.0588	0.7605	1.8093	1.0300
4	0.0057	0.7605	3.3511	1.0260
5	0.0646	0.7600	4.7622	1.0220
6	0.1185	0.7590	6.0538	1.0180
7	0.1678	0.7570	7.2364	1.0155
8	0.2132	0.7570	8.3189	1.0140
9	0.2545	0.7555	9.3097	1.0100
10	0.2924	0.7540	10.2163	1.0035
11	0.3269	0.7505	11.0449	0.9880
12	0.3585	0.7465	11.8018	0.9630
13	0.3873	0.7385	12.4929	0.9255
14	0.4137	0.7280	13.1231	0.8725
15	0.4373	0.7065	13.6983	0.8075
16	0.4590	0.6755	14.2221	0.7265
17	0.4784	0.6320	14.6995	0.6345
18	0.4960	0.5730	15.1346	0.5345
19	0.5119	0.4990	15.5311	0.4275
20	0.5265	0.4130	15.8929	0.3185
21	0.5398	0.3165	16.2229	0.2085
22	0.5521	0.2120	16.5241	0.1010
23	0.5633	0.1035	16.7987	−0.0080
24	0.5736	−0.0100	17.0499	−0.1110
25	0.5833	−0.1230	17.2793	−0.2090
26	0.5900	−0.2100	17.4885	−0.3030

It is assumed that the estimation results are not affected by irradiance levels. In Section 3.1, voltage and current measurements taken using the 57 mm diameter commercial (RTC France) silicon solar cell under 1 sun (1000 W/m^2) at 33 °C. In Section 3.2, voltage and current measurements were taken using a solar module (Photowatt-PWP 201) in which 36 polycrystalline silicon cells are connected in series under 1 sun (1000 W/m^2) at 45 °C.

It is worthwhile to mention that lowering the irradiance levels will not affect the estimation results in general. However, reducing it below 0.25 sun will shrink the unsaturated region of the I–V curve, which results into gathering many data points in the saturation region. From estimation point of view, this will lead to bad estimation results. It is assumed that all solar cells in one module are identical and operating under same environmental conditions.

3.1. Case study 1: Solar cell (single and double diode models)

In this case, solar cell data given in Table 1 is employed to extract the cell parameters using the single and double diode models. The extracted parameters for the single diode model are shown in Table 2 along with the root mean squared error (RMSE) while Table 3 shows the double diode parameters. Based on the extracted parameters, the I–V data set is reconstructed. This is simply done by back

Table 3
Estimated parameters for the double diode model.

Parameter	SA
I_{ph}	0.7623
I_{SD1} (μA)	0.4767
R_s (Ω)	0.0345
G_{sh} (S)	0.0232
n_1	1.5172
I_{SD2} (μA)	0.0100
n_2	2.0000

Table 2
Estimated parameters for the single diode model.

Case	Item	Reference Easwarakhanthan et al. (1986)	Reference AlRashidi et al. (2011)	Reference Bouzidi et al. (2007)	SA
Solar cell (single diode)	I_{ph}	0.7617	0.7608	0.7607	0.7620
	I_{SD} (μA)	0.9980	0.3223	0.3267	0.4798
	R_s (Ω)	0.0313	0.0364	0.0364	0.0345
	G_{sh} (S)	0.0156	0.0186	0.0166	0.0232
	n	1.6000	1.4837	1.4816	1.5172
	RMSE	0.2863	0.6251	0.3161	0.0017

Table 4
IAEs based on the extracted parameters (single diode model).

Measurement	V_a (V)	I_a (A)	IAE based on reference Easwarakhanthan et al. (1986)	IAE based on reference AlRashidi et al. (2011)	IAE based on reference Bouzidi et al. (2007)	IAE based on SA
1	−0.2057	0.7640	0.00054	0.00011	0.00035	0.00098
2	−0.1291	0.7620	0.00134	0.00069	0.00038	0.00171
3	−0.0588	0.7605	0.00175	0.00088	0.00072	0.00204
4	0.0057	0.7605	0.00074	0.00032	0.00035	0.00097
5	0.0646	0.7600	0.00031	0.00092	0.00083	0.00049
6	0.1185	0.7590	0.00045	0.00093	0.00074	0.00058
7	0.1678	0.7570	0.00162	0.00012	0.00041	0.00172
8	0.2132	0.7570	0.00074	0.00083	0.00045	0.00084
9	0.2545	0.7555	0.00115	0.00037	0.00008	0.00132
10	0.2924	0.7540	0.00103	0.00026	0.00025	0.00138
11	0.3269	0.7505	0.00182	0.00104	0.00158	0.00250
12	0.3585	0.7465	0.00100	0.00118	0.00169	0.00225
13	0.3873	0.7385	0.00063	0.00231	0.00268	0.00266
14	0.4137	0.7280	0.00304	0.00078	0.00084	0.00005
15	0.4373	0.7065	0.00341	0.00307	0.00258	0.00055
16	0.4590	0.6755	0.00522	0.00433	0.00293	0.00056
17	0.4784	0.6320	0.00658	0.00617	0.00343	0.00177
18	0.4960	0.5730	0.00575	0.01024	0.00568	0.00148
19	0.5119	0.4990	0.00248	0.01685	0.00999	0.00055
20	0.5265	0.4130	0.00011	0.02287	0.01326	0.00111
21	0.5398	0.3165	0.00269	0.03006	0.01732	0.00191
22	0.5521	0.2120	0.00391	0.03681	0.02060	0.00123
23	0.5633	0.1035	0.00359	0.04344	0.02359	0.00050
24	0.5736	−0.0100	0.00542	0.05419	0.03064	0.00094
25	0.5833	−0.1230	0.00033	0.05915	0.03167	0.00453
26	0.5900	−0.2100	0.00034	0.06944	0.03917	0.00250
Total IAE			0.05599	0.36735	0.21222	0.03712

Table 5
IAEs based on the extracted parameters (double diode model).

Measurement	V_a (V)	I_a (A)	IAE based on SA
1	−0.2057	0.764	0.00248
2	−0.1291	0.762	0.00271
3	−0.0588	0.7605	0.00258
4	0.0057	0.7605	0.00108
5	0.0646	0.76	0.00021
6	0.1185	0.759	0.00005
7	0.1678	0.757	0.00076
8	0.2132	0.757	0.00041
9	0.2545	0.7555	0.00020
10	0.2924	0.754	0.00039
11	0.3269	0.7505	0.00051
12	0.3585	0.7465	0.00006
13	0.3873	0.7385	0.00032
14	0.4137	0.728	0.00249
15	0.4373	0.7065	0.00194
16	0.459	0.6755	0.00301
17	0.4784	0.632	0.00408
18	0.496	0.573	0.00358
19	0.5119	0.499	0.00122
20	0.5265	0.413	0.00026
21	0.5398	0.3165	0.00103
22	0.5521	0.212	0.00088
23	0.5633	0.1035	0.00025
24	0.5736	−0.01	0.00180
25	0.5833	−0.123	0.00303
26	0.59	−0.21	0.00053
Total IAE			0.03587

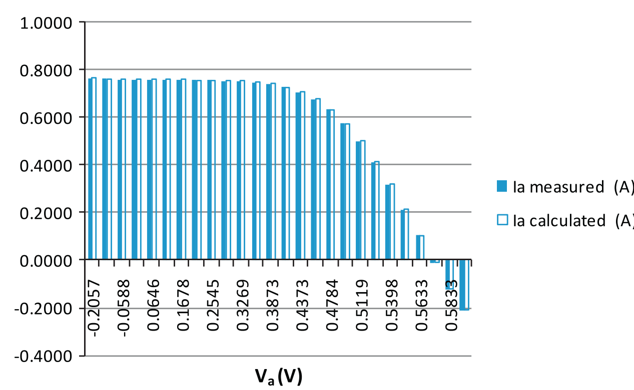

Fig. 5. I–V characteristics for the solar cell (single diode model).

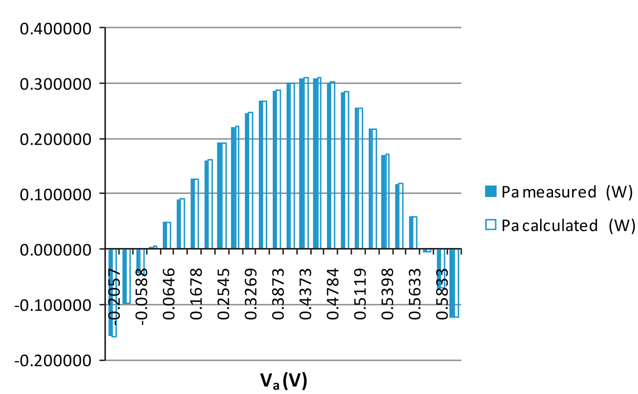

Fig. 6. P–V characteristics for the solar cell (single diode model).

substitution in Eqs. (5) and (6) with I_a is considered as unknown while V_a is known. The current is then calculated using Newton method. The resultant IAE for each data point is shown in Tables 4 and 5 for the single and double models respectively. The obtained IAE values for the single diode model are compared with those obtained using three other techniques (Easwarakhanthan et al., 1986; AlRashidi et al., 2011; Bouzidi et al., 2007).

Table 4 shows that, the summation of the IAE obtained using the parameters estimated via SA technique is 0.03712. A reduction in IAE summation is clear when SA results are compared with other reported outcomes which are 0.055993, 0.367349 and 0.212223 respectively. Moreover, comparison between the summations of IAE for the single and double models, using SA, shown in Tables 4 and 5 clearly indicates that the double diode model is slightly more accurate than its counterpart. A difference of 0.02% is noted between the two models which implies the suitability and accuracy of the single diode model. Figs. 5 and 6 show the I–V and P–V characteristics based on the extracted parameters for the solar cell (single diode model).

3.2. Case study 2: PV module (single diode model)

In this case, PV module data from Table 1 is used to extract the PV model parameters given in Eq. (7). Based on the insignificant difference in model accuracy between the single and double diode models illustrated in the previous case study, only single diode model is used in this case.

The extracted parameters for the PV module are shown in Table 6 along with comparable results reported from previous studies. Similar curve fitting procedure, as in case study 1, is done and the IAE for each measurement is calculated and presented in Table 7. Examining Table 7 reveals that similar pattern is noted. Comparing SA outcomes with other reported results, SA algorithm clearly outperformed other competing methods in terms of IAEs summation. The I–V and P–V characteristics for the PV module based on the extracted parameters are shown in Figs. 7 and 8.

Table 6
Parameters extraction for the PV module.

Case	Item	Reference Easwarakhanthan et al. (1986)	Reference AlRashidi et al. (2011)	Reference Bouzidi et al. (2007)	SA
PV module	I_{ph}	1.0313	1.0318	1.0339	1.0331
	I_{SD} (μA)	3.1756	3.2875	3.0760	3.6642
	R_s (Ω)	1.2053	1.2057	1.2030	1.1989
	G_{sh} (S)	0.0014	0.0018	0.0018	0.0012
	n	48.2889	48.4500	48.1862	48.8211
	RMSE	0.0118	0.7805	0.6130	0.0027

Table 7
IAEs based on the Extracted Parameters (PV Module).

Measurement	V_a (V)	I_a (A)	IAE based on reference Easwarakhanthan et al. (1986)	IAE based on reference AlRashidi et al. (2011)	IAE based on reference Bouzidi et al. (2007)	IAE based onSA
1	0.1248	1.0315	0.00213	0.00220	0.00008	0.00006
2	1.8093	1.0300	0.00303	0.00378	0.00165	0.00064
3	3.3511	1.0260	0.00127	0.00265	0.00050	0.00141
4	4.7622	1.0220	0.00056	0.00141	0.00077	0.00349
5	6.0538	1.0180	0.00226	0.00024	0.00197	0.00541
6	7.2364	1.0155	0.00199	0.00101	0.00124	0.00529
7	8.3189	1.0140	0.00042	0.00388	0.00155	0.00296
8	9.3097	1.0100	0.00253	0.00642	0.00399	0.00083
9	10.2163	1.0035	0.00602	0.01032	0.00772	0.00282
10	11.0449	0.9880	0.00660	0.01126	0.00844	0.00370
11	11.8018	0.9630	0.00650	0.01145	0.00837	0.00403
12	12.4929	0.9255	0.00544	0.01059	0.00722	0.00350
13	13.1231	0.8725	0.00235	0.00756	0.00393	0.00100
14	13.6983	0.8075	0.00231	0.00742	0.00360	0.00152
15	14.2221	0.7265	0.00012	0.00471	0.00082	0.00044
16	14.6995	0.6345	0.00125	0.00309	0.00068	0.00122
17	15.1346	0.5345	0.00062	0.00307	0.00040	0.00036
18	15.5311	0.4275	0.00115	0.00173	0.00126	0.00080
19	15.8929	0.3185	0.00039	0.00234	0.00001	0.00074
20	16.2229	0.2085	0.00161	0.00255	0.00103	0.00189
21	16.5241	0.1010	0.00521	0.00505	0.00448	0.00534
22	16.7987	−0.0080	0.00056	0.00067	0.00023	0.00059
23	17.0499	−0.1110	0.00005	0.00228	0.00075	0.00006
24	17.2793	−0.2090	0.00024	0.00319	0.00052	0.00000
25	17.4885	−0.3030	0.00227	0.00675	0.00296	0.00262
Total IAE			0.05688	0.11561	0.06418	0.05071

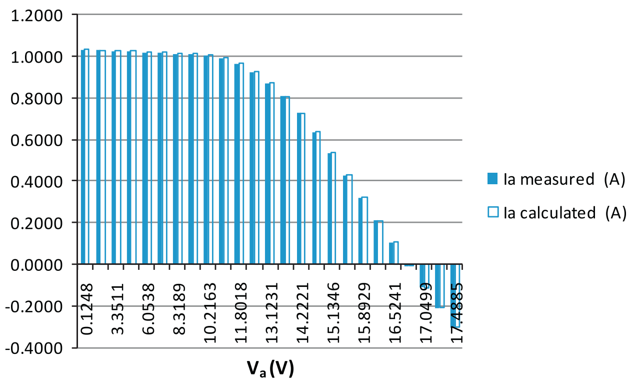

Fig. 7. *I–V* characteristics for the PV module.

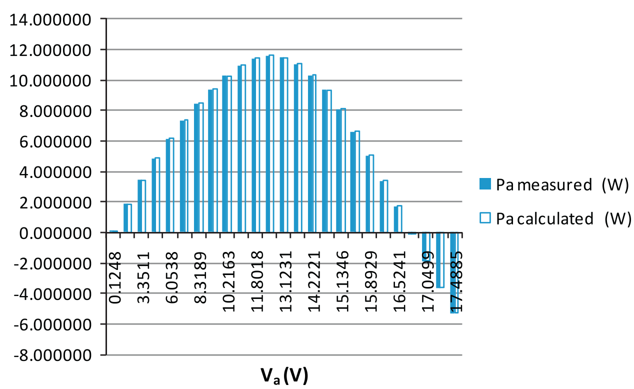

Fig. 8. *P–V* characteristics for the PV module.

3.3. Statistical analysis

In order to test the quality of the fit to the experimental data, statistical analysis of the results is performed. The RMSE and the mean absolute error (MAE) are the fundamental measures of accuracy. The resultant residuals are also subjected to a whiteness test.

The RMSE and MAE are given by:

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(e_i)^2} \tag{12}$$

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|e_i| \tag{13}$$

where, e is the relative error, i.e. $e = \frac{(I_{measured} - I_{calculated})}{I_{measured}}$, N is the number of measurements.

The computed values of the statistical factors show high accuracy in both cases as tabulated in Table 8.

When compared to references' values, RMSE and MAE computed from SA results are much lower than the corresponding reference' values as shown in Table 8. In addition, the proposed method reduces the overall estimation error (in an absolute sense) at a very low standard deviation.

3.3.1. Whiteness test

The objective of the whiteness test is to ensure that a selected model adequately describes a given set of data. The whiteness test can be achieved by the following two steps:

1. Examination of the estimated residual graph (exploratory analysis); and

2. Calculation of the residual autocorrelation function (RACF) at different time lags (confirmatory analysis).

The RACF can be calculated as:

$$RACF_k = \frac{\sum_{t=k+1}^{N}\varepsilon_t\varepsilon_{t-k}}{\sum_{t=1}^{N}\varepsilon_t^2} \tag{14}$$

where, k: is the time lag, ε_t is the estimated residual at time t calculated as $\varepsilon_t = (I_{\text{measured}} - I_{\text{calculated}})$.

The RACF value ranges from −1 to +1. If a given value (other than the first one) is significantly different from zero, it will fall outside a confidence interval level. Whiteness test results shown in Figs. 9 and 10 confirm the higher quality of results obtained.

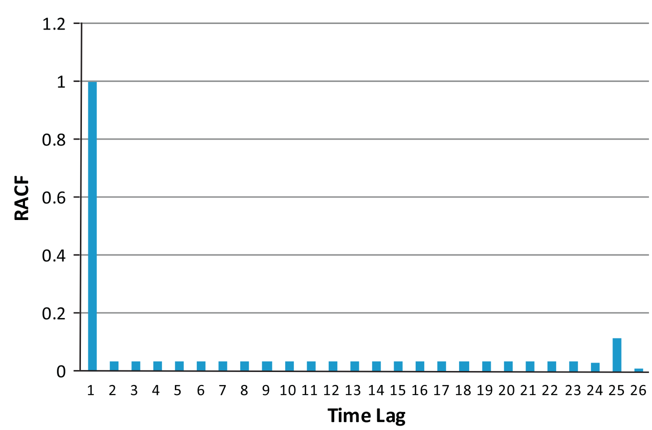

Fig. 9. Results of the whiteness test for the solar cell case.

Table 8
Statistical factors for different case studies.

Method	Solar cell		PV module	
(Single diode)	RMSE	MAE	RMSE	MAE
Reference Easwarakhanthan et al. (1986)	0.00291	0.00215	0.00305	0.00228
Reference AlRashidi et al. (2011)	0.02561	0.01413	0.00572	0.00462
ReferenceBouzidi et al. (2007)	0.01429	0.00816	0.00370	0.00257
SA	0.00174	0.00143	0.00266	0.00203

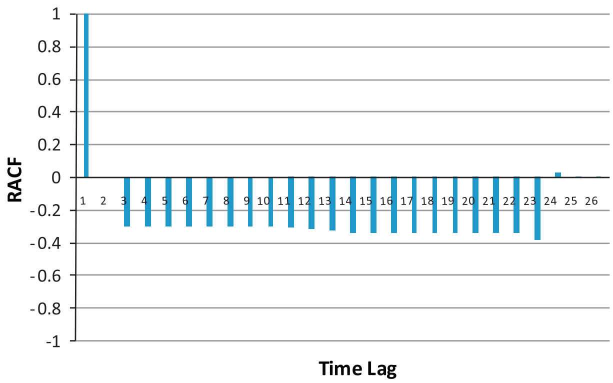

Fig. 10. Results of the whiteness test for the PV module case.

4. Conclusion

This paper presents a SA algorithm for estimating solar cell parameters. Different models, namely single diode, double diode, and photovoltaic module, are used to test the performance of the proposed approach in tackling this estimation problem. The solution framework is implemented and tested using actual recorded data. Outcomes obtained using SA algorithm, especially when compared to other competing methods, are quite promising and deserve serious attention. It sheds light on the SA potential as a valuable new tool for parameters estimation and system identification as it relieves system modeling from the regular oversimplifying assumptions such as continuity, convexity, and differentiability required by other traditional estimation techniques. In addition, obtained results are examined using error and statistical analyses to show their accuracy. In future work, impact of different operating conditions such as shading on solar cell modeling and parameters estimation will be investigated.

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